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Online fault detection for industrial processes through Kalman filter

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ABSTRACT

Industrial processes suffer from a wide range of damages including normal wear, environmental changes, physical structural defects and so on. This paper describes the possibility of system health management based on a prediction model, i.e., state space model realized by Kalman filter. The categorical target was mapped to numerical values in advance for this purpose. To deal with the time-varying and streaming characteristics of the industrial process, the model is applied in an online fashion. Comparing with conventional fault detection techniques, this model has the advantages of monitoring not only the production process of interests through observation equation, but also the structural anomalies described via unseen states estimation. In addition, the process and measurement noises provide valuable information about the unstructured uncertainties caused by other reasons. Experiments have been conducted to valid the effectiveness of the proposed method.

1. INTRODUCTION

Industrial facilities may incur damage over time as a result of prolonged use and the typical deterioration associated with regular operation. It is imperative to identify such damage at an early stage to mitigate further deterioration and avoid associated losses. The corresponding system health management is usually delivered by the data-driven models.

In this domain, the fault detection, or anomaly detection is usually formulated as the classification problem of multivariate time series. Typically, the data in this domain is commonly known as ”sensor data” as it is instrumented through various sensors utilized for process monitoring and subsequently collected for the purpose of analysis. These data provide valuable and relevant information related to the system health. Unlike detecting outliers for univariate time series and multivariate time series (Blázquez-García, Conde, Mori, & Lozano, 2021; Braei & Wagner, 2020), which focus on the data mining of the time series to get rid of unwanted and uninteresting data, such as noise, we aim to explore fault types that are related to physical failure and structural damages (Chandola, Banerjee, & Kumar, 2009).

In this context, each data instance is associated with a label that denoting the health state of the data as *normal* or *abnormal*, or other multiple fault types. These labels are usually obtained by domain experts, resulting in a significant amount of effort required to acquire the labeled training dataset. The process of classification involves training a model or classifier using a set of labeled data instances, and subsequently using the trained model to classify a new or test instance into one of the available classes.

One challenge of classification-based techniques is that the assigned label provides no other useful or meaningful information regarding the test instances. For example, some times the health condition for the data instance might be somewhere between completely abnormal and healthy, which makes an anomaly score a better and more reasonable choice. This can be realized by transforming the categorical labels to continuous values and then a regression model can be trained for prediction of the anomaly scores (Platt, 1999). This way, the human expert can be alarmed when early abnormal pattern is showing up but not to the point of completely abnormal yet and take the necessary precautions

Another challenge of fault detection for industrial processes is the normal behavior of the system keeps evolving and changing, as a result of the dynamical and nonstationary characteristics of the dynamical system (Kadlec, Grbić, & Gabrys, 2011). Therefore, a fixed model fail to capture this important feature can has difficulty being applied in real-world applications. One solution for this dynamic factor is to utilize dynamic models rather than static models. In this study, we take advantage of the state-space models (SSM) to represent the model evolve via state transition equation.

Traditionally, SSM have been used for a wide range of applications, such as controller design and observer selection for multiple input and multiple output systems (Zhang, Xue, & Gao, 2014), system identification(Favoreel, De Moor, &

Overschee, 2000), and data fusion of multi-rate sampled and delayed data (Fatehi & Huang, 2017), etc. This study discusses the possibility of taking advantage of SSM for online fault detection in industrial processes.

For state estimation and prediction, Kalman filter is applied (Meinhold & Singpurwalla, 1983; Bishop & Nasrabadi, 2006). Since it was proposed by Rudolf Kalman in 1960s, Kalman filter has been applied in numerous fields and various applications including but not limited to engineering, navigation, and economic research. The algorithm is simple, efficient but powerful, adopting a Bayesian approach to estimate the system state.

2. METHODOLOGY

First, we introduce the transformation of categorical target labels into continuous variable which work with a regression model. This can be done by setting up a mapping rule manually. For example, in the case of binary classes, i.e., normal and faulty conditions, they can be mapped into two distinctive values. In this study, we map them to 0 and 1, respectively. As shown in the figure, the normal status as well as the abnormal status are now represented by numerical values of 0 and 1, but they are not necessarily integers when it comes to prediction. A value between 0 and 1 suggests different severity of the system fault.

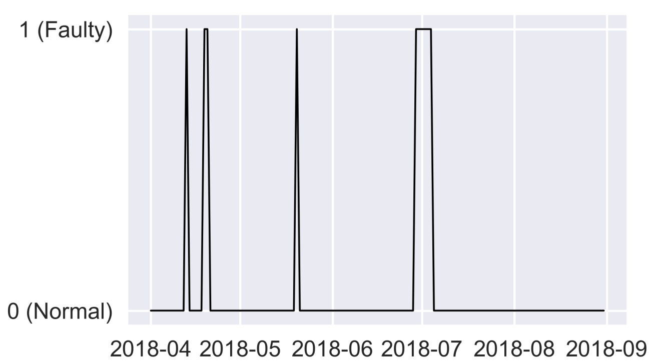

Figure 1. The mapping of the target labels.

2.1. Problem formulation

Next, the online fault detection is formulated under the framework of SSM. Assuming the unobserved $k \times 1$ state vector θ_n, the regression parameter, and the transformed labels y_n, the model can be written as follows:

$$\text{(state equation)} \qquad \boldsymbol{\theta}_n = \mathbf{A}\boldsymbol{\theta}_{n-1} + \boldsymbol{w}_n \quad (1)$$
$$\text{(Observation equation)} \qquad y_n = \boldsymbol{x}_n\boldsymbol{\theta}_n + v_n, \quad (2)$$

where $\mathbf{A}$ is the $k \times k$ transition matrix and $\boldsymbol{w}_n$ the additive Gaussian noise, with zero mean and covariance matrix $\mathbf{Q}$. $\boldsymbol{x}_n$ is the $1 \times k$ sensor data that relates the measurements to the state, and v_n is an error term distributed with mean zero and covariance matrix $\mathbf{R}$.

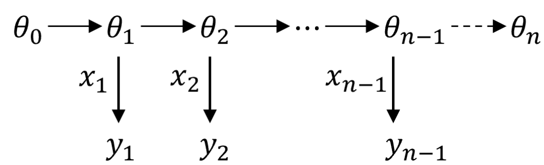

Figure 2. Illustration of dynamic system by SSM.

According to the above formulation, an illustration for this dynamic model is provided in Fig. 2. The system is initialized by the initial regression coefficient $\boldsymbol{\theta}_0$, and then passed on to the next states. For each of the estimated state $\boldsymbol{\theta}$, the system health can be obtained when the sensor data $\boldsymbol{x}$ is available. Compared to traditional model with a fixed model, the dynamic model allows the regression to vary with time. For the optimal estimate of the state, we apply Kalman filter for state estimation and prediction.

2.2. Kalman filter

Generally speaking, Kalman filter is a recursive procedure that fuses mixed sources of information. For soft sensor applications, we are particularly interested to find the optimal state estimate based on the prediction of the next latent state $\boldsymbol{\theta}_n^-$ and the actual corresponding observation y_n. Suppose the previous optimal state mean vector $\boldsymbol{\theta}_{n-1}^+$ and optimal estimated state covariance matrix $\mathbf{P}_{n-1}^+$ are known, then $\boldsymbol{\theta}_n^+$ and $\mathbf{P}_n^+$ will be updated by the following forward recursions of Kalman filter equations

$$\boldsymbol{\theta}_n^- = \mathbf{A}\boldsymbol{\theta}_{n-1}^+ \quad (3)$$
$$\boldsymbol{\theta}_n^+ = \boldsymbol{\theta}_n^- + \mathbf{K}_n(y_n - \boldsymbol{x}_n\boldsymbol{\theta}_n^-) \quad (4)$$
$$\mathbf{P}_n^- = \mathbf{A}\mathbf{P}_{n-1}^+\mathbf{A}^T + \mathbf{Q} \quad (5)$$
$$\mathbf{P}_n^+ = (\mathbf{I} - \mathbf{K}_n\boldsymbol{x}_n)\mathbf{P}_n^- \quad (6)$$
$$\mathbf{K}_n = \mathbf{P}_n^-\boldsymbol{x}_n^T(\boldsymbol{x}_n\mathbf{P}_n^-\boldsymbol{x}_n^T + \mathbf{R})^{-1}, \quad (7)$$

with initialization of $\boldsymbol{\theta}_0^-$ and $\mathbf{P}_0^-$. According to these equations, the update of the state variable $\boldsymbol{\theta}_n^+$ in (4) is done by take the prediction $\boldsymbol{\theta}_n^-$ and add a correction term, proportional to the prediction error $(y_n - \boldsymbol{x}_n\boldsymbol{\theta}_n^-)$. The weight of the latter is controlled by the Kalman gain $\mathbf{K}_n$, which is the ratio of the uncertainty of the prediction and the uncertainty of the new measurement. While the state covariance $\mathbf{P}_n^+$ is estimated in a similar way.

The recursive process determines the state estimate and prediction is done in an online manner, i.e., the system model will be adjusted as the new measurement comes in. This is an advantage for application in real-time environments.

3. Experiment results

3.1. Data set

To validate the proposed method, we used a open data set available in Kaggle datasets[1]. The data were collected in a small-scale centrifugal water pump in the USA during April 1st 2018 to August 31st 2018, and sampled minute-by-minute throughout the day. There are 52 sensors provided in total, likely to representing the motor frequency, motor speed, motor current, pump impeller speed, pump bearing temperature, pump inlet pressure, etc. Correspondingly, the system health was marked either as normal or failure. The objective is to predict the future machine status based on the sensor observations.

Some important preprocessing steps performed on this data set need to be clarified. First, the original data was downsampled to a daily frequency, which largely decreases the data size to more manageable level. Next, the sensors that contain missing values were removed from the feature set. After these two steps, the data set was composed by 153 observations of 44 features, among which the first 76 instances are utilized as the training data and the rest for testing. Furthermore, the categorical target variable was mapped to numerical values, as shown in the beginning of Sec.2. Finally, dimensionality reduction was performed by recursive feature elimination with cross validation (Granitto, Furlanello, Biasioli, & Gasperi, 2006), which resulted in selecting 8 features as the representation of the whole 44 sensors.

3.2. Evaluation metrics

Since we transform and formulated the fault detection problem as a regression model, the prediction error based evaluation metrics are utilized. Specifically, the root mean square error (RMSE) and mean absolute error (MAE) were calculated according to

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|. \tag{9}$$

In the formula, y_i denote the ground truth of the ith observation of machine status while $\hat{y}_i$ refers to the prediction made by the dynamic model.

3.3. Comparative experiments

In this section, the results of the comparative experiments are shown. First, the least square regression (OLS) is viewed as the base line. Then, the recursive least square approach (R-OLS) was compare as well, as there are some similarities between them. As for the Kalman filter, two types of prediction are considered. The first is off-line prediction (KF-offline), where the regression coefficient $\boldsymbol{\theta}_t = \boldsymbol{\theta}_n$ for all $t > n$, which means the future model parameter remains the same as the last time step estimate of the training data. While the other way is making predictions and updating the model online (KF-online) as the new measurement becomes available. This approach is consistent with the equations in (3) - (7) and will adjust the model taking in to the system change and is more accurate usually. Note that the initialization state vectors for Kalman filter is the OLS solution, the initial state covariance matrix a diagonal matrix with the diagonal elements equal to 0.0001, the transition matrix $\mathbf{A}$ identity matrix, the process noise covariance matrix also the same diagonal matrix, and measurement variance set as 0.005.

Evaluation	OLS	R-OLS	KF-offline	KF-online
RMSE	0.1811	0.1194	0.1781	0.0987
MAE	0.1099	0.0739	0.1055	0.0608

Table 1. Prediction errors of the comparative methods.

The prediction errors of 4 comparative methods are shown in Table 1. The two static models, the OLS and KF-offline had less desirable prediction performance than the other two dynamic models, and among which Kalman filter offline had lower prediction error than OLS. On the other hand, the recursive OLS has improved by 34% compared by OLS, but still was inferior than the Kalman filter online prediction.

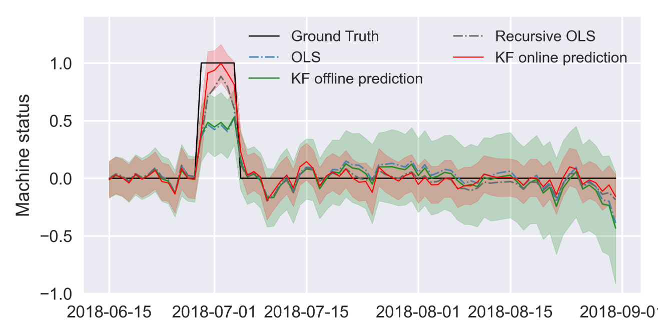

Figure 3. Predictions plot of the comparative methods.

Fig. 3 provided more details about the performance of comparative methods. It can be observed that Kalman filter offline prediction gave higher predictions for system failure and lower predictions for normal status. However, both of them predicted system failure with values around 0.5, which include ambiguities in terms of accuracy. In comparison, the two recursive methods gave predictions much closer to the ground truth. Particularly, the Kalman filter predictions come with a prediction interval, and in the case of offline prediction, the prediction uncertainty accumulated and piled up little by little as no feedback from the actual measurements were offered.

[1]https://www.kaggle.com/datasets/nphantawee/pump-sensor-data

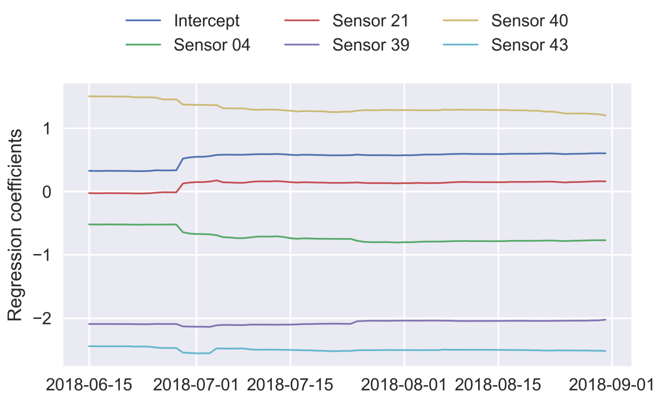

Figure 4. Change of some regression coefficients

To understand the model dynamic, the regression coefficients of several selected sensor data as well as the intercept are shown in Fig.4. This figure demonstrates the variations of the regression parameters, particularly around July, all the coefficients had obvious changes. After that, the regression parameters were more stable and only minor variations were observed. This figure highlights the adaptability of the dynamic model and helps understand the nature of the proposed method.

4. Discussion and conclusion

To cope with the challenge of system dynamics existed in the industrial processes for fault detection problem, we propose to utilize the framework of SSM to explicitly represent the model dynamic. Particularly, the fault detection problem is formulated and interpreted as a regression problem for more explainable and convincing detection result. Therefore, we first transformed the categorical machine status into continuous values. In this context, the proposed model resembles traditional soft sensor models. Next, we applied Kalman filter for optimal state estimates and state predictions, where the recursive procedure updates the state variables online. Comparison experiments on a real-world water pump data set showed the effectiveness of the online Kalman filter. Furthermore, the analysis of the results confirmed the assumption of the dynamics of the system and the corresponding adaptability of the proposed method.

There are some aspects that need further discussion and clarifications. First, although the case study in this paper has binary labels for the health condition of the system, in practice, however, the historical data may be inadequate to accurately represent the full range, and industrial processes can often encounter unprecedented issues. To handle unseen anomalies, the proposed model has online learning in nature that can adapt and update the model parameters. Furthermore, the change of the system noise and measurement noise represent and indicate dynamics or external factors that can not be captured by the system, as well as inaccuracies in the measurement process itself.

Last, we list some potential future extensions to make the proposed model more flexible and effective. First, the SSM in this paper are limited to the linear cases, which can be extended to nonlinear SSM or particle filters to account for more complex dynamics. Meanwhile, sophisticated algorithms can be developed to deliver more quantified estimations for the unstructured model uncertainties. Finally, it is important to incorporate domain-specific knowledge into the model, and this could involve in combining physics-based models.

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