Aliasing Signal Separation for Superimposition of Inductive Debris Detection Using CNN-Based DUET

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***Abstract*—Wear debris which contain multiple degrading information are of great interest to the running machines' health management. Among the several kinds of debris detection methods, inductive sensors have shown great potential for the online monitoring applications, along with which the superimposed voltage caused by the debris with short distances becomes a major factor influencing the accuracy of the detection. An improved convolutional neural network (CNN) combined with degenerate unmixing estimation technique (DUET) is proposed in the paper which offers an online solution for the inductive aliasing signal separation. The experimental result shows that the proposed method is effective and provides an alternative online approach of the original two-dimensional weighted histogram method.**

Keywords—aliasing signal separation; inductive debris detection; degenerate unmixing estimation technique; health management

I. INTRODUCTION

Wear is one of the failure modes of the running machines. The mechanism of wear is very complex and involves multiple physical and chemical processes. Wear debris are believed to be directly related to the wear status of the machines.

As one of the crucial method to acquire the wear state of a running machine, oil debris detection has been paid much attention [1]. The accurate detection of wear debris will provide a possibility for the remaining useful life prediction and achieve the condition based maintenance [2]. Compared with other methods, the inductive debris detection sensors are not only capable of providing accurate characteristics of the wear products but also take advantages in non-invasion, easy installation and recognizing ferrous and non-ferrous wear debris [3].

The electromagnetic induction principle intrinsically determines that when several wear debris pass through a sensor with short spatial lengths, there will be a superimposition of the induced voltages, which is the essence of the aliasing signal and affects the accuracy of the inductive methods. At present, the capability of detection reaches micron level [4, 5], while the aliasing may waste this micron-level ability if there is no proper separation method. Several works have been done on the aliasing problem. Zhong et al. [6] proposed a novel layout for the superimposed inductive voltages detection and a theoretical analysis was given. Li et al. [7] proposed a method by conducting the degenerate unmixing estimation technique (DUET) on a serial layout of detection sensors and the experiment showed the effectiveness of the method. Later, Li combined the DUET method with artificial neural networks and tested different network structures [8]. According to their result, convolutional neural network (CNN) is deemed to provide the best performance. There are three main shortcomings of the original DUET method on the debris aliasing signal separation, which converge on the two-dimensional weighted histogram method. Firstly, being different from the original application on the speech signals, real time processing is needed for debris signals. Secondly, instead of one-time separation for a speech signal, large amount of debris signal segments are queued up for being processed. Thirdly, manual operation of the two-dimensional weighted histogram may introduce human errors into the method.

Aiming at solving the defects mentioned above, an improved CNN combined with DUET is proposed in the paper. CNN is employed as an alternative solution to extract key features for separation. However, when using CNN, a critical problem is that the disordering of the features prevents the original networks from giving valid results. Although the indicator shows a high accuracy by the original networks, the truth is that the output estimations trend to be equal, which means the original method cannot learn the characteristics of the training dataset. A new training target and a corresponding evaluating indicator are given out to improve the original CNN method. The next part will firstly introduce the so-called disordering features problem and its effect on the networks and then, the improvement.

II. CONVOLUTIONAL NEURAL NETWORK BASED DEGENERATE UNMIXING ESTIMATION TECHNIQUE

A. The disordering features in networks for aliasing signals

When using the artificial neural networks to solve a regression problem, the training dataset usually consists of input data and labeled outputs. For the labeled outputs, each output may be given a certain meaning like mean value, and variance. In fact, not all of the labeled outputs can be divided, though it is rarely seen. When using the serial layout of detection sensors to get two aliasing signals for the separation, the two signals can be described as

$$y_1(t) = \sum_{i=1}^{n} s_i(t) \tag{1}$$

$$y_2(t)=\sum_{i=1}^{n} a_i s_i(t-\delta_i) \tag{2}$$

where $s_i(t)$ is the induced voltages by one of the passing through particles, a_i and δ_i are the corresponding attenuation and relative phase difference of the particle. If the aliasing signals serve as the input and the output $s_{\text{label}}=\{\delta_1,\delta_2,...,\delta_n\}$ is the set of the relative phase differences where n is the number of the particles. The labeled output can be any element in

$$S_{\text{label}}=\{(x_1,x_2,...,x_n)\,|\,x_1,x_2,...,x_n\in s_{\text{label}}, x_1\neq x_2\neq ...x_n\}. \tag{3}$$

Then, we can find that the labeled output does not have a specific meaning. Each of the outputs is only one characteristic of the superimposed voltages and cannot be ordered by parameters like attenuation or phases before being recognized. This is the disordering problem. Assuming that two similar groups of sources pass though the inductive sensor, each group contains two sources. The difference of the two groups is the exact phases of the sources in the first group is opposite to that in the second group. In other words, the phase of the first source in the first group equals that of the second source in the second group and the phase of the second source in the first group equals the phase of the first source in the second group. So the relative phases of the two groups of sources are the same, which means if both of the two groups of sources pass through the inductive sensor, the relative phase difference will be the same and the output of the sensor will be the same. If these disordered data are used for the training of the neural networks and the network are perfectly trained by these two groups of data, when a new groups of data with two sources is being tested, what we expect to obtain is that the first output is corresponding to the exact phase of the first source, and the second output is corresponding to the exact phase of the second source. However, the output of the network tends to be the average because of the two training groups of data, which means that the first output is the average of the first source and the second source. Same thing also happens to the second output. Then, the network cannot provide us the right phases of sources.

The superimposition of the induced voltages caused by two debris particles is shown in Fig. 1. Similar phenomenon shows when detect the debris using image-based method that there may be an overlapping of the debris images [9, 10]. The observable output is shown in the lower figure and the original is shown in the upper figure.

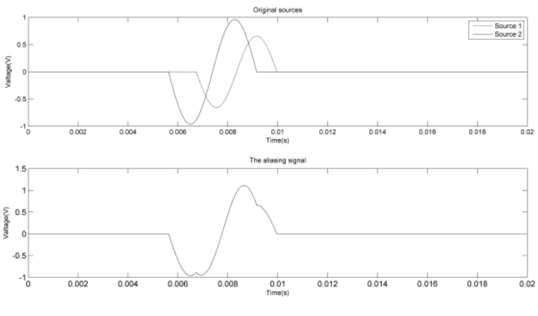

Fig. 1 The superimposition of induced voltages

Compared with the original networks, the schematic structure of the network with disordering features is shown in Fig. 2, from which we can see that in the original network, the labeled data are regarded as separated outputs and that in the network with disordering features are regarded as an assemble. The assemble describes the disordering features of the original sources of the superimposed signals. The proposed network structure combining CNN becomes the improved CNN used in our work.

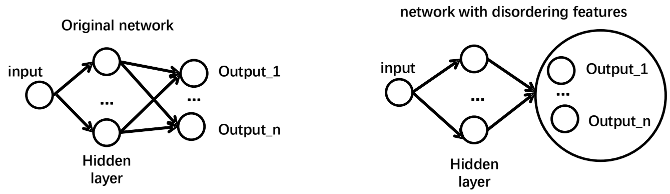

Fig. 2. Schematic structure of the networks

The original training target for the regression networks is to minimize the loss function where mean square error (MSE) is usually used. By minimizing the MSE, the difference between the output of the original network and the labeled value can be decreased effectively. However, when the structure becomes the network with disordering features, the original one-one corresponding training target will lead to a indistinguishable result. The training target is then to minimize the loss function

$$LS=\frac{\sum_{i=1}^{n}(\sum_{j=1}^{n}x_j{}^i-\sum_{j=1}^{n}\hat{x}_j{}^i)^{\frac{2}{i}}}{n}+\lambda\varphi(x,\hat{x}),\ x\in s_{\text{label}},\hat{x}\in s_{\text{out}} \tag{4}$$

where φ is the penalty function which is defined as the difference of the variance of the predicted values and the variance of the labeled values and λ is its coefficient.

The original evaluating method which can only be used to evaluate the one-one corresponding training performance is then modified as the minimum of

$$\frac{\sum_{i=1}^{n}(x_i-\hat{x}_i)^2}{n},(\hat{x}_1,\hat{x}_2,\dots\hat{x}_n)\in s_{\text{label}},(\hat{x}_1,\hat{x}_2,\dots\hat{x}_n)\in s_{\text{out}}. \tag{5}$$

With the modified training target and accuracy, the output layer of the network is regarded as a group instead of individual neurons, which is also the improvement of the network for debris feature extraction.

B. CNN based DUET for debris signal separation

By using the DUET to separate aliasing signals in Eq. (1) and Eq. (2), the time-domain signals are firstly transferred to time-frequency domain by short time Fourier transform (STFT) using a Hamming window

$$\hat{s}_i(\tau,\omega):=F^W[s_i](\tau,\omega):=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}W(t-\tau)s_i(t)e^{-j\omega t}\mathrm{d}t. \tag{6}$$

For a certain serial layout of detection sensors with n signals mixed, the aliasing signals can be rewritten as

$$\begin{bmatrix}\hat{y}_1(\tau,\omega)\\ \hat{y}_2(\tau,\omega)\end{bmatrix}=\begin{bmatrix}1 & \cdots & 1\\ a_1e^{-j\omega\delta_1} & \cdots & a_ne^{-j\omega\delta_M}\end{bmatrix}\begin{bmatrix}\hat{s}_1(\tau,\omega)\\ \vdots\\ \hat{s}_n(\tau,\omega)\end{bmatrix} \tag{7}$$

where $\hat{y}(\tau,\omega)$ is the STFT of $y(t)$ and for each (τ,ω). If the attenuations $\tilde{a}_i(\tau,\omega)$ and delays $\tilde{\delta}_i(\tau,\omega)$ which are defined as

$$\tilde{a}(\tau,\omega)=\left|\frac{\hat{y}_2(\tau,\omega)}{\hat{y}_1(\tau,\omega)}\right| \tag{8}$$

$$\tilde{\delta}(\tau,\omega)=\left(\frac{1}{\omega}\right)\angle\left(\frac{\hat{y}_2(\tau,\omega)}{\hat{y}_1(\tau,\omega)}\right) \tag{9}$$

By using the two-dimensional weighted histogram method, a good estimation of the attenuations and the delays can be obtained. The two-dimensional weighted histogram method is shown in Fig. 3.

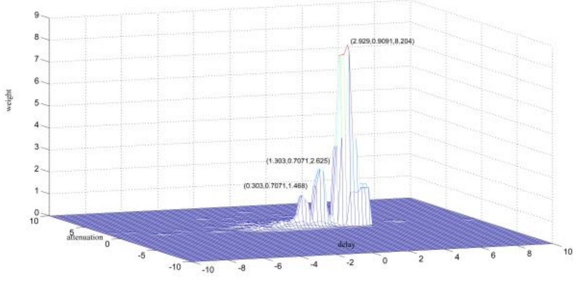

Fig. 3 two-dimensional weighted histogram method

Then, the aliasing signals can then be separated by the mask function which is defined as

$$M_i(\tau,\omega):=\begin{cases}1 & \left(\tilde{a}(\tau,\omega),\tilde{\delta}(\tau,\omega)\right)=(a_i,\delta_i)\\ 0 & \text{otherwise}\end{cases} \tag{10}$$

and finally by the inverse short time Fourier transform (ISTFT), the separated signals can be obtained.

If an aforementioned improved CNN is used as the feature extraction method instead of the original two-dimensional weighted histogram method, the flow chart of the CNN based DUET can be shown in Fig. 4. Because for two certain inductive sensors, the amplification coefficients can be regarded as constants, only the delays are extracted from the network.

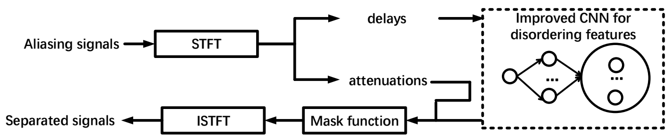

Fig. 4. Flow chart of CNN based DUET

III. Case Study and Discussion

Before the case study for the debris signal separation, an example is given out to validate the effectiveness of the improvement of the proposed network with disordering features. The input dataset is generated by $\{(I_1,I_2)\,|\,I_1\sim U(1,100),I_2\sim U(100,500)\}$ and the corresponding output features for each (I_1,I_2) are defined as $S_1=\{(O_1,O_2)\,|\,O_1=I_1-I_2,O_2=(I_1+I_2)/2\}$. Assuming that the two output features cannot be distinguished, there will also be labels from $S_2=\{(O_1,O_2)\,|\,O_1=(I_1+I_2)/2,O_2=I_1-I_2\}$. Considering the bounding case that half of the labels are from S_1 and half are from S_2, both the input with label from S_1 and that with the label from S_2 are served as the training dataset for a feedforward network which contains one hidden layer and the hidden layer contains 10 neurons. All of the 500 groups of training data are initially normalized before the training. Another 250 groups of data are generated for test.

The results of the test dataset by the original network and the improved network are shown in Fig. 5 and Fig. 6 in which the labeled points are marked in red and the predicted points are marked in blue which are connected by lines. The lengths of the lines are the normalized distance between the two features. If the original error is used to evaluate the accuracy of the two networks, the error of the original network is about 0.05 and that of the improved network is about 0.2, which means the original network performs less error in the case. But actually the result shown in Fig. 6 by the improved method is much better than that by the original network. So the original evaluation method does not provide us an accurate result. Fig. 7 shows the zoomed in result of Fig. 6, from which we can see that every two groups of neighboring data have the same predicted value because the two groups share the same input but the order of the labels are swapped. Comparing the two results shown in Fig. 5 and Fig. 6, the improved network surely performs better while the original evaluating method makes a mistake by confusing the disordering features. Evaluating by the new evaluating method, the error of the improved network is about 0.01 which is better than that of the original network whose error is 0.05.

In this case, the simple calculation case is designed to be well fitted by a simple artificial network. By conducting disordered data onto the original network, we can find that the two output features are nearly the same which is not consistent with the assumption. The improved network gives out an acceptable result to the problem. The original evaluating method provides a mistaken result and shows that the original method is better. The new evaluating method corrects the mistake and is more suited for the disordering problem.

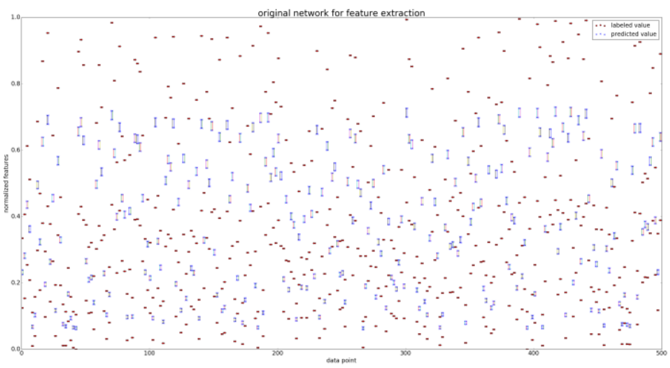

Fig. 5. Feature extraction using original network

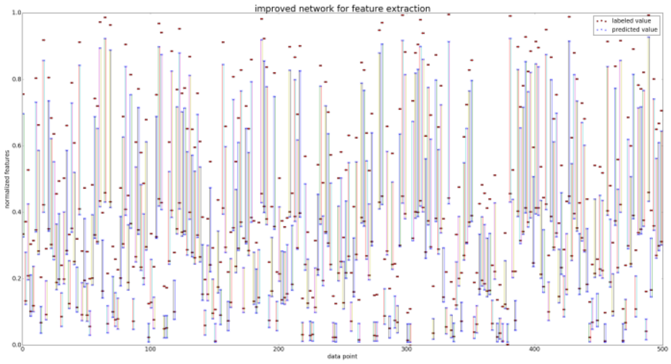

Fig. 6. Feature extraction using improved network

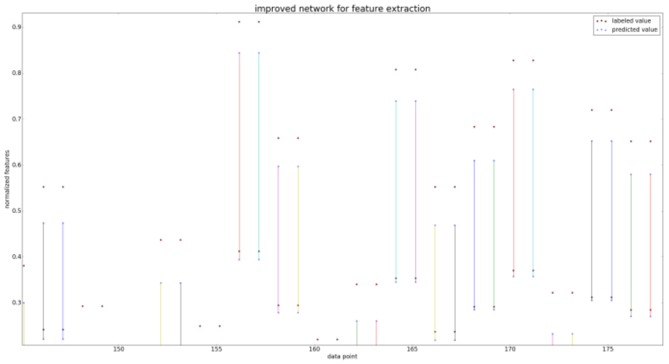

Fig. 7. Zoomed in result using improved network

Then we displays a case using the improved CNN and the original CNN for the aliasing feature recognition. An experimental dataset with 3500 groups of data is used for the debris aliasing signals feature extraction test. Among them, 3000 groups serves as the training data and 500 groups serves as the test data. Each aliasing signal is superimposed by three sources. A simple CNN whose structure is shown in Fig. 8 is used: The original filtered signals from the two sensors with serial layout are the input of the network. Each signal segment is fixed to 500 points. Then the signals are featured by the convolutional layer whose convolutional cores are in the size of 30×2. 30 feature maps can be obtained in the convolutional layer. The size of each feature maps is 470×1. An average pool layer is used for the feature maps and the we can then get 30 maps in the size of 235×1. All the neurons are connected to a full connection layer with 256 neurons. The outputs of the network are 3 neurons which stands for the collection of 3 exact phases of the superimposed voltage signals. Because the attenuations of the two sensors are assumed to be constants, by the exact phases we can carry out the separation of aliasing signals by the DUET framework.

The testing results of the original method and the improved method are shown in Fig. 9 and Fig. 10, respectively. If we use the original evaluating method, the error of the original method is about 0.08 and that of the improved method is about 0.11. It seems that the original method is better. The variance of the improved network is 0.47 and that of the original network is 0.0015. The variance of the labels is 0.48. So the variance of the original network is far different from the actual data, which means the original network fails to learn the characteristics of the training dataset and the lower error does not make sense. By using the new evaluating method, the error of the original method is about 0.08 and the error of the improved method is about 0.05. The improved method promote the accuracy by 3% and avoid the disordering problem under the new evaluating method.

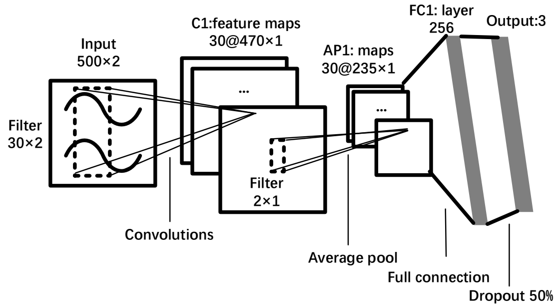

Fig. 8. CNN structure

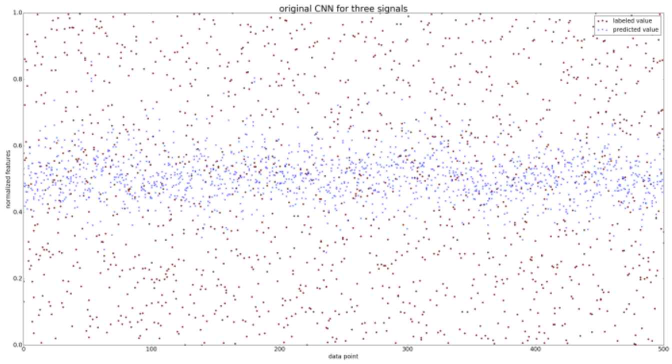

Fig. 9. Debris Aliasing signals with three sources using original CNN

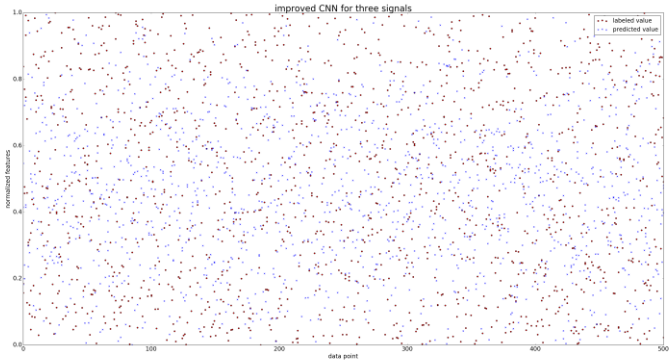

Fig. 10. Debris Aliasing signals with three sources using improved CNN

IV. Conclusions

This paper proposed a CNN based DUET method for debris aliasing signal separation. By redefining the training target and accuracy evaluating method, the improved CNN successfully learned the characteristics of the training dataset with disordering delay features. By using the experimental data to test the trained improved CNN for the debris aliasing signal separation, the improved CNN promotes the accuracy of the tested data by 3% compared with the original CNN. The accuracy evaluated by the new method is approximate 95%, which validate the effectiveness of the proposed method.

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