Sensitivity enhanced method for fault detection and prediction of elevator doors using a margin maximized hyperspace

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ABSTRACT

This paper proposes a novel fault classification and prediction method by addressing a margin maximized hyperspace (MMH) to solve the problem, absent of any label at a highly imbalanced dataset, which is a frequent but challenging problem in real-world industries. The proposed method features three characteristics. First, knowledge-based feature manipulation is conducted using reference and feedback physical properties and the manipulated features are used for training the proposed neural network because the features contain rich information for classifying and predicting faults of the system of interest. Second, VAE transforms high-dimensional input features into a low-dimensional feature space. This nonlinear space transformation reduces the complexity of the classification securing high accuracy and robustness of fault classification in the MMH. Third, the acquired MMH through VAE with Bayesian optimization statistically allocates two extremes of major (normal) and minor (faulty) clusters at the origin and unity at the feature space, indicating that the sensitivity of fault prediction is maximized. The method would be highly effective in that the model only focuses on separating major and minor clusters deciding each health condition but ignores minor differences within the clusters which confuse users. The effect of the method is demonstrated with field measurements of an elevator door stroke dataset comprising normal, degradation, and faulty states in open and close strokes. The systematic analysis shows that these characteristics contribute to improving accuracy and robustness for fault classification. Specifically, knowledge-based feature manipulation improves accuracy, and VAE enhances sensitivity in separating each cluster and locational constancy. Moreover, the MMH is effective in predicting potential faults without any label for a highly imbalanced dataset. The proposed method provides the remaining useful lifetime (RUL) using distances from normal and faulty clusters at the MMH, which enables quantitatively providing RUL of the system without any definition of RUL. Considering that many systems deployed on fields lack information for fault life or residual useful life, the proposed method would be practical and effective for real-world applications.

1. INTRODUCTION

Fault detection and diagnosis (FDD) has garnered significant attention and extensive research in diverse domains, encompassing automobiles, plants, and various mechanical systems. This inclination arises from the customers' desire to minimize system downtime, as it directly impacts both profitability and safety considerations. Data-driven FDD methods have gained significant popularity due to their inherent flexibility and capability to capture complex phenomena in real-world systems. These methods rely solely on using data and models to address the intricate nonlinear relationships that exist within the system, thereby offering a powerful approach to FDD. Data-driven methods can be broadly classified into two categories: supervised and unsupervised learning, based on whether they require labeled data or not. Unsupervised learning methods have garnered considerable attention due to their ability to operate without the need for labeled data. In contrast, supervised learning often necessitates expert system intervention for making individual decisions, which can be costly and impractical when implementing these methods in real-world scenarios. The autoencoder (AE) has gained significant popularity in the field of fault detection and diagnosis (FDD) due to its ability to capture nonlinear relationships within the input data by compressing it into a low-dimensional feature space using an encoding layer and reconstructing it with a decoding layer. A specific type of AE, known as the Variational Autoencoder (VAE), incorporates a sampling layer for representing statistical distributions within the hyperspace, resulting in enhanced robustness. However, VAE models possess certain limitations. The distribution of input data tends to vary with each trial, and the boundaries between clusters that need to be distinguished can become indistinct, posing challenges when applying these models to real-world FDD scenarios. To address these limitations, this study proposes the concept of a margin-maximized hyperspace (MMH). The MMH enables effective fault detection and prediction in unlabeled and highly imbalanced datasets, which are prevalent but challenging conditions encountered in real-world problem-solving. The primary contribution of this study can be summarized as follows:

- The knowledge-based feature manipulation technique is proposed. The manipulated features contain effective information to reflect the current health state of the door motor, increasing detection accuracy.
- In this study, we propose the concept of the MMH, which aims to maximize the distance between major and minor clusters. By strategically placing the major cluster at the origin and the minor cluster at unity, the opposite extreme of the origin in the hyperspace, our proposed MMH enables users of the model to effectively differentiate between healthy and faulty states. This positioning of the clusters facilitates clear and distinct boundaries, enhancing the accuracy of fault detection and classification.
- To validate the effectiveness of the proposed method, we conducted experiments using field measurements obtained from a real-world elevator door. The dataset encompasses various states, including normal, faulty, and degradation states, specifically focusing on open and close strokes. The results of our analysis confirm that the proposed method ensures a significant separation between the major and minor clusters. Moreover, we demonstrate that by leveraging the distances from both clusters, it is possible to approximate the Remaining Useful Life (RUL). This finding underscores the practical utility of the proposed method in accurately estimating the remaining lifespan of the system under consideration.

2. METHOD

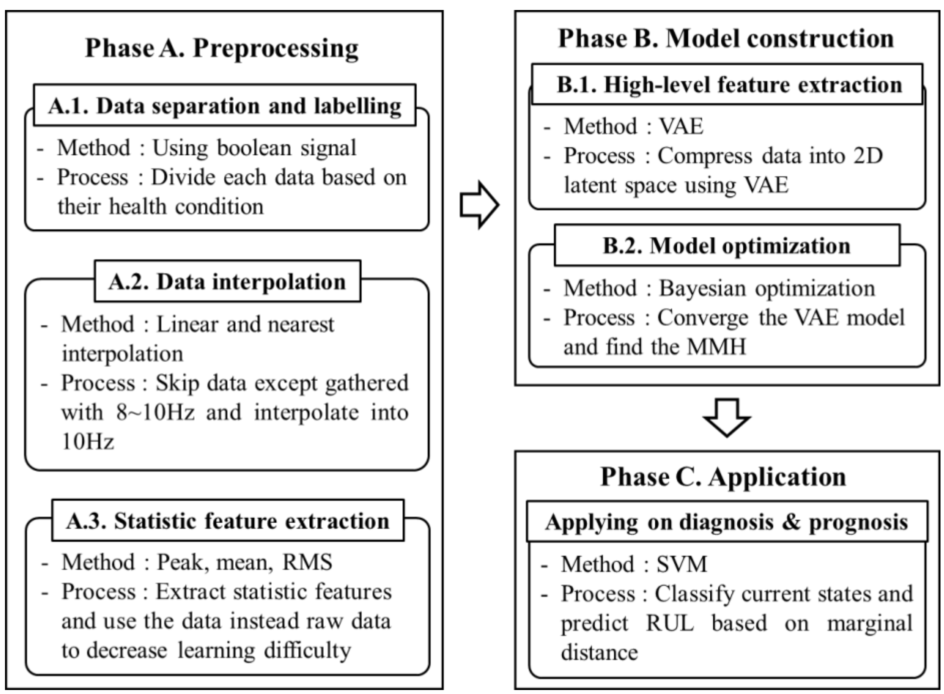

Figure 1. Flowchart of the proposed prognosis method

The entire process of the method consists of three phases described in Fig 1. First, the raw measurements of elevator door stroke acquired in time series format were preprocessed into the form of each stroke by using digital signals for control (Phase A in Fig 1). Then the data were separated and interpolated into the same frequency, 10 Hz. Specifically, different types of interpolation techniques were applied depending on their characteristics, i.e., linear interpolation for real-number type data, and nearest interpolation for digitized signals. The health state of each stroke was also distinguished by an expert in this phase. Note that the true states were required for testing the accuracy of the model, not for training. The distribution of strokes for each stroke type and health state is shown in Table 1. Note that the slight difference between the number of open and close strokes came from preprocessing processes because the strokes incorrectly collected due to signal problems were removed from the dataset. Second, statistical features were manually extracted so that each stroke could be trained and tested by machine machine-learning framework, resulting in 21 features in total. During the statistical feature extraction process, feature manipulation was also conducted based on domain knowledge so that the features highly correlated to motor health could be effectively extracted. Then, each type of stroke was subsequently passed through VAE to transform the input data into a low-dimensional hyperspace which only contains information about motor health conditions (Phase B in Fig 1). The architecture of the VAE used in this study is described in Figure 2. Note that the area of hyperspace is restricted to 1×1 by passing through the sigmoid layer for each dimension. Next, the Bayesian optimizer was utilized to maximize the sensitivity to separate normal and faulty clusters at hyperspace for vanilla AE, and to find available hyperparameter for VAE because the convergence of the algorithm highly depends on the hyperparameter settings but guarantees maximized distance between two clusters as long as the model converges. The acquired MMH from VAE was applied for classifying faults and predicting RULs based on the distribution on the hyperspace and distance from two clusters (Phase C in Fig 1).

Table 1. Distribution of strokes for each health state

Stroke type	Health states			Total strokes
	Normal	Degradation	Faulty	
Open	22605	32	36	22673
Close	22646	0	31	22677

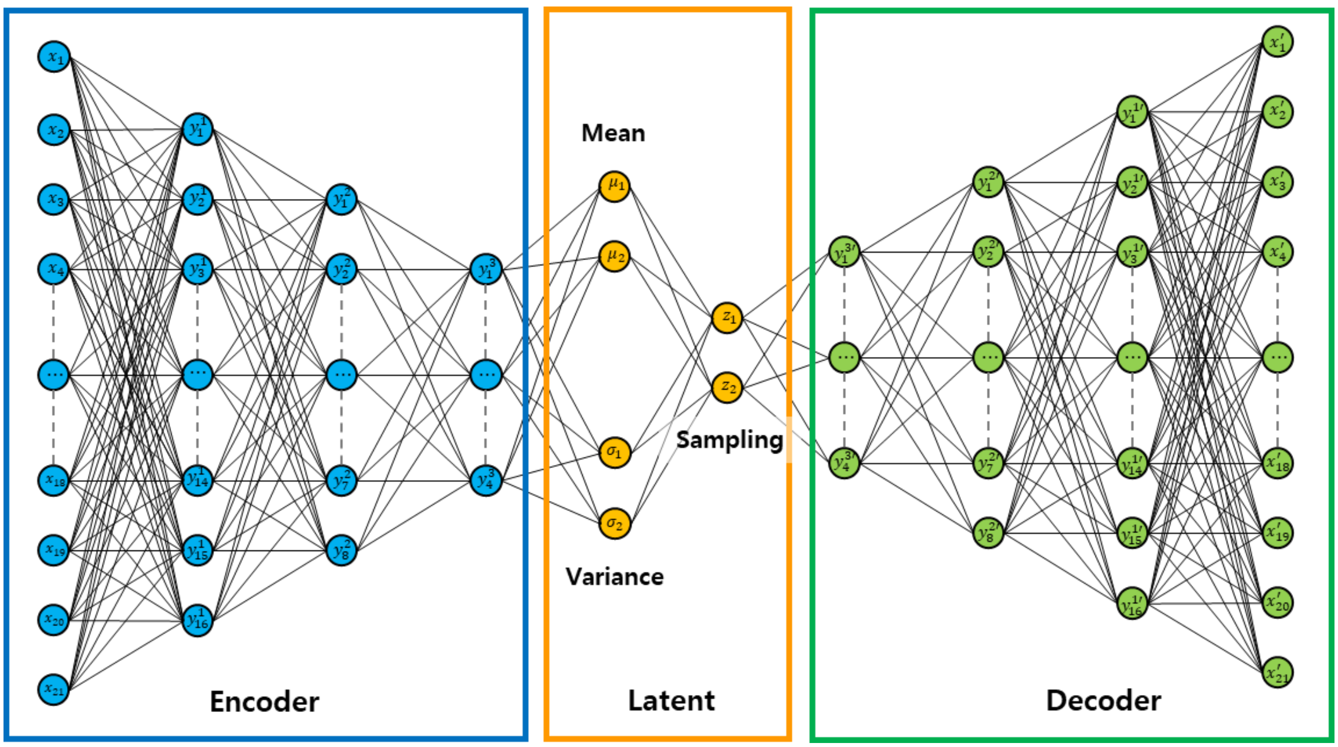

Figure 2. The architecture of the VAE used for the method

3. RESULT AND DISCUSSION

In this section, we emphasize the benefits of utilizing MMH in effectively distinguishing between major (normal) and minor (faulty) clusters. To quantitatively evaluate and compare the performance of VAE and AE, both types of AEs were optimized using Bayesian Optimizer, to ensure a fair comparison. The marginal distance separating two clusters was set to be an objective value to be maximized.

Table 2 shows the marginal distance between normal and faulty clusters using different types of AEs, i.e., vanilla AE and VAE. Theoretically, the maximum distance between two clusters is $\sqrt{2}$, which is the diagonal length of square one on a side. The distances calculated from vanilla AE are 0.9747 and 0.9979 for open and close strokes, and 1.4142 same for both strokes with VAE, which is a maximum distance in the 1×1 fixed hyperspace area. This result suggests that the result is closer to a global minimum which contains information about health when VAE is used for feature extraction, whereas the AE might converge to the local minimum and be vulnerable to noise and other information irrelevant to health information.

Table 2. Marginal distance between two clusters for each type of AEs

Stroke type	Type of AE	
	AE	VAE
Open	0.73	1.41
Close	0.98	1.41

Statistical values for each cluster are presented to compare the clustering performance depending on the types of AE and emphasize the effectiveness of VAE. The values include mean and variance because the locational consistency of each cluster and gathering performance within a cluster can be observed by watching those values. Constant mean and low variance for different types of strokes denote the robustness of the feature extractor. Table 3 shows the statistical values for each stroke whereas Table 3 (a) and (b) represent statistical values for open and close strokes. The values are calculated for each dimension because the latent space for both AEs was set as two. Constant means and low variances were observed when VAE was utilized for both open and close strokes, whereas chaotic mean and higher variance were shown when vanilla AE was utilized for feature extraction. The result shows the effectiveness of VAE separating two clusters into each extreme in hyperspace. When using a VAE, the major cluster comprising most of the distribution and the minor cluster containing only a few numbers are constantly transformed into the origin (i.e., [0,0]) and ones (i.e., [1,1]), two extremes in the hyperspace, whereas the two clusters were randomly distributed in hyperspace when using vanilla AE. This confirms the assumption that VAE would play a regulation role in separating two clusters to maintain each dimension of the hyperspace as a standard normal distribution. This characteristic has a huge advantage when making decisions because a lack of consistency leads to hesitation.

Table 3. Statistical comparison of clustering performance for different types of AEs as a feature extractor

a) Open strokes

Health state	Dimension	AE		VAE	
		Mean	Var	Mean	Var
Normal	Dim 1	0.68	2.3e-3	4.3e-9	3.7e-24
	Dim 2	0.42	7.6e-2	1.9e-9	1.9e-29
Faulty	Dim 1	0.11	3.2e-4	1.0	0
	Dim 2	0.91	9.4e-3	1.0	0

b) Close strokes

Health state	Dimension	AE		VAE	
		Mean	Var	Mean	Var
Normal	Dim 1	0.5e-4	5.0e-6	1.9e-9	1.4e-25
	Dim 2	0.23	3.2e-2	2.1e-9	1.6e-25
Faulty	Dim 1	1.0	0.0	1.0	0.0
	Dim 2	7.4e-3	1.9e-10	1.0	0.0

The MMH method can effectively predict the RUL even in the absence of explicit RUL information. Figure 3 illustrates the MMH and the estimated RULs calculating ratio based on distances from each cluster to the location of individual data points, depicted by different colors from sky blue to violet. The results are presented for both the AE approach (Figure 3 (a), (b)) and the VAE approach (Figure 3 (c), (d)). In each figure, two lines indicate the lines passing through the support vectors of each cluster, while the red, blue, and green points represent strokes corresponding to faulty, healthy, and degradation states. This observation highlights that estimating a degradation state becomes feasible within the MMH, as the hyperspace is appropriately regulated to primarily capture the major differences between the healthy and faulty clusters, particularly during open strokes. In contrast, attempting to estimate a degradation state using features extracted from an AE would be inappropriate, as the normal and faulty state clusters are widely and randomly distributed, resulting in confusion when making precise decisions.

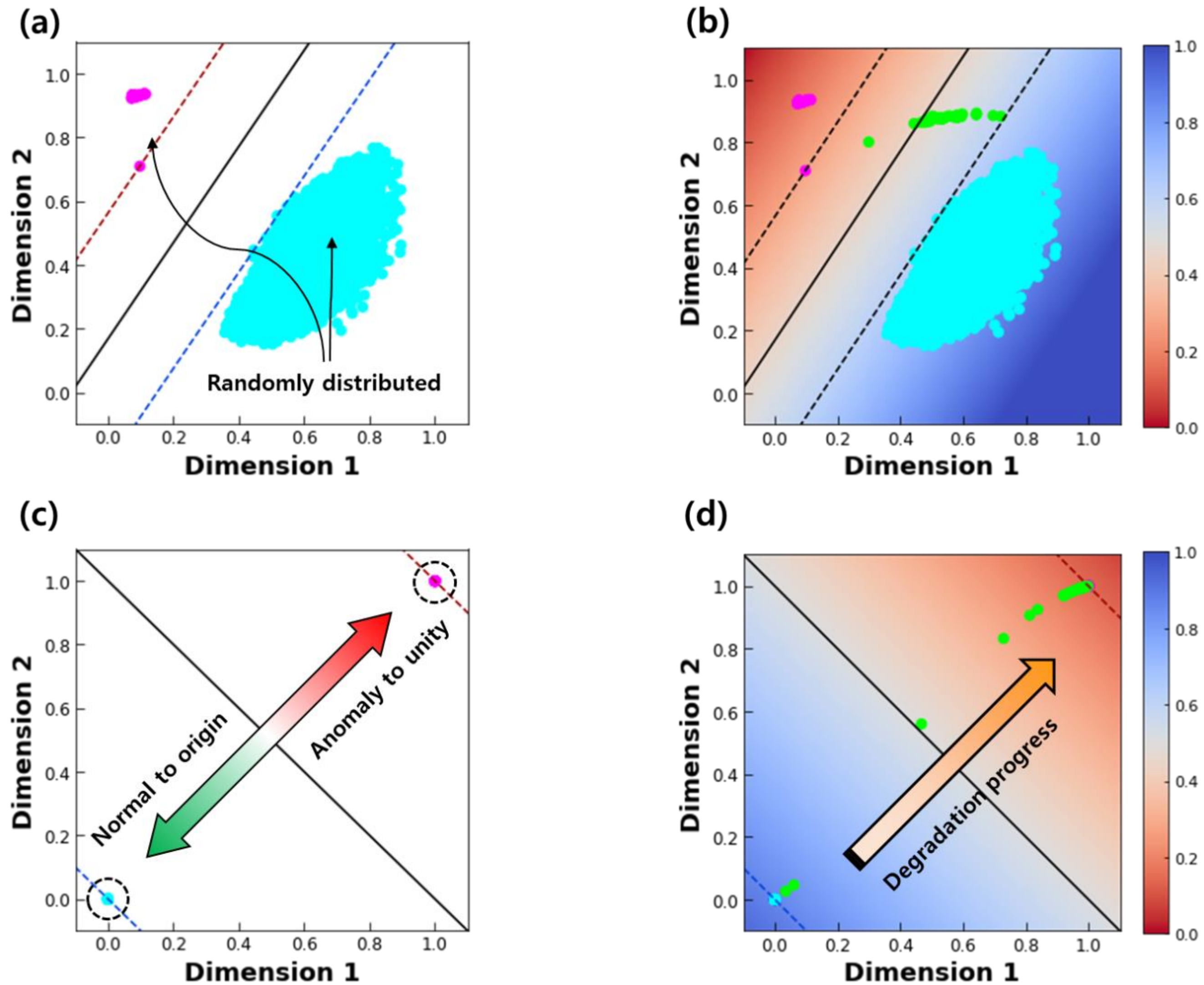

Figure 3. Data distribution of open strokes at feature space for different types of AEs

4. CONCLUSION

This study proposed the MMH method where sensitivity to separate normal and abnormal clusters is maximized. The proposed method demonstrates an effective approach for classifying two clusters within an unlabeled and imbalanced dataset, even in the absence of information regarding the remaining useful life, which is a challenging but frequent condition for solving real-world problems. The method introduced in this paper encompasses three key characteristics. Firstly, the proposed method incorporates knowledge-based feature manipulation to enhance the characterization of health states in the elevator door motor. This step provides additional information that contributes to accurate fault diagnosis. Next, high-level features are extracted using the VAE technique, enabling statistical nonlinear space transformation. Despite a significant reduction in dimensions, these features exhibit exceptional classification performance. Subsequently, the MMH is obtained through Bayesian optimization, aiming to maximize the distance between the major and minor clusters. The MMH serves as a valuable tool for classifying health states during diagnosis and predicting the RUL by utilizing the distances from each cluster. The efficacy of the MMH method is validated using real-world measurements obtained from elevator doors. The results demonstrate the method's effectiveness in accurately classifying various health states, indicating that the hyperspace has been trained to primarily contain information highly relevant to each health condition. As part of future work, it is recommended to gather additional data from diverse testbeds to further verify the robustness of the method. Additionally, efforts should be made to incorporate the fault detection and prediction algorithm based on the proposed method into practical applications.

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BIOGRAPHIES

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