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Research on Fault Diagnosis of Hydro-Pneumatic Suspension Blockage Based on GASF-CNN

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Abstract: *The performance degradation and safety risks associated with altered stiffness and damping in hydro-pneumatic suspensions are often caused by blockages. This paper presents an intelligent fault diagnosis method based on the Gramian Angular Summation Field (GASF) and a Convolutional Neural Network (CNN) for the precise identification and classification of blockage severity. Firstly, a single-wheel hydro-pneumatic suspension vibration test platform was developed for blockage-fault experiments. Then, by installing a throttle valve within the hose, five levels of partial blockage faults (30%-50%) were simulated. Subsequently, the body acceleration signals were acquired under sinusoidal excitations at various frequencies. To enable effective fault diagnosis, the one-dimensional time-series acceleration data were transformed into two-dimensional GASF images, which preserve critical temporal dependencies in the system's dynamic behavior. A CNN-based diagnostic model was then developed and trained on this GASF-image dataset for accurate blockage severity classification. The experimental results demonstrate that the proposed GASF-CNN approach achieves outstanding diagnostic accuracy across all tested conditions, with robustness confirmed under noisy conditions, demonstrating its potential for practical applications.*

Keywords: *Hydro-Pneumatic Suspension, Blockage Severity, Fault Diagnosis, Gramian Angular Summation Field, Convolutional Neural Network*

1. Introduction

The suspension system is a critical subsystem of a vehicle chassis, directly affecting driving safety, stability, and ride comfort [1]. Among various suspension types, hydro-pneumatic suspension (HPS) systems are extensively deployed in military and engineering vehicles due to their superior stiffness and damping characteristics [2]. However, such vehicles often operate under harsh conditions, where the HPS systems endure sustained high pressure, impact loads, and cyclic stresses, resulting in elevated failure rates. Statistical analyses indicate that suspension-related faults account for approximately 13% of total vehicle failures [3]. Notably, hydraulic line blockage represents a particularly detrimental progressive degradation mode in the HPS systems, typically initiated by oil contamination or particulate deposition. This fault may fundamentally alter the HPS's stiffness and damping characteristics [4], degrade suspension performance, and may precipitate critical vehicle instability.

Currently, the maintenance of HPSs still primarily relies on periodic inspections and corrective repairs, lacking early warning capabilities and precise diagnostic methods. Consequently, research on the intelligent fault diagnosis methods for critical components of HPS is of great importance for enhancing vehicle operational and maintenance levels and ensuring safety. Existing studies have primarily focused on the diagnosis of macro-level faults, such as oil and air leakage [5-6], while studies on internal faults are relatively scarce. This is primarily attributed to the weakness and indistinctiveness of their signals, making it difficult to effectively isolate these signals from the complex system response.

Deep learning has demonstrated significant potential in mechanical fault diagnosis in recent years. A convolutional neural network (CNN) enables end-to-end intelligent diagnosis by autonomously extracting discriminative features from raw data. To harness CNNs' superior image processing capabilities, time-series encoding techniques have been widely adopted. For example, the Gramian Angular Summation Field (GASF) effectively transforms one-dimensional time-series signals into two-dimensional images while preserving temporal dependencies and amplitude information [7], thereby facilitating CNN-based feature extraction. Although the GASF-CNN framework has proven successful across multiple diagnostic applications [8-10], its implementation for diagnosing hydraulic blockages in HPS remains notably underexplored, representing a critical gap in current research.

This study adopted a GASF–CNN-based fault diagnosis method to quantitatively assess blockage severity in a HPS system. A dedicated single-wheel HPS vibration test platform was developed to simulate graded blockage conditions and acquire corresponding body-acceleration response data. The acquired temporal signals were subsequently converted into two-dimensional feature representations using GASF, and a tailored CNN architecture was implemented to achieve precise blockage severity classification.

2. Single-Wheel HPS Vibration Test

In this study, a blockage fault was simulated by inserting an adjustable flow valve inline in the hose between the actuating cylinder and the accumulator, and different blockage severities were further emulated by varying the valve opening. On this basis, single-wheel HPS vibration tests were conducted. As shown in Figure 1, the blockage-level labeling procedure used an inclinometer to partition the valve opening and mark percentage graduations, so that the valve opening could be used during experiments to represent the severity of blockage.

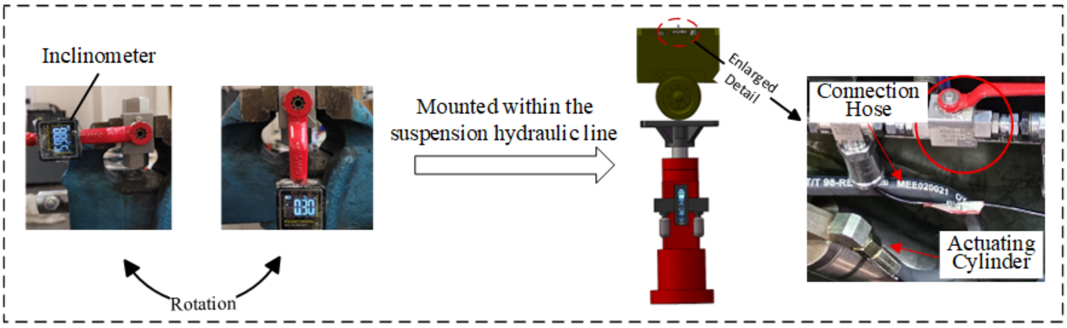

Figure 1: Schematic of the blockage severity marking procedure.

The marking procedure was as follows: first, using an inclinometer, the fully closed angle of the adjustable throttle valve was measured to be approximately 88.65°, and the fully open angle approximately 0.30°. Next, the adjustable angular range was divided into ten equal intervals and labeled 0%–100%, with the fully open position defined as 0% blockage and the fully closed position as 100% blockage. As the objective of this study was to acquire vibration signals under different blockage levels, the valve was assumed to be linear with respect to opening, and nonlinear effects were neglected.

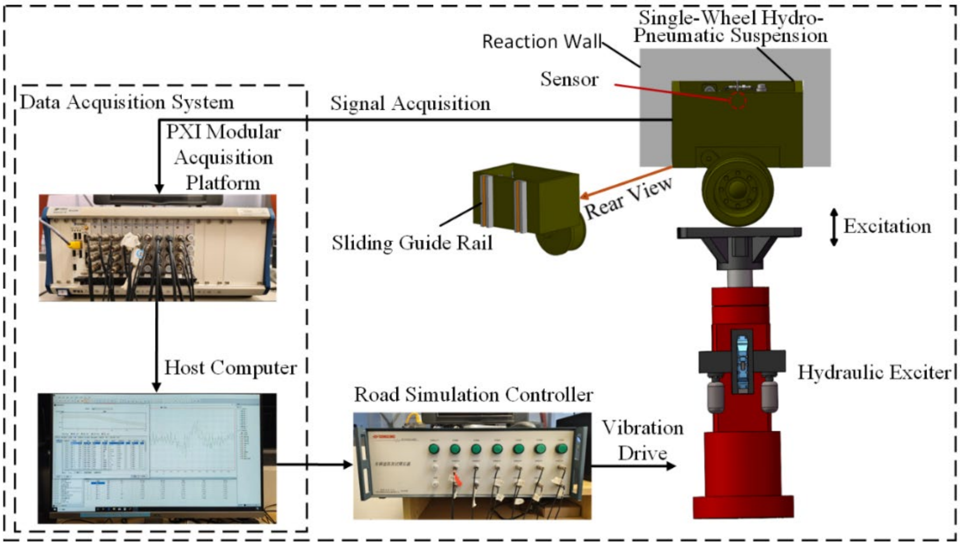

Figure 2: Schematic of the single-wheel hydro-pneumatic suspension vibration test bench.

Figure 2 shows the single-wheel hydro-pneumatic suspension vibration test bench, which consists primarily of a servo-hydraulic shaker, a single-wheel hydro-pneumatic suspension, a data-acquisition system, a road-simulation controller, and sensors. The test procedure was as follows: first, the single-

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wheel suspension—equipped with an inline throttle valve in the hose—was mounted on the hydraulic shaker. Two vertical guide rails were installed on the rear side of the vehicle body and connected to a reaction wall to maintain lateral balance and ensure strictly vertical motion. Next, an accelerometer was installed at the body's center to measure the vertical acceleration at that location. Finally, the excitation amplitude and frequency were configured in the vibration-testing software, and body-acceleration signals were collected for blockage levels of 30%, 35%, 40%, 45%, and 50% under sinusoidal excitations of 1 Hz, 2 Hz, 3 Hz, 5 Hz, and 10 Hz, yielding 25 datasets in total, with a sampling rate of 2048 Hz.

According to ISO 2631-1:1997 (Mechanical vibration and shock—Evaluation of human exposure to whole-body vibration—Part 1), the frequency range of interest for evaluating the effects on "health, comfort, and perception" is 0.5–80 Hz. This indicates that the effective content of vertical vehicle-vibration responses is mainly concentrated within this band. Therefore, a 50 Hz low-pass filter was applied to the raw signals. This cutoff preserves the fundamental responses and low-order harmonics induced by the 1–10 Hz excitations, while effectively suppressing higher-frequency components dominated by noise. Taking the body-acceleration signal acquired under a 5 Hz sinusoidal excitation as an example, the signal after 50 Hz low-pass filtering is shown in Figure 3.

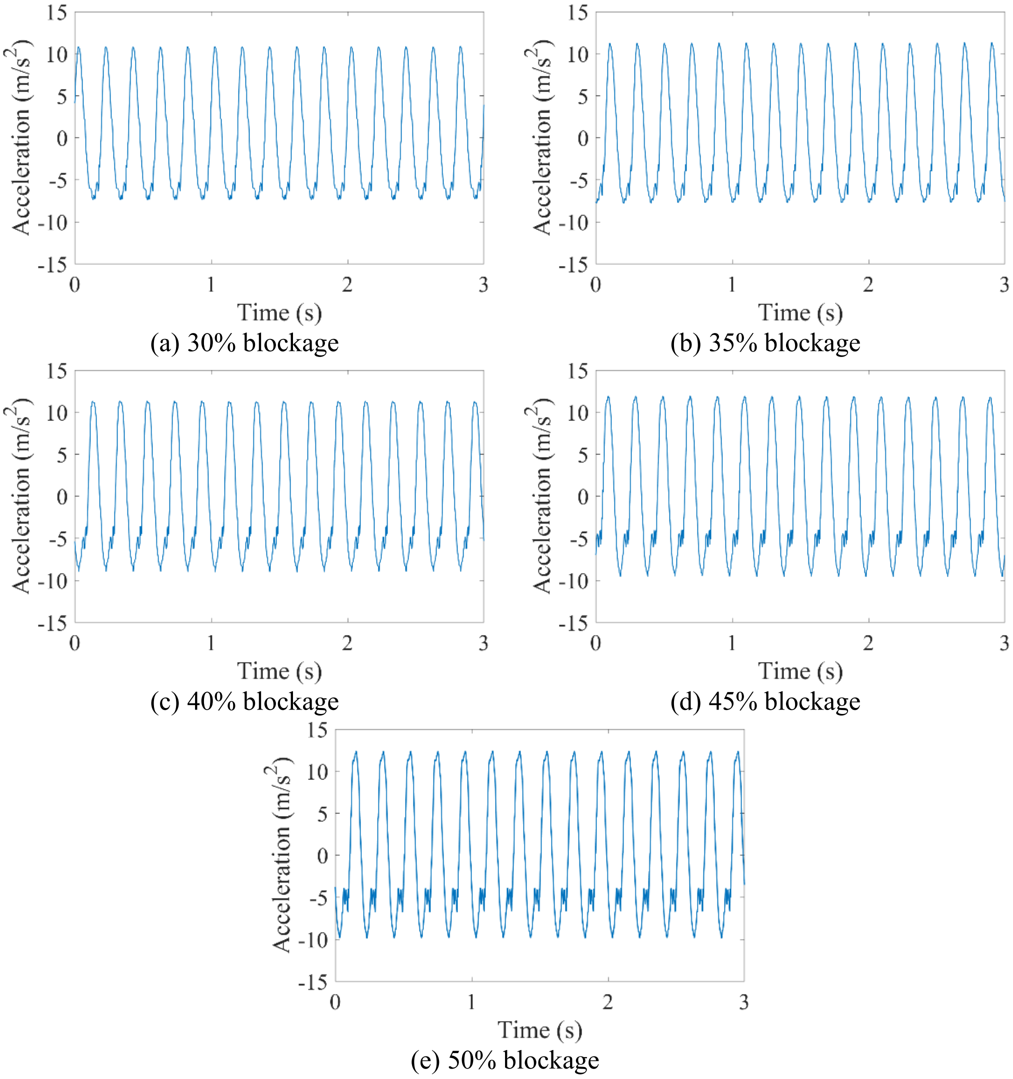

Figure 3: Vehicle acceleration signal under 5 Hz excitation after 50 Hz low-pass filtering.

3. GASF-CNN-Based Diagnostic Model for Blockage Severity in HPS

Considering the periodic nature of the vibration-test data, this study adopted a combined GASF–CNN approach to train a diagnostic model for blockage severity in a hydro-pneumatic suspension. To prevent information leakage from test samples, the signals were split into training and test sets in an 8:2 ratio before any segmentation. The filtered signals were then segmented using a sliding window with a length

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of 2,048 samples and a step of 512 samples. Figure 4 illustrates the sliding-window scheme. The windowed one-dimensional time series were subsequently converted into two-dimensional images via the GASF method and supplied to the CNN as inputs.

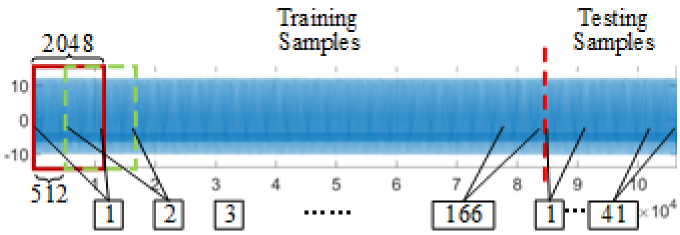

Figure 4: Sliding-window schematic.

The CNN comprises four convolutional blocks that extract fault features from the GASF-transformed images and perform blockage severity classification. Feature extraction is carried out by four blocks, each consisting of a 3×3 convolution layer, batch normalization, a ReLU activation, and 2×2 max pooling. A global average pooling layer then reduces the feature maps to 4×4, followed by a classifier composed of three fully connected layers; Dropout is applied in the fully connected layers to mitigate overfitting. The output layer contains five neurons corresponding to the five blockage severities. The network configuration is given in Table 1.

Table 1: CNN architecture and parameters.

Layer type	Parameter setting	Output size（C×H×W）	Activation
Input		1×64×64	
Conv + BN	16 filters,3×3, padding=1	16×64×64	ReLU
Max pool	2×2	16×32×32	
Conv + BN	64 filters,3×3, padding=1	64×32×32	ReLU
Max pool	2×2	64×16×16	
Conv + BN	128 filters,3×3, padding=1	128×16×16	ReLU
Max pool	2×2	128×8×8	
Conv + BN	256 filters,3×3, padding=1	256×8×8	ReLU
Global avg pool	4×4	256×4×4	
Flatten		4096	
FC	512 units	512	ReLU
FC	128 units	128	ReLU
Output	5 units	5	

4. Experiment Results and Analysis

All training and testing in this study were conducted under the same hardware and software environment: Windows 11, an Intel Core i7-10870H CPU, and an NVIDIA GeForce RTX 2060 GPU. The models were implemented in PyCharm using the PyTorch framework (version 2.3.1) with GPU acceleration via CUDA 12.1 and cuDNN 9.5.1.

For each image dataset converted from body-acceleration signals under sinusoidal excitations at 1 Hz, 2 Hz, 3 Hz, 5 Hz, and 10 Hz, a diagnostic model for blockage severity was trained using the cross-entropy loss. The image size was 64×64. The training, validation, and test sets were split in a 6:2:2 ratio. Training hyperparameters were set as follows: 50 epochs, a batch size of 128, an initial learning rate of 0.0001, the Adam optimizer, and a regularization coefficient of 0.0001.

Taking the 5 Hz case as an example, the training loss and accuracy curves are shown in Figure 5. As indicated by Fig. 5, the loss drops rapidly and converges by the 10th epoch, at which point the validation accuracy reaches 100%. This suggests that, under sinusoidal excitation, different blockage severities manifest clearly distinguishable features, and that the model learns the dominant patterns early in training.

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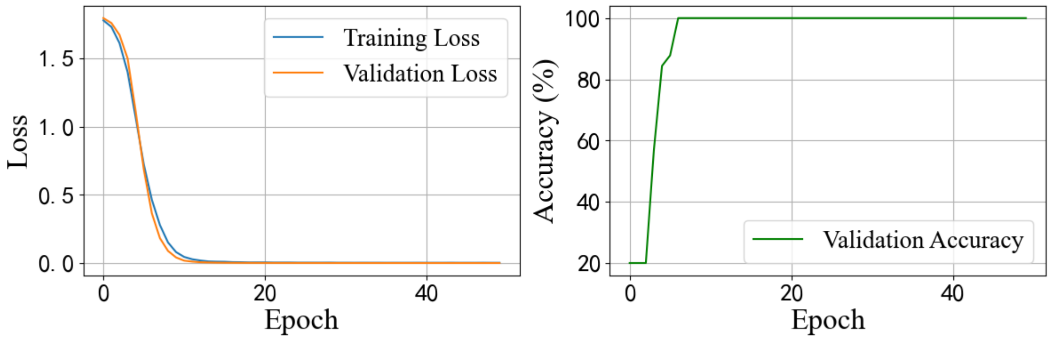

Figure 5: Training curves (loss and accuracy) for the 5 Hz model

Based on the trained blockage severity models, performance was evaluated on the test sets under sinusoidal excitations at 1 Hz, 2 Hz, 3 Hz, 5 Hz, and 10 Hz. The mean test accuracies at each frequency are shown in Table 2. The results indicate that, across all excitation frequencies, the average diagnostic accuracy exceeds 99%. This confirms that GASF images effectively preserve the distinctive patterns of vibration signals at different blockage severities, and that the CNN possesses strong feature-learning and classification capabilities, enabling precise discrimination among five blockage levels.

Table 2: Mean test accuracy at different excitation frequencies.

Excitation frequency	1Hz	2Hz	3Hz	5Hz	10Hz
Mean accuracy	100%	100%	99.59%	100%	100%

The high diagnostic accuracy achieved by the GASF-CNN blockage severity model under sinusoidal excitation may be attributed to the following: (1) clear boundaries between blockage levels; (2) the repeatability and consistency of vibration responses under sinusoidal excitation, which yield small intra-class differences and pronounced inter-class differences, facilitating the CNN's learning of discriminative features; (3) suppression of high-frequency noise by applying a 50 Hz low-pass filter to the raw signals; and (4) the GASF, which encodes one-dimensional time-series signals into two-dimensional images while preserving temporal structure and amplitude information, thereby enhancing pattern visualization and separability. Consequently, the model's strong performance in this study results from the combined effects of clear fault boundaries, data quality, and signal-encoding strategy, and is reasonable and reproducible under the specified conditions.

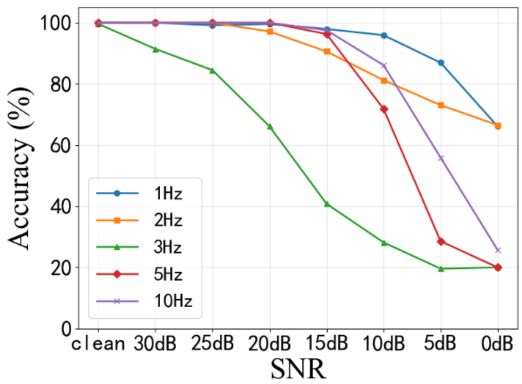

Figure 6: Noise test results of the blockage severity diagnostic model under different sinusoidal excitations.

To further assess robustness, noise experiments were conducted by superimposing Gaussian white noise of varying intensity onto the original signals to construct test signals with different signal-to-noise ratios (SNRs): 30 dB, 25 dB, 20 dB, 15 dB, 10 dB, 5 dB, and 0 dB. The results, summarized in Figure 6 for different sinusoidal excitations, show that when the SNR is at least 15 dB, the diagnostic accuracy remains above 95% at all frequencies. Even at 10 dB, accuracies exceed 70% for all models except the 3 Hz case. These findings indicate that the proposed GASF-CNN model exhibits strong robustness to noise, stemming mainly from two factors: first, the GASF transformation imparts a smoothing effect on random noise, yielding visually stable images; second, the CNN learns higher-level features that are sensitive to fault patterns yet insensitive to noise.

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5. Conclusions

This study adopted a GASF–CNN–based fault-diagnosis approach for blockage in hydro-pneumatic suspensions, enabling identification of different blockage severities. A single-wheel hydro-pneumatic suspension vibration test bench was built, five blockage levels (30%, 35%, 40%, 45%, 50%) were emulated, and body-acceleration signals were collected under sinusoidal excitations at 1, 2, 3, 5, and 10 Hz. The one-dimensional vibration signals were then encoded into two-dimensional images via GASF, and a CNN with four convolutional blocks was constructed to diagnose blockage severity. The main conclusions are: (1) Under 1, 2, 3, 5, and 10 Hz sinusoidal excitations, the GASF-CNN model achieves diagnostic accuracies of at least 99% across the five blockage levels. (2) Noise tests show strong anti-interference capability. When the signal-to-noise ratio is at least 15 dB, the diagnostic accuracy remains at or above 95% for 1, 2, 5, and 10 Hz, whereas the model trained at 3 Hz is comparatively less robust. (3) Combining GASF image encoding with CNN feature learning avoids complex hand-crafted feature engineering and enables end-to-end diagnosis from raw signals to blockage severity, providing an effective solution for component-level fault diagnosis of hydro-pneumatic suspensions.

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