

Fault diagnosis of a marine power-generation diesel engine based on the Gramian angular field and a convolutional neural network

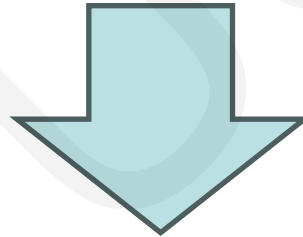
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Research problem

Only part of the data in the vibration signal contains critical fault feature information.

Existing methods of signal preprocessing cause some loss of information.



Existing network models have insufficient ability to learn key fault features, thus affecting the accuracy of machinery fault diagnosis.

Method

A combination of spatial domain image fusion and convolutional neural network containing multiple attention mechanisms is used to solve the above problem.

● 1 Gramian Angular Field

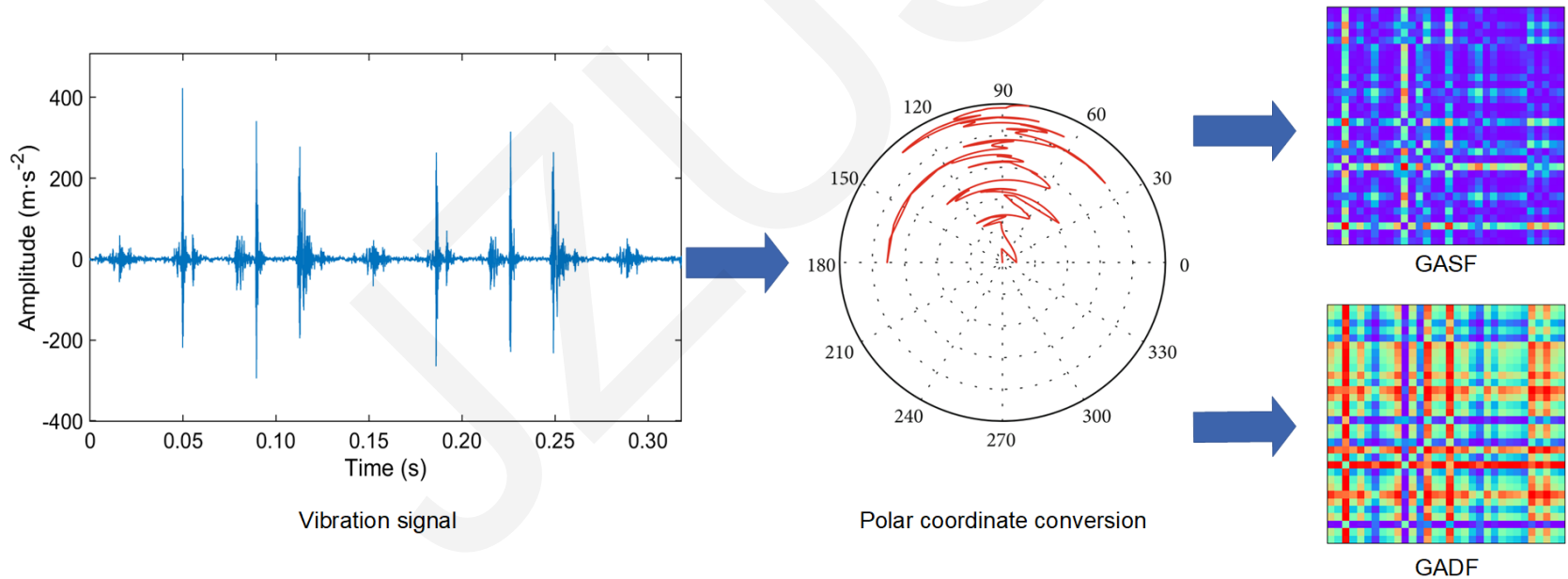


Fig. 1 GAF conversion process

Method

● 2 Image Fusion

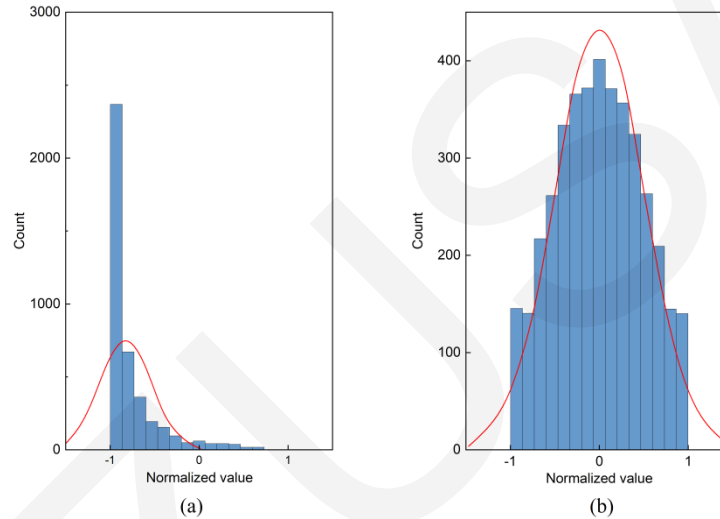


Fig. 2 The density histogram of GASF and GADF: (a) GASF matrix density histogram; (b) GADF matrix density histogram

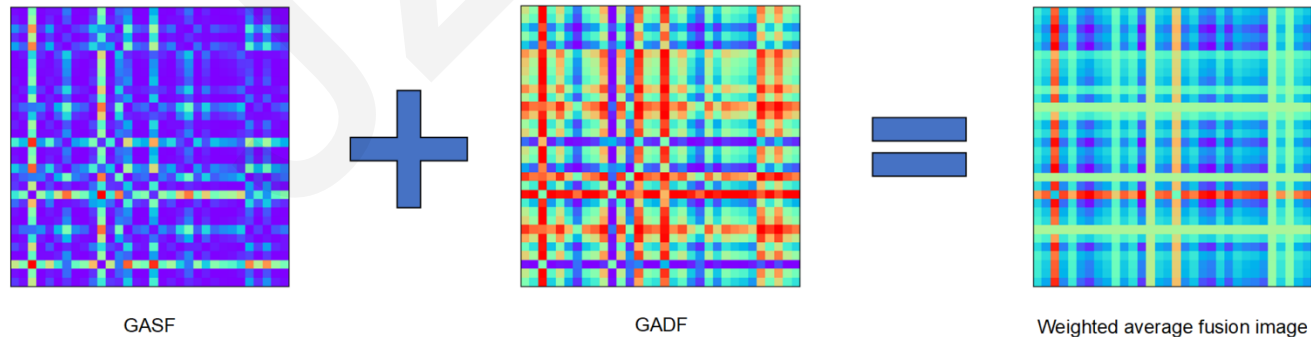


Fig. 3 Image-fusion process

Method

● 3 Improvements in Attention Mechanisms

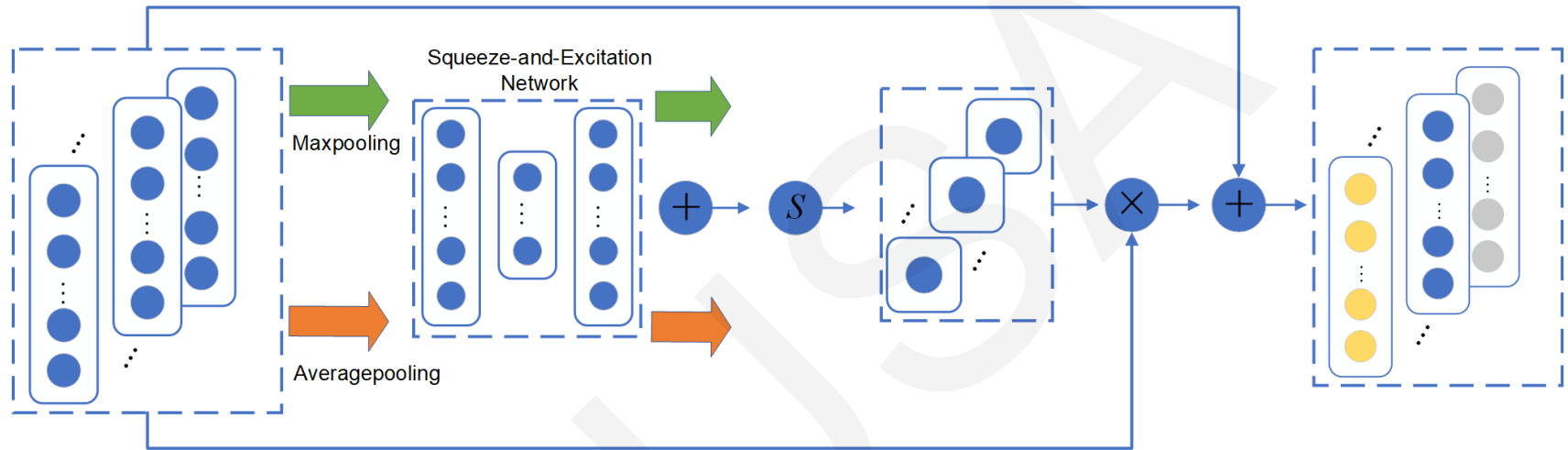


Fig. 4 Channel attention mechanism

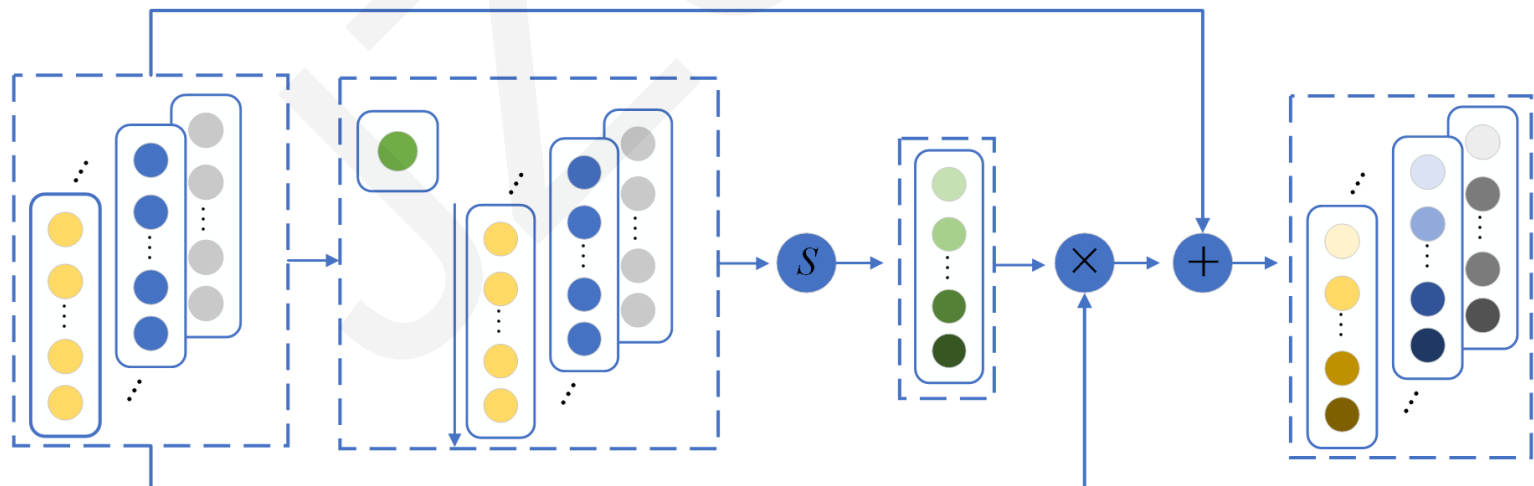


Fig. 5. Temporal attention mechanism

Method

● 4 The CNN Structure and Main Parameters

Name	Structure parameters	Output size
Image input	$64 \times 64 \times 3$	$64 \times 64 \times 3$
Conv_1	$32@2 \times 2$, Stride= [1], Padding= [2]	$67 \times 67 \times 32$
Batchnorm_1	-	$67 \times 67 \times 32$
Maxpool_1	3×3 , Stride= [2], padding= [0]	$33 \times 33 \times 32$
Multi-attention mechanism_1	$64@1 \times 1 \times 1$ (Time attention mechanism)	$33 \times 33 \times 32$
Relu_1	ReLU	$33 \times 33 \times 32$
Conv_2	$32@3 \times 3$, Stride= [1], Padding= [2]	$35 \times 35 \times 32$
Batchnorm_2	-	$35 \times 35 \times 32$
Maxpool_2	3×3 , Stride= [2], Padding= [0]	$17 \times 17 \times 32$
Multi-attention mechanism_2	$128@1 \times 1 \times 1$ (Time attention mechanism)	$17 \times 17 \times 32$
Relu_2	ReLU	$17 \times 17 \times 32$
Fc_1	-	$1 \times 1 \times 100$
Relu_3	ReLU	$1 \times 1 \times 100$
Dropout	0.5	$1 \times 1 \times 100$
Fc_2	-	$1 \times 1 \times 7$
Softmax	-	$1 \times 1 \times 7$
Class output	-	$1 \times 1 \times 7$

Method

● 5 CNN Performance

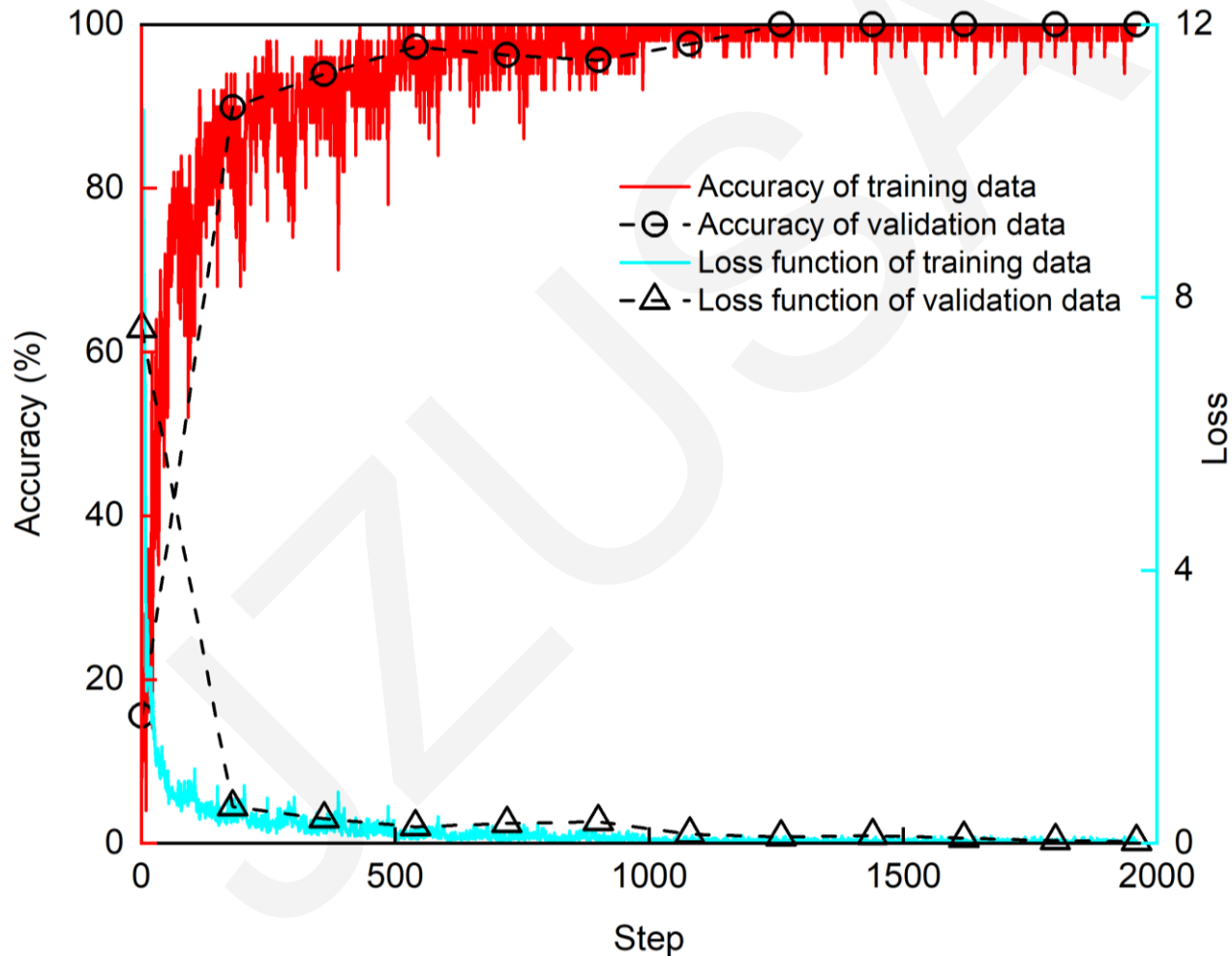


Fig. 12 The CNN model training and validation process

Conclusions

1. Using a multi-attention mechanism, interference information such as noise can be suppressed, and the CNN feature-extraction capability can be optimized. With strong noise, the diagnostic accuracy of the model with a multi-attention mechanism is 14.8% better than the model without the mechanism.

2. The average accuracy is above 94% with all SNRs. The proposed method has better noise immunity and stability than the four other methods.

3. Fused images provide more adequate feature information for the neural network, which improves fault-identification accuracy.

4. The variable-load experiments illustrate that the accuracy of the proposed model can be maintained above 89%, proving that it has good stability.