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The input pattern problem on deep learning applied to signal analysis and processing to achieve fault diagnosis

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Dear editor,

Generally, one of the most prominent features of modern industrial systems is the massive amount of data collected from various sensors, which poses great challenges to traditional methods of capturing, managing, and storing such huge amounts of data. Similar challenges exist in efficiently interpreting the information obtained with the process measurements [1–3]. To address this issue, we use a data-driven method, which is considered to be the most effective and desirable method to address this issue and whose typical methods are deep learning models [4]. Moreover, currently, deep learning models are often employed to solve some recognition problems in practical industrial systems and they can be used to improve their recognition accuracy [1, 2, 4].

Currently, fault diagnosis in practical industrial systems can be generally achieved by signal-processing technique-based methods. Moreover, in practical industrial systems, the information reflecting the operational conditions of the system is mainly collected from various signal monitors, which can be confusing for many engineers in terms of the input of the deep learning models [5–8]. Usually, it is important to employ these deep learning models to achieve fault diagnosis by extracting the relevant information from these various signal monitors. However, to the best of our knowledge, the typical deep learning models are often suitable only for handling input data with a structural property, such as the data from image recognition, face recognition, and speech recognition [4]. Currently, deep learning models mainly refer to the following four architectures: deep belief networks (DBNs), convolutional neural networks (CNNs), stacked auto-encoders (SAEs), and recurrent neural networks (RNNs) [4]. However, various monitoring signals cannot completely satisfy this required structural property. Therefore, it becomes a problem worthy of study as to how to convert the monitoring signals into structural and suitable input data that can be employed to meet the input requirements of existing typical deep learning models.

To the authors' knowledge, training a deep learning model using input data without structural features will result in failure to achieve fault diagnosis. Finally, this study considers this important problem, and we have attempted to study the similarities and differences in the basic input patterns between these four typical deep learning models. Moreover, we call this problem the input pattern problem.

Model and methodology. To the authors' knowledge, the model and methodology of fault diag-

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nosis for dynamic systems can be broadly considered as a typical structure, as shown in Figure 1(a), including model-based fault diagnosis, data-driven fault diagnosis, and intelligent fault diagnosis. From Figure 1(a), it should be noted that fault diagnosis can be classified into three levels: component level, device level, and system level. Each level has its totally different challenges on the number, type, and even information contained in the monitoring signals. Generally, fault diagnosis at the component level always involves single-signal analysis and processing, and much research has already been done in this area. Fault diagnosis at the device level mainly refers to the actuator, sensor, and controller, etc., and the characteristics of this level involve not only single-signal analysis and processing but also complicated feature analysis from multiple monitoring variables. Finally, there is no doubt that fault diagnosis at the system level involves a signal-processing technique with a huge amount of multiple monitoring signals [3, 5–9].

Moreover, deep learning models can be regarded as a gray box, which can be employed to solve many problems, such as nonlinearity and strong coupling, as shown in Figure 1(a) [2]. In regard to the safety of the entire system, it is of great significance to achieve fault diagnosis and discover potential hidden structures via the analysis and processing of all types of monitoring signals [8]. However, to the authors' knowledge, there are few researchers who have studied the problem of both the analysis and the processing of a single signal and multiple signals based on deep learning models, and this study is an attempt to study this problem.

As mentioned before, fault diagnosis at both the device and the system level involves a complicated feature analysis from multiple monitoring variables. Naturally, the most important work is to attempt to construct a basic input pattern of the deep learning model. Moreover, the solution to this problem will generally affect the pros and cons of the fault diagnosis performance, and it can be considered as the premise of fault diagnosis based on deep learning. Therefore, in this study, the basic input pattern has been designed with the idea of a single monitoring signal, as shown in Figure 1(b). The only difference is that the procedure of the input pattern converts a high-dimensional signal into a one-dimensional signal, which is then coarse-grained or subjected to feature extraction. Furthermore, when the dimension is set to 1, the input pattern will degenerate to its simple form with a single monitoring signal.

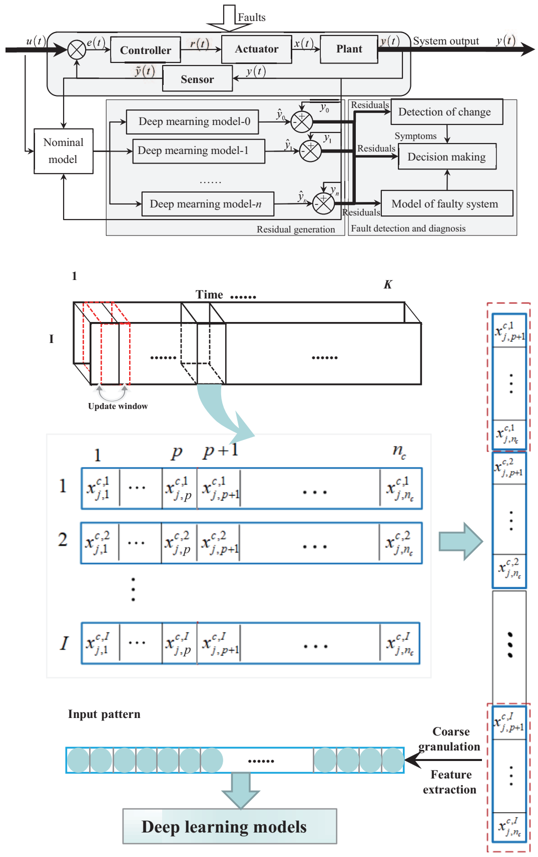

Figure 1 (Color online) (a) Typical structure of fault diagnosis based on a deep learning model. (b) Input pattern procedure of the deep learning model with multiple monitoring variables.

Remark 1. It should be noted that the input pattern of deep learning models should have extracted features or coarse-grained information without time characteristics, namely, the input data should be designed to satisfy some structured patterns. Moreover, owing to the limited space, the example is mainly based on SAEs.

Simulation and results. This study considered two situations: one was fault diagnosis with multiple monitoring variables and that evolved from the Tennessee Eastman (TE) chemical process system. The other one was fault diagnosis with only one monitoring variable and that evolved from a fault sensor from a practical industrial system. This letter is not focused on the discussion of the deep learning model; instead, it focuses on the use of combined sparse SAEs and a soft-max classifier to construct a simple deep learning model with 49 input layer nodes and 25 hidden layer nodes.

The TE chemical process system has been widely accepted as a benchmark for the study of monitoring systems, and its 33 variables had been selected as the operational process monitoring variables, which were combined with the input pattern of the deep learning model [8, 9]. The length of all the monitoring variables was 1440 sample points with approximately 3 min of interval, and the train-to-test ratio was uniformly set to 7:3. The related parameters of the deep learning model can be described as follows: the learning rate was set to 0.01; the maximum number of iterations was 1000; the weight decay parameter was set to 0.003; the desired average activation of the hidden units was set to 0.1; the weight decay parameter was set to 3.

Indeed, this is a typical fault diagnosis at the system level with multiple monitoring variables. The simulation results were achieved with the aforementioned deep learning model. However, the minimum accuracy was as low as 34.1$\pm$0.02%. Fortunately, the accuracy of the five simulation tests was as high as 90.8$\pm$0.02%, 88.6$\pm$0.05%, 90.7$\pm$0.03%, 90.9$\pm$0.09%, and 81.0$\pm$0.09%, which means that the deep learning model needs to combine other methods or the updated related parameters of the SAEs to improve the recognition accuracy.

The second simulation example was a fault diagnosis with only one monitoring variable with four faults in the sensor. The length of this single signal was 4800 sample points with about 20 s of interval. The deep learning parameters can be described as follows: the learning rate was set to 0.001; the maximum number of iterations was 10000; the weight decay parameter was set to 0.0001; the desired average activation of the hidden units was set to 0.1; the weight decay parameter was set to 3. Moreover, other relevant conditions were the same as those in the first simulation example. The single signal was decomposed into six sub-components, and each one had its features extracted to construct the spectrum map, which can then be fed to the deep learning model to achieve fault diagnosis. Moreover, the recognition results of these four faults were 90.9$\pm$0.06%, 90.0$\pm$0.04%, 99.4$\pm$0.02%, 99.3$\pm$0.06%, and 99.8$\pm$0.03%.

The results of these two simulations can be employed to illustrate that the original multiple monitoring variables should be designed to satisfy some structured patterns, and this will have a certain effect on deep learning models. To some extent, the results obtained by the SAEs with only one hidden layer and one visible layer showed that there is still some room for further improvements. Because of the limited paper space, the other results will not be described here.

Conclusion and further work. Among the top issues in implementing fault diagnosis based on deep learning models, we think that the procedure shown in Figure 1(b) can be considered as the most basic input pattern of deep learning models; namely, the input data should be designed to satisfy some structured patterns. Moreover, the single monitoring signal can simply be considered as an ordinary one. It should be noted that the methods for feature extraction or coarse-graining are not limited to just one type of methods, but rather may include a huge number of other approaches. In addition, the SAEs used in this study had only one hidden layer and one visible layer, and their model parameters were also rough. It means that further work should focus on stacking more layers or combining some other models to achieve better optimization with highly hierarchical features. On the other hand, in practical industrial systems, how to reform the input data to solve the imbalance between healthy and abnormal data is another aspect of future research.

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