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COMBUSTION CONDITION MONITORING THROUGH DEEP LEARNING NETWORKS

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ABSTRACT

Combustion condition monitoring is essential in a power plant for maintaining stable operations and operational safety. Therefore it is crucial to develop an intelligent combustion monitoring system. Existing traditional methods not only need a large quantity of labeled data but also require rebuilding monitoring model for new conditions. Aiming these problems, the present study proposes a novel approach combining denoising auto-encoder (DAE) and generative adversarial network (GAN) to monitor combustion condition. By using the learning mechanism of the GAN, the robust feature extraction ability of DAE as a generator is improved. These features are then fed into the Gaussian process classifier (GPC) for condition identification. Especially, newly occurring conditions can be correctly classified by simply training the GPC, rather than training from scratch. Experiments performed on a gaseous combustor indicate that the proposed approach can extract representative features accurately and achieve high performance in combustion condition monitoring with the accuracy of 98.5% for original conditions and 97.8% for the new conditions.

Keywords: Combustion condition monitoring, Generative adversarial network, Gaussian process classifier

1. INTRODUCTION

Combustion condition monitoring is an essential part of advanced combustion control, which is helpful for detecting abnormal combustion state. Whereas the abnormal combustion state reduces combustion efficiency and increases pollutant emissions (e.g., NOx, SO2). So it is of great attention to develop an intelligent combustion condition monitoring tool. A great deal of efforts has been devoted to develop combustion condition monitoring systems [1]. Among them, soft-computing technology combined with flame imaging and image processing technology has been attracted and received considerable attention for both laboratory and industrial applications. In general, there are two main stages in combustion condition monitoring based on imaging and soft computing, i.e. feature extraction and then condition monitoring.

Feature extraction is the most important step, which has been studied extensively. For instance, Sun et al. [2] analyzed the HSI (Hue, Saturation, Intensity) characteristic parameters of heavy oil-fired images. These essential features are further analyzed and utilized in the stage of process monitoring. Bai et al. [3] built a kernel support vector machine (SVM) classifier based on the principal component analysis (PCA) features. From these studies, it can be concluded that the essential features of the combustion state are the key to achieve satisfactory monitoring performance. However, most of the traditional methods have two main deficiencies such as (i) feature extraction process requires prior knowledge of image processing as well as comprehensive knowledge of the specific problem (ii) most of the algorithms provide poor performance which cannot meet the requirement of the power plant operators.

Clearly, it is desirable to develop an intelligent combustion monitoring tool that can utilize flame images to learn effective and robust features. Recently, deep learning neural network has received considerable attention in the application of combustion study [4]. For example, Wang et al. [5] established a convolutional neural network (CNN) framework to identify the combustion state of the power plant furnace. However,

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an obvious problem with the deep learning network is that a large quantity of labeled data is needed, which is difficult to acquire.

This paper presents a novel combustion condition monitoring approach based on deep learning networks. A combined denoising auto-encoder and generative adversarial network (DAE-GAN) is developed to extract the flame representative features. A Gaussian process classifier (GPC) is used to perform intelligent condition monitoring after supervised training with a few items of available labeled data. In this approach, a massive amount of easily accessible unlabeled flame images are utilized to learn useful and robust features. Only a few items of labeled images are needed, which is an advantage in a practical application. In addition, after simply retraining trained GPC, new conditions can be correctly classified by the proposed approach.

2. METHODOLOGY

2.1 Overall strategy

The technical strategy of the proposed approach is shown in Fig. 1, which consists of feature extraction and condition monitoring. It includes the following main steps.

Step 1: The flame images are collected by a high-speed CCD camera under different operation conditions. These images are resized into the same size and normalized to the set the value between 0 and 1.

Step 2: Build DAE-GAN and initialize parameters. The feature learning network (DAE-GAN) is established.

Step 3: The generator and the discriminator of the DAE-GAN are iteratively optimized by the adversarial machine learning mechanism for the unlabeled images. This is the unsupervised feature learning process.

Step 4: In the supervised learning process, the features of the labeled images are extracted by the trained DAE-GAN, and then used to train the GPC.

Step 5: Combustion condition monitoring with the trained GPC.

Step 6: As new conditions may occur, the trained GPC can be further trained with a few labelled images of the new conditions. The further trained GPC can monitor the combustion conditions including the new ones.

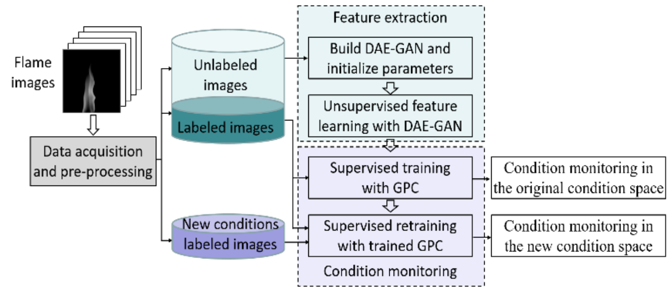

Fig 1 Overall strategy of combustion condition monitoring

2.2 Feature extraction

The auto-encoder (AE) is a symmetrical neural network, which is composed of encoder and decoder [6]. The input sample is mapped to the encode vector through the encoder, and the encoding vector is remapped to the output sample through the decoder. By minimizing the reconstruction error between the input sample and the output sample, the representative encodes vector is obtained. However, the basic AE cannot guarantee strong learning ability as it can lead to the obvious solution that simply copies the input [7].

The denoising auto-encoder (DAE) integrates denoising code into the AE that aims to extract useful information [8]. The input sample of the DAE is corrupted by noise. The decoder reconstructs the encode vector to obtain sample free of noise.

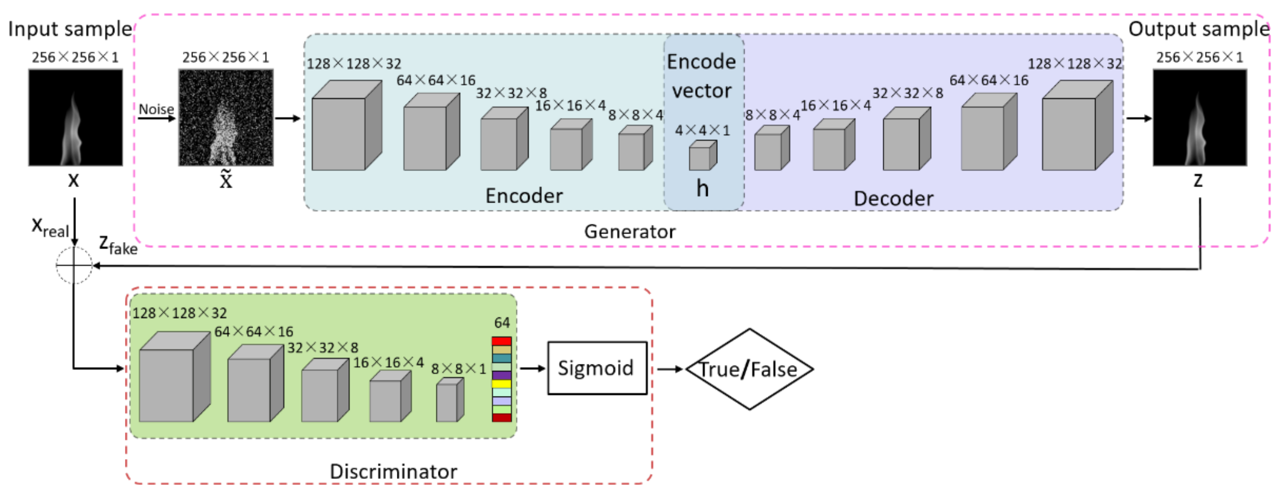

Fig 2 The structure of the designed DAE-GAN

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In this study, the GAN is applied to further improve the expressive capacity of the DAE. The structure of the designed DAE-GAN is shown in Fig. 2, which includes a generator and a discriminator. The input sample x is corrupted into $\tilde{x}$ by the white Gaussian noise with a certain signal-to-noise ratio (SNR). The encoder maps the $\tilde{x}$ to the encode vector h, and the decoder maps the hidden units h to a reconstruction z. In each training step of the DAE-GAN, the generator produces some fake samples from the DAE, and the discriminator is trained by generated fake samples mixed with a few true examples. Then the generator is rewarded for generating examples to fool the discriminator. The generator and discriminator continuously confront each other and optimize themselves until the Nash equilibrium is reached [9]. Finally, the DAE can well generate new samples which could cheat discriminator, so as to capture the potential distribution of the original samples.

2.3 Condition monitoring

In this study, the GPC is established for the condition classification based on the features of the labeled image. The Gaussian process is a stochastic process that involves the generalization of the Gaussian probability distribution to functions. Under certain cases, Gaussian processes can be considered equivalent to large neural networks. The details can be found in [10].

3. DATA COLLECTION AND DESCRIPTION

3.1 Data description

Experiments are carried out on the laboratory-scale combustor. The flame images are acquired by the high-speed monochrome camera with resolution up to 260*384 pixels at 1000 frame s^{-1}. As listed in Table 1, the total dataset includes seven conditions of different air flow (AF) and fuel flow (FF) ratios. For each condition, 4000 images are collected.

Table 1. Combustion conditions in the total dataset.

Dataset	Condition	FF (ml/min)	AF (m3/min)	Number of image
Dataset A	1	500	0.5	4000
	2	500	1	4000
	3	500	1.5	4000
	4	500	2	4000
	5	500	2.5	4000
Dataset B	6	400	0.5	4000
	7	400	1.8	4000

The total dataset is divided into two parts: dataset A with five conditions as the original condition and dataset B with all the remaining two conditions as the new condition. 80% of dataset A is selected to form the dataset A1, and the remaining 20% to form the dataset A2. Then, 92% of the dataset A1 is chosen as the dataset A3, while the remaining 8% as dataset A4. Similarly, 80% of dataset B is selected to form the dataset B1, and the remaining 20% to form the dataset B2. Then, 8% labeled data of dataset B1 is selected to form the dataset B3. Fig. 3 illustrates the structure of the dataset.

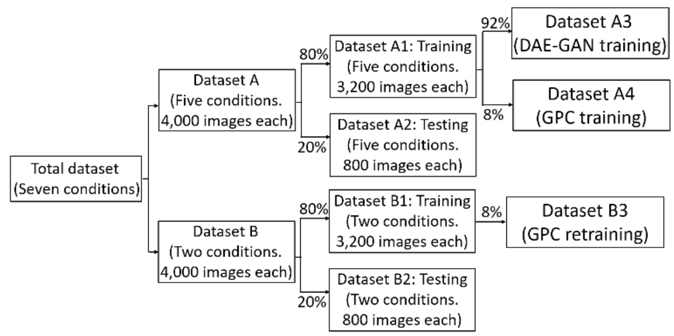

Fig 3 Structure of the dataset

3.2 Training process

The unsupervised DAE-GAN training is performed based on the dataset A3 without labeled information. Note that the dataset A3 is destroyed by white Gaussian noise before being used with the SNR of 24 dB, which is obtained via cross-validation with other values. All the weights of the DAE-GAN are initialized with a Gaussian distribution with a standard deviation of 0.02. The supervised GPC training is performed on the labeled samples of the dataset A4. The retraining dataset is formed by dataset A4 and dataset B3.

4. RESULTS AND DISCUSSION

4.1 Results

The dataset A2 is used for model testing, including the original five conditions. The test trial is repeated 10 times with the same epoch of 80. As shown in Fig. 4, all the testing accuracy of five conditions is over 97.2% with an average of 98.5%. The results demonstrate the effectiveness of the proposed method for combustion condition monitoring with a large amount of unlabeled data and a few items of labeled data. In addition, Fig. 4 also shows that the testing accuracy of seven conditions composed of dataset A2 and dataset B2 is above 96.8% with an average of 97.8%. It can be inferred that the proposed method is able to monitor new conditions by

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simply retraining the GPC, instead of training from scratch.

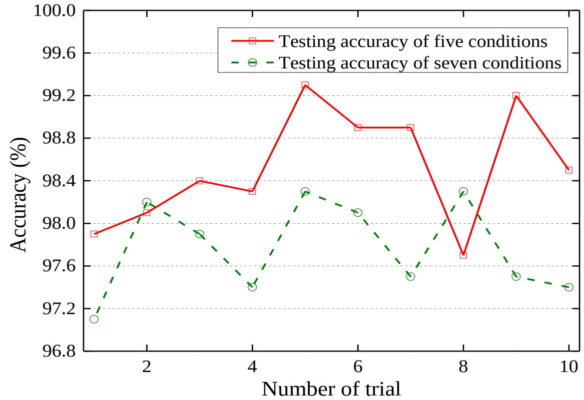

Fig 4 Overview of the testing accuracy

4.2 Discussion

The robustness of the proposed approach is also verified with different noise levels. The dataset A3 is corrupted by different levels of white Gaussian noise with the SNR from 30 to 6 dB with a step size of 6. For each level of noise, 10 trials are carried out and the averaged result is listed in Table 2. The testing accuracy of five conditions and seven conditions are represented by R1 and R2 accordingly. The results show that the testing accuracies with the SNR of 30 and 24 dB are almost the same as those with no noise. With the increase in the noise level, the accuracy decreases gradually. Overall, this approach has a good anti-noise ability, which is useful for noisy data that usually capture in a harsh environment.

The performance of the GPC is studied compared with other neural network classifiers, i.e., random forest (RF), Linear SVM, and Kernel SVM. The testing results are summarized in Table 3. The comparison results show that the GPC provides high accuracy, which outperforms traditional classifiers.

The proposed approach is useful where the availability of labeled data is quite limited. It is important to investigate the robustness of the method on the different ratio of labeled data to unlabeled data. Therefore, further study is carried out by changing the fraction of dataset A4 that is used for GPC training from 1 to 10% with a step size of 1. The effect of the proportion of dataset B3 to dataset B1 on the testing accuracy of seven conditions is also studied. Fig. 5 shows the result of the average accuracy for 10 trials. The results indicate that the accuracy rises rapidly with the fraction of labeled data increasing from 1 to 6%. It is seen that even with 4% of labeled data, the accuracy is above 96%, which shows that the features learned from unlabeled data are representative. With further increase of labeled data, the accuracy tends to increase slightly and became stable. The result shows that the proposed approach achieves satisfactory accuracy and excellent identification ability of new conditions even with very few items of labeled data.

Table 2. Testing accuracy under different SNRs.

SNR (dB)	No noise	30	24	18	12	6
R1 (%)	98.5	98.2	97.6	88.2	76.5	76.3
R2 (%)	97.8	97.1	96.9	83.9	70.9	74.7

Table 3. Testing accuracy under different classifiers.

Classifiers	Proposed approach	RF	Linear SVM	Kernel SVM
R1 (%)	98.5	92.6	96.1	97.2
R2 (%)	97.8	90.3	95.8	96.2

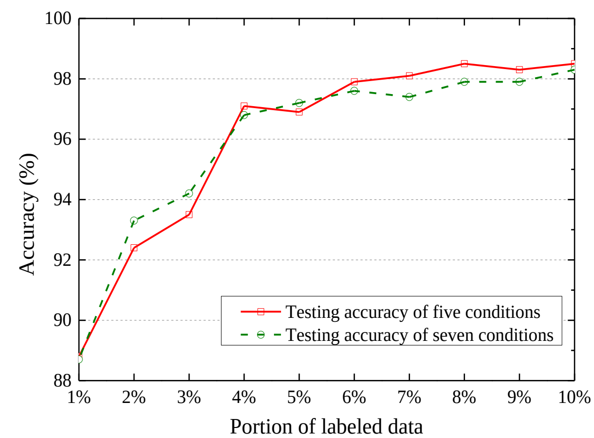

Fig 5 Effect of portion of labeled data

4.3 Visualization of learned features

In order to demonstrate that the proposed approach is able to learn effective features and distinguish the representative features automatically, the features learned by the DAE-GAN is visualized via a technique ‘‘t-SNE” [11]. The t-SNE is an effective data visualization technique for high-dimensional data. In this study, the dimensionality reduction technique ‘‘t-SNE” is used to convert the 16-dimensional features to a two-dimensional map. The resulting maps of the new testing dataset consisting of dataset A2 and dataset B2 is shown in Fig. 6. It can be seen that the DAE-GAN features of different conditions are separated well. More details can be included in the final paper.

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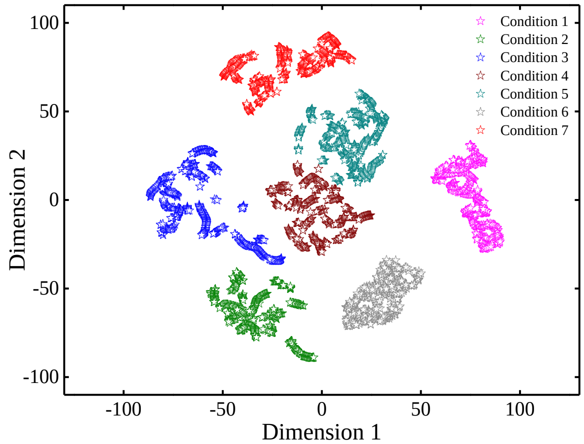

Fig 6 Visualization of learned features

5. *CONCLUSIONS*

This paper presents an intelligent approach for combustion condition monitoring based on DAE-GAN and GPC. This approach overcomes the typical drawbacks of the traditional methods. The DAE-GAN can automatically extract robust features from a massive quantity of unlabeled data. Only a small amount of labeled data is needed to train the GPC for condition identification. In addition, the proposed approach is able to recognize newly occurring conditions by simply retraining the GPC with a few items of new condition labeled data. The robustness of the proposed approach was evaluated by corrupting the original images with different levels of noise. Compared with the traditional classifiers, the proposed GPC is able to provide better accuracy for identifying the combustion conditions.

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