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COMBUSTION CONDITION MONITORING THROUGH DEEP LEARNING NETWORKS

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ABSTRACT

In a power plant, combustion condition monitoring is essential for maintaining stable operations and operational safety. Therefore, it is crucial to develop an intelligent combustion condition monitoring method. Existing methods not only need a large quantity of labeled data but also lack of generalization ability for monitoring the new condition. Aiming these problems, the present study presents a novel approach combining denoising autoencoder (DAE) and generative adversarial network (GAN) to monitor combustion condition. With the aid of the learning mechanism of the GAN, the learning ability is improved to learn representative features. These learned features are then fed into the Gaussian process classifier (GPC) for condition identification. Furthermore, new conditions can correctly be classified by simply retraining the established GPC using a small amount of labeled data under the new conditions, rather than training from scratch. Experiments were performed on a gaseous combustor and results indicate that the proposed approach can extract representative features accurately and provides higher accuracy for condition identification such as 99.4% for original conditions and 99.5% for the new conditions.

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

1. INTRODUCTION

Combustion condition monitoring is a vital part of advanced combustion control. Accurate identification of combustion condition is also crucial for detecting abnormal combustion state. Whereas the abnormal combustion state reduces combustion efficiency and increases pollutant emissions (e.g., NOx, SO_2). Hence, it is crucial to develop an intelligent condition monitoring tool. A great deal of efforts has been devoted to this area [1-2]. Among them, soft-computing techniques combined with flame imaging and image processing has been attracted and received considerable attention for both laboratory and industrial-scale combustion test facilities. Generally, two different stages involved in combustion condition monitoring based on imaging and soft computing based techniques, 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. [3] extracted the HSI (Hue, Saturation, Intensity) characteristic parameters of heavy oil-fired images. These color features are further analyzed and utilized in the stage of process monitoring. Bai et al. [4] built a kernel support vector machine (SVM) classifier based on the principal component analysis (PCA) features. From the above studies, it can be concluded that the essential features of the combustion state are the key to achieve satisfactory monitoring performance. However, most 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) poor performance provided by most of the algorithms and cannot meet the requirement of the power plant engineers/operators.

Clearly, it is a desire to develop a reliable technique that can utilize flame images to learn effective and robust features. Recently, deep learning neural network has received considerable attention in the combustion studies [5]. For example, Wang et al. [6] established a convolutional neural network (CNN) framework to recognize the combustion state of the boiler furnace. However, an obvious problem with the deep learning network is that a large quantity of labeled data is needed, in practice which is difficult to achieve.

This paper presents a novel approach for combustion condition monitoring that addresses the drawbacks of the existing methods. A combined denoising autoencoder and generative adversarial network (DAE-GAN) is developed to extract representative features automatically from unlabeled flame images in an unsupervised manner. A Gaussian process classifier (GPC) is established to monitor combustion condition after supervised training with a few labeled data. After simply retraining established GPC, new conditions can be classified correctly 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. Mainly, it includes the following steps:

Step 1. The flame images are acquired and sorted. Each image is resized into 256(H)×256(V) and normalized by its maximum value.

Step 2. A feature learning network (DAE-GAN) is established and its parameters are initialized.

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

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

Step 5. After that combustion condition was identified out using the established GPC for the original dataset.

Step 6. If a new condition occurs, the established GPC can be retrained with a few labeled images from the new condition. Then, the new condition can be identified by the retrained GPC.

2.2 Feature extraction

The autoencoder (AE) is a symmetrical neural network, which is composed of encoder and decoder. The input sample is mapped to the encode vector through the encoder. The encoded vector is then remapped to the output sample through the decoder. To minimize the reconstruction error between the input and the output samples, a representative encodes vector is obtained. However, the basic AE cannot guarantee strong learning ability as it can lead to an obvious solution that simply copies into the input sample [7].

In order to extract sensitive features, a denoising autoencoder (DAE) is integrated into the basic AE, where the input samples of the DAE are corrupted by noise. The decoder reconstructs the encode vector to obtain sample free of noise. The mean square error (MSE) is commonly used as a loss function for the DAE,

$$L_{z,x} = \frac{1}{M}\sum_{i=1}^{M}\|z^m - x^m\|^2 \quad (1)$$

where M represents the sample size; each input sample x^m can be reconstructed to z^m through DAE.

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 DAE is considered as the generator of the DAE-GAN. The input sample x is corrupted into $\tilde{x}$ through the stochastic mapping. Different types of corruption processes may be considered such as white Gaussian, salt-and-pepper and masking noises. Here, white Gaussian noise is used. The corrupted sample $\tilde{x}$ is then mapped to the encode vector h by the encoder. Finally, the encode vector h is remapped to a reconstruction z by the decoder. In the

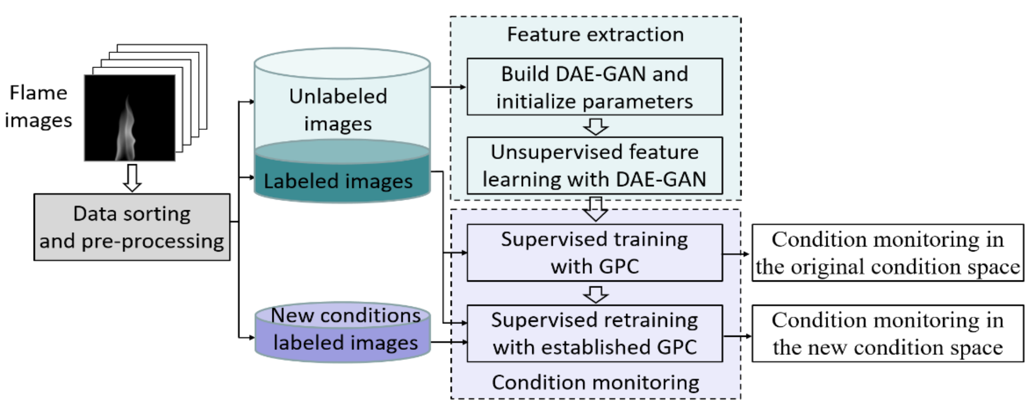

Fig 1 Overall strategy of combustion condition monitoring

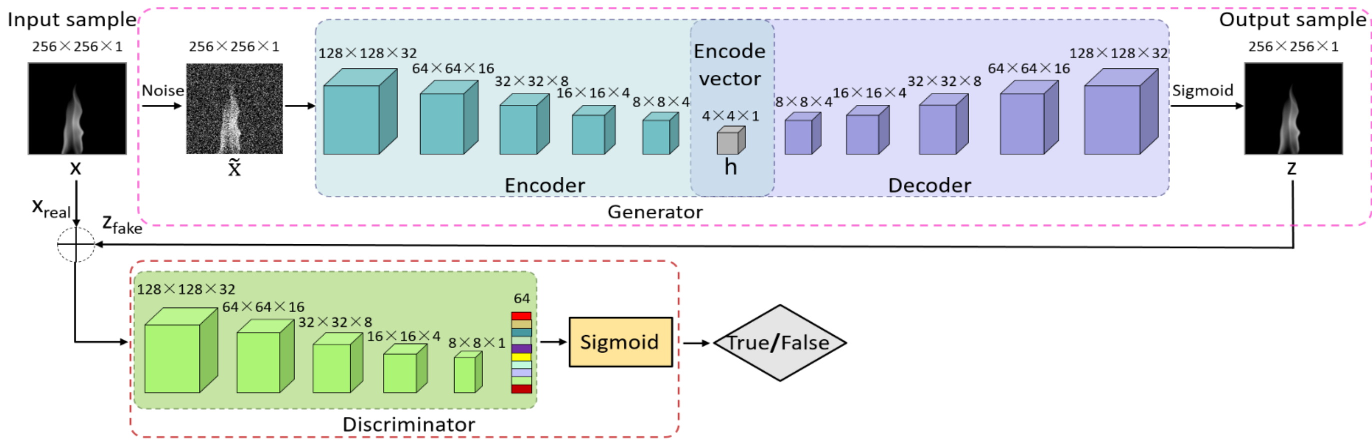

Fig 2 The structure of the designed DAE-GAN

encoder and discriminator, the convolutional filters with a size of 3×3 and a strider of 2 are used for feature learning. In the decoder, the feature mapping is first dimensionally extended through the up-sampling layer and then processed by the convolution filters with a size of 3×3 and a strider of 1. The Rectified Linear Unit (ReLU) is selected as the activation function of the hidden neurons, while the sigmoid function is only used in the output layer of the decoder and discriminator.

In each training step of the DAE-GAN, the generator DAE produces some fake samples. The discriminator is trained by these fake samples mixed with a few true examples. Then the generator is rewarded for generating examples to fool the discriminator. Through the adversarial machine learning mechanism, the generator and discriminator continuously confront each other and optimize themselves until the Nash equilibrium is reached [8]. The objective function implements a min-max adversarial game between generator (G) and discriminator (D),

$$\min_G \max_D V(D,G) = E_{x\sim P_{data}(x)}[logD(x)] + E_{\tilde{x}\sim P_g(\tilde{x})}\left[log\left(1-D\left(G(\tilde{x})\right)\right)\right] \quad (2)$$

where $P_{data}(x)$ and $P_g(\tilde{x})$ denote the prior distribution of input sample x and corrupted sample $\tilde{x}$; $D(\cdot)$ is the output of discriminator D, where the activation function is sigmoid. $G(\tilde{x})$ is the output of generator G, which has the same dimension as x. Once the training process is completed, the generator DAE can well reconstruct the original input sample, so as to achieve the purpose of capturing the distribution of the input sample.

2.3 Condition monitoring

The GPC is established for combustion condition identification. The reason to use the GPC in this context stems is it has a genuine probabilistic model that can estimate the probability of each input sample belonging to each class [9]. Assuming that a data set $D = (\boldsymbol{X}, \boldsymbol{Y})$, where $\boldsymbol{X} = \{x_i | i = 1,2,\dots,m\}$ and $\boldsymbol{Y} = \{y_i \in (-1,1) | i = 1,2,\dots,m\}$ collect the inputs and class labels respectively. The GPC with a probit measurement model can be expressed as:

$$p\left(\boldsymbol{Y}\middle|f(\boldsymbol{X})\right) = p\left(y_i\middle|f(x_i)\right) = \int_{-\infty}^{y_i f(x_i)} \mathrm{N}(z|0,1)\,dz \quad (3)$$

where $f(\boldsymbol{X}) \sim GP\left(0, K(\boldsymbol{X}, \boldsymbol{X}')\right)$ a latent function; GP is a Gaussian Process; $K(\boldsymbol{X}, \boldsymbol{X}')$ is the covariance function. Here, the Gaussian radial basis function (RBF) is chosen:

$$K(\boldsymbol{X}, \boldsymbol{X}') = \sigma^2 \exp\left(-\frac{\|\boldsymbol{X}-\boldsymbol{X}'\|^2}{2\ell^2}\right) \quad (4)$$

where σ^2 denotes the signal variance; ℓ denotes the characteristic length-scale.

3. DATA COLLECTION AND DESCRIPTION

3.1 Data description

Experiments were carried out on the laboratory-scale combustion test rig. The flame images were captured by the high-speed monochrome camera with a resolution of 260×384 pixels at 1000 f/s (frames per second). Table 1 depicts the overview of the dataset obtained from seven different combustion conditions under the different air flow (AF) and fuel flow (FF) ratios. For each condition, 4000 images are collected.

Table 1. Overview of the dataset.

Dataset	Condition	FF (ml/min)	AF (m3/min)	Total images
A	1	500	0.5	4000
	2	500	1.0	4000
	3	500	1.5	4000
	4	500	2.0	4000
	5	500	2.5	4000
B	6	400	0.5	4000
	7	400	1.8	4000

Example flame images of the seven conditions are shown in Fig. 3. Although the flame appearance (size, brightness, structure, etc.) varied with the air-fuel ratios, it is difficult to distinguish the differences manually those appearances, which is impractical. Therefore, the proposed method is applied to monitor the combustion conditions.

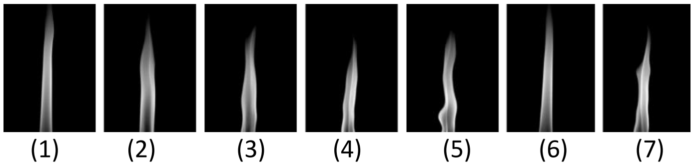

Fig 3 Example images of seven conditions

In order to eliminate the influence of different image sizes and accelerate the convergence speed of the neural network, all chosen images are pre-processed. The process is as described above (step 1). The pre-processed dataset is divided into two parts: dataset A with five conditions considered as the original conditions and the remaining two conditions (dataset B) as the new conditions.

Fig. 4 illustrates the overall structure of the dataset. 80% of dataset A is selected to form the dataset A1, and the remaining 20% to form the dataset A2. Then, 94% of the dataset A1 is chosen as the dataset A3, while the remaining 6% 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, 6% labeled data of dataset B1 is chosen to form the dataset B3.

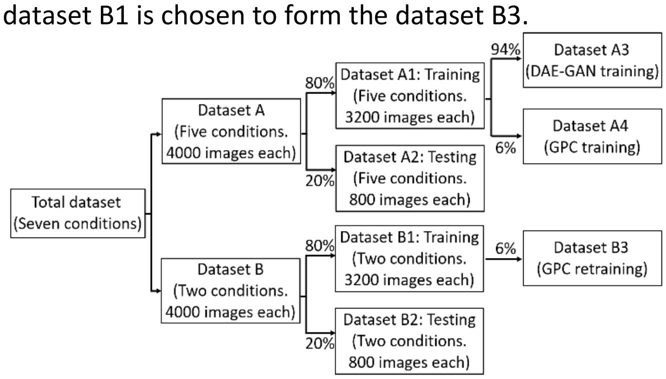

Fig 4 Structure of the dataset

3.2 Training process

Without labeled information, dataset A3 is used to train the unsupervised DAE-GAN. In particular, the dataset A3 is also destroyed by white Gaussian noise (signal-to-noise ratio (SNR)) of 12 dB. All the iterative number of epochs is set to 60. All the weights of the DAE-GAN are initialized by Gaussian distribution with a standard deviation of 0.02. The supervised GPC training is performed based on the labeled samples of the dataset A4. The dataset B3 is used to retrain the established GPC.

4. RESULTS AND DISCUSSION

4.1 Results

The test trial was repeated 10 times to guarantee the reliability of the result. The testing accuracy under dataset A2 referred to R1, and a combination of datasets A2 and B2 referred to R2. As shown in Fig. 5, all the trials of R1 achieve >98.8% testing accuracy with an average of 99.4%. The results demonstrate the effectiveness of the proposed method for combustion condition monitoring with a large number of unlabeled data and a small amount of labeled data. In addition, it can be seen that the average testing accuracy of R2 reaches 99.5%. It's suggested that the proposed method performs well in in the monitoring of new conditions by simply retraining the established GPC, instead of training from scratch.

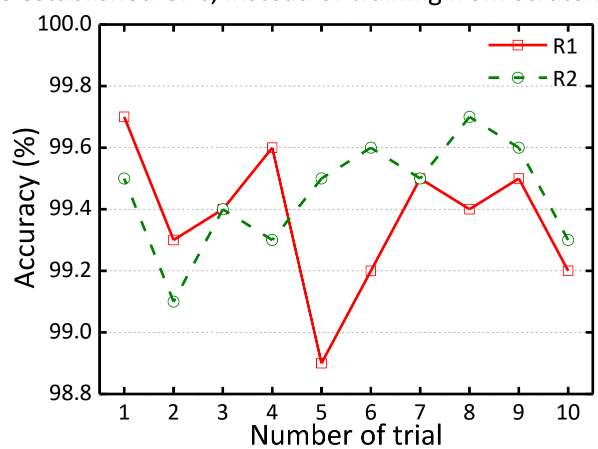

Fig 5 Overview of the testing accuracy

To investigate the overall recognition of combustion conditions, a total of 1400 flame images (200 per condition) are randomly selected from dataset A2 and dataset B2 for testing. Fig. 6 illustrates the recognition results. As can be seen, although there is some false recognition, most of the samples can be recognized accurately with a success rate of up to 99.5%.

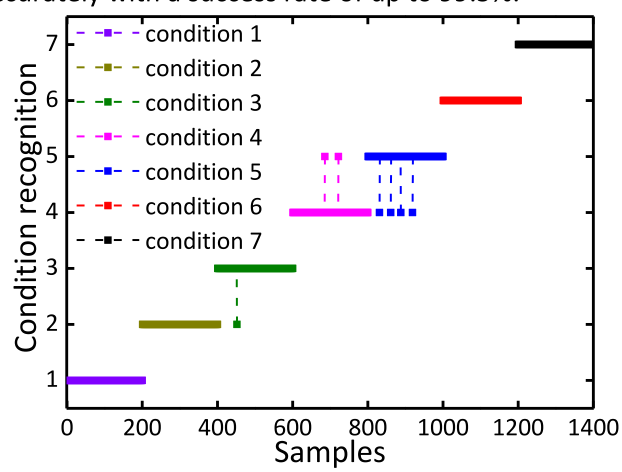

Fig 6 Condition recognition under dataset A2 and dataset B2

4.2 Discussion

4.2.1 Comparison of monitoring performance with different levels of noise

The robustness of the proposed approach is verified with different noise levels. The testing datasets (A2 and B2) is corrupted by different levels of white Gaussian noise with the SNR value of 36 to 6 dB and a step size of 6. For each level of noise, 10 trials were carried out and the averaged result is listed in Table 2. The results show that the testing accuracies with the SNR of 36 and 30 dB are almost the same as those with no noise. While the SNR is 24 dB and 18 dB, the accuracies slightly decrease. Even if the SNR is 12 dB, the proposed approach can still achieve 92.1% testing accuracy of R1 and 94.1% testing accuracy of R2. With the further increase in noise level, the performance of this approach will be seriously degraded. In this case, noise isolation or other processing methods (such as wavelet transform) should be considered when the images are acquired and pre-processed. Overall, this approach has a good anti-noise ability, which is useful for noisy data that usually capture in a harsh environment.

Table 2. Testing accuracy under different SNRs.

SNR (dB)	No noise	36	30	24	18	12	6
R1 (%)	99.4	99.3	99.2	98.6	96.9	92.1	68.5
R2 (%)	99.5	99.4	99.3	98.8	97.5	94.1	46.8

4.2.2 Comparison of monitoring performance with different features of learning methods and classifiers

A trial is also carried out to compare DAE-GAN monitoring performance with two deep learning methods (DAE and AE-GAN). Notably, the network structure of DAE is the same as the generator of DAE-GAN, while AE-GAN is completely the same with DAE-GAN. The noise level of the training samples for the DAE is also set to 12 dB. F_1-score is used to evaluate the classification ability of different methods in a range of value [0, 1]. When F_1-score is close to 1, it indicates that the method has a strong recognition ability.

Fig.7 shows comparison results of different features learning methods under SNR of 18 dB. It can be seen that the F_1-score of the DAE-GAN is at least 0.95, higher than that of DAE and AE-GAN in all conditions. On the one hand, the DAE-GAN is better than AE-GAN as AE-GAN has no resistance against noise. This clearly indicates that the anti-noise ability of the proposed method is improved by integrating denoising code. On the other hand, through the adversarial learning mechanism of DAE-GAN, the generator and discriminator are concurrently optimized, which is further enhanced the capacity of feature expression.

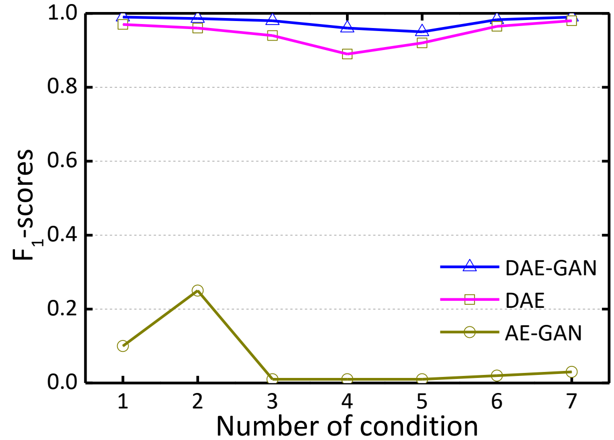

Fig 7 F_1-score under dataset A2 and dataset B2

Comparison of the GPC with typical neural network classifiers is conducted, including Softmax, Linear SVM, Kernel SVM, and random forest (RF). The testing results as listed in Table 3 show that the GPC provides higher performance compared to the other classifiers.

Table 3. Testing accuracy under different classifiers.

Classifiers	GPC	Soft-max	Linear SVM	Kernel SVM	RF
R1 (%)	99.4	96.8	96.4	98.6	89.3
R2 (%)	99.5	97.6	97.4	98.8	92.6

4.2.3 Effect a portion of labeled data

The proposed approach is useful where the availability of labeled data is limited. It is important to investigate the robustness of the method on the different ratios 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 8% with a step size of 1. Meanwhile, the effect of the proportion of dataset B3 to dataset B1 on the testing accuracy is also studied. Fig. 8 shows the result of the average accuracy for 10 trials.

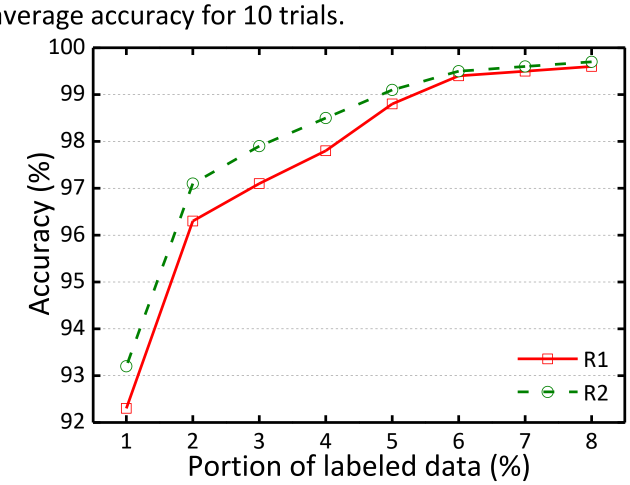

Fig 8 Effect of a portion of labeled data

The results indicate that the accuracy improves rapidly with the fraction of labeled data increasing from 1 to 5%. It can be seen that even with 3% of labeled data, the accuracy is above 97%, 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 portions 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, the features learned by the DAE-GAN is visualized via a technique ‘‘t-SNE” [10]. 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 dataset A2 and dataset B2 are shown in Fig. 9. It can be seen that the DAE-GAN features of different conditions are separated well. More details can be included in the final paper.

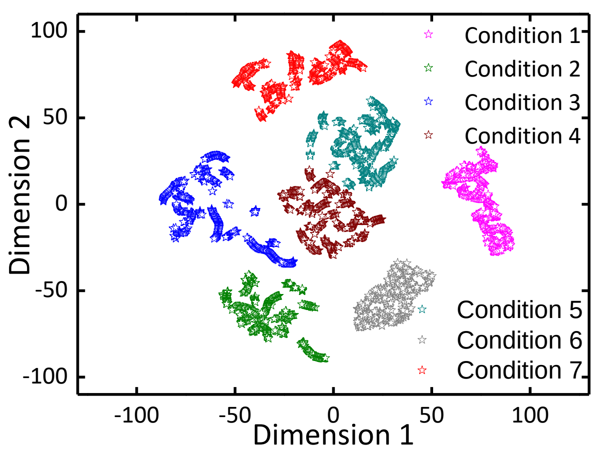

Fig 9 Visualization of learned features

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 number of unlabeled data. Only a small amount of labeled data is needed to train the GPC. In addition, the proposed approach is able to recognize newly occurred conditions by simply retraining the established GPC with a few numbers 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 different feature learning methods and classifiers, the proposed approach is able to provide better accuracy for identifying the combustion conditions.

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