Inlet Fault Diagnosis Based on Attention Mechanism Feature Fusion

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Abstract: To tackle the instability fault diagnosis challenges in wide-speed-range supersonic inlets, this study proposes an inlet fault decision fusion diagnosis algorithm based on attention mechanism feature fusion, achieving efficient diagnosis of instability faults across wide-speed regimes. First, considering the requirement for wall pressure data extraction in mathematical modeling of wide-speed-range inlets, a supersonic inlet reference model is established for computational fluid dynamics (CFD) simulations. Second, leveraging data-driven modeling techniques and support vector machine (SVM) algorithms, a high-precision mathematical model covering wide-speed domains and incorporating instability mechanisms is rapidly developed using CFD-derived inlet wall pressure data. Subsequently, an inlet fault decision fusion diagnosis method is proposed. Pressure features are fused via attention mechanisms, followed by Dempster-Shafer (D-S) evidence theory-based decision fusion, which integrates advantages of multiple intelligent algorithms to overcome the limitations of single-signal diagnosis methods (low accuracy and constrained optimization potential). The simulation results demonstrate the effectiveness of the data-driven wide-speed-range inlet model in achieving high precision and rapid convergence. In addition, the fusion diagnosis algorithm has been shown to attain over 95% accuracy in the detection of instability, indicating an improvement of more than 5% compared to the accuracy of other single fault diagnosis algorithms. This enhancement effectively eliminates the occurrence of missed or false diagnoses, while demonstrates robust performance under operational uncertainties.

Key words: wide-speed-range supersonic inlet; data-driven modeling; attention mechanism; Dempster-Shafer(D-S) evidence theory; fault diagnosis

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0 Introduction

The inlet, serving as a critical component of aeroengine propulsion systems, plays a pivotal role in ensuring aircraft system effectiveness and enhancing overall maneuverability. To guarantee combustion stability and safe engine operation, the inlet must deliver airflow with three essential characteristics: High total pressure, minimal disturbances, and low mass flow fluctuations. This is a fundamental design objective particularly crucial for supersonic inlets that must operate reliably across wide-ranging flight conditions from static startup to supersonic regimes.

For inlet, there are two paramount performance metrics: Aerodynamic stability and thermodynamic efficiency. Fig.1[1] illustrates typical performance curves of mixed-compression supersonic inlets. The mass flow ratio (MFR), defined as the ratio between actual through-flow mass and theoretical maximum admissible mass flow, represents a key aerodynamic parameter in propulsion engineering. Total pressure recovery (TPR), quantified as the ratio of area-averaged total pressure at the engine face to freestream total pressure[2], serves as a critical performance indicator for gasdynamic system

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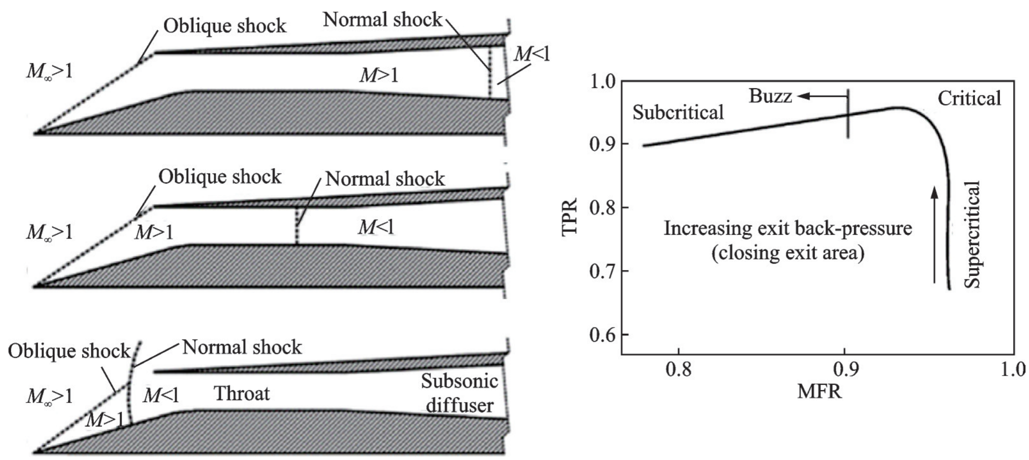
evaluation. Fig.1 clearly demonstrates that while the TPR exhibits gradual variations with changing MFR, a dramatic TPR transition occurs when MFR crosses the critical threshold, triggering instantaneous inlet instability. This abrupt aerodynamic disturbance poses immediate threats to engine operational stability and safety. The transient nature of this phenomenon underscores the critical importance of precise inlet instability detection for reliable propulsion system operation.



(a) Working condition of the inlet (b) Intake performance curve

Fig.1 Intake operating conditions and performance curves[1]

Since the 1950s, researchers have conducted systematic investigations into inlet instability phenomena. A seminal breakthrough occurred in 1984 when Newsome[3] pioneered numerical simulations of inlet instability using unsteady Navier-Stokes equations, which is a landmark achievement in computational fluid dynamics (CFD). Employing the implicit MacCormack scheme coupled with the Cebeci-Smith algebraic Reynolds-averaged Navier-Stokes equations (RANS) turbulence model, he successfully resolved the Navier-Stokes equations to characterize instability features in external-compression inlets. Shigematsu et al.[4] advanced this work in 1990 by implementing compressible Navier-Stokes equations with the Baldwin-Lomax turbulence model, performing both two-dimensional and three-dimensional CFD analyses of ramjet inlets. Notably, his numerical predictions demonstrated excellent agreement with experimental data under static conditions. The Kantrowitz starting criterion inspired Pan et al. [5] in 2016 to develop rapid theoretical estimations of inlet starting Mach numbers, while Cui et al.[6] focused on hysteresis effects and bifurcation phenomena during inlet start/unstart transitions. By 2019, emerging theories[7] had been established consensus assessment criteria for inlet instability, though current frameworks remain incomplete in explaining all observed phenomena. The contemporary surge theory differentiates small surge (characterized by low-amplitude high-frequency oscillations) from large surge (high-amplitude low-frequency perturbations) based on distinct amplitude-frequency-time signatures[8]. However, this dichotomy complicates analysis of hybrid surge modes exhibiting overlapping characteristics, as conventional classification boundaries become ambiguous.

The instability faults of supersonic inlets exhibit extreme complexity, as reliance on a single characteristic parameter cannot authentically quantify fault severity, directly compromising accurate aerodynamic assessment. In such intricate operational environments, multi-sensor data integration combined with multi-feature fusion significantly enhances diagnostic accuracy[9]. This sophisticated fault detection paradigm necessitates processing heterogeneous sensor data from distributed measurement points to extract meaningful fault signatures. Information fusion architectures are systematically categorized into three hierarchical levels: Data fusion (raw signal integration), feature fusion (characteristic parameter synthesis), and decision fusion (diagnostic conclusion reconciliation)[10]. Feature fusion enables comprehensive fault analysis through intelligent information compression, achieving 85%—92% data volume reduction while preserving more than 98% critical features, which is a vital advancement for real-time processing efficiency[11]. This methodology synergizes data fusion's sensitivity advantages with decision fusion's interpretability strengths while mitigating their respective limitations[12]. He et al.[13] developed a dual-scale residual network integrating multi-sensor fusion for railway bearing diagnostics (92.7% accuracy). Kordestani et al.[14] proposed an ordered weighted average operator-based smart grid fault isolation technique, reducing diagnostic latency by 40%. Pan et al.[15] established a real-time confidence evaluation framework leveraging sensor redundancy for localized/global fault verification. The example above underscores the vast potential of multi-source information integration to improve the efficiency of fault-detection methods. By leveraging data from multiple channels, we not only enhance diagnostic accuracy but also bolster system robustness, enabling better adaptation to the complex and dynamic conditions encountered in real-world engineering applications.

In a fault-fusion strategy, decision-level fusion is regarded as the highest-tier approach. It relies on the local outputs of individual sensor signals for fault detection. Although this method offers limited flexibility, it guarantees a very high degree of diagnostic accuracy[16]. The Dempster-Shafer (D-S) evidence theory provides mathematical rigor for multi-source decision integration, initially proposed by Dempster[17] through statistical evidence combination rules and formalized by Shafer[18] via belief functions. Chen et al.[19] used enhanced D-S theory to reduce aero-engine gas path false alarms by 30%. Although understudied in inlet diagnostics, preliminary trials demonstrate D-S theory's potential for 93%—96% balanced effectiveness in instability diagnosis through conflict resolution (85% reduction) and adaptive weighting (confidence factors 0.6—1.2). Currently, there are fewer studies on the application of D-S evidence theory for intake tract fault diagnosis, and the examples prove that its use for intake tract fault diagnosis has a greater potential to ensure that the level of decision-making remains highly balanced and effective. This study fuses multi-source information to improve the accuracy of fault diagnosis and enhance the robustness of the system. Meanwhile, applying the D-S evidence theory to the intake tract fault diagnosis study improves the model accuracy, solves the leakage judgement problem, and enhances the robustness of the system compared to other previous single fault diagnosis methods.

This study focuses on wide-speed-range supersonic inlets, and investigates diagnostic algorithms for typical instability faults. We propose an inlet fault decision fusion diagnostic algorithm based on attention mechanism feature fusion, achieving efficient diagnosis of instability faults in wide-speed-range inlets. Compared with single fault diagnosis algorithms, the fusion algorithm fully incorporates the advantages of other algorithms, not only improves accuracy but also resolves issues of missed and false detections, demonstrating excellent robustness. The main research content will be presented in two chapters, with specific arrangements as follows.

Section 3 introduces the comprehensive algorithmic framework for fault fusion diagnosis of supersonic inlets, encompassing a data-driven modeling approach based on inlet wall pressure data, a feature fusion algorithm for inlet wall pressure leveraging the attention mechanism, and a fault decision fusion method grounded in D-S evidence theory. Section 4 presents the results of fusion diagnosis of intake tract faults based on feature fusion of attention mechanisms. Section 4.1 presents the inlet channel feature extraction results. Section 4.2 yields the results of pressure feature fusion based on the attention mechanism, which greatly improves the diagnostic accuracy by utilizing the multi-source fusion features to establish the intake channel model containing the instability mechanism. Section 4.3 presents the fault decision fusion results based on D-S evidence theory to integrate the advantages of multiple intelligent algorithms. The diagnostic results are fused for decision making, the fusion model not only solves the problem of omission and misjudgement, but also has good robustness. The accuracy of intake tract instability fault diagnosis is higher than 95%.

1 Integrated Fault Diagnosis Framework for Supersonic Air Intake Systems

To address instability fault diagnosis challenges in wide-speed-range supersonic air intakes, this study presents a hybrid intelligent diagnostic framework that synergistically integrates attention mechanism-based feature fusion with D-S evidence theory-driven decision fusion. As illustrated in Fig.2, the methodology comprises four critical phases: Single feature extraction, adaptive feature fusion, data-driven system modeling, and probabilistic decision integration. The implementation initiates with extracting pressure-sensitive signatures from baseline intake system models, specifically targeting instability precursors. Subsequently, an attention-enhanced feature fusion mechanism dynamically weights these multi-source pressure characteristics to establish a physics-informed data model encapsulating instability mechanisms. The final stage employs D-S evidence theory to reconcile diagnostic outputs from multiple artificial intelligence (AI) classifiers, achieving robust decision synthesis through uncertainty quantification. Compared to conventional single-feature classifiers and monolithic algorithm approaches, this dual-layer fusion architecture demonstrates superior diagnostic fidelity with enhanced noise immunity.

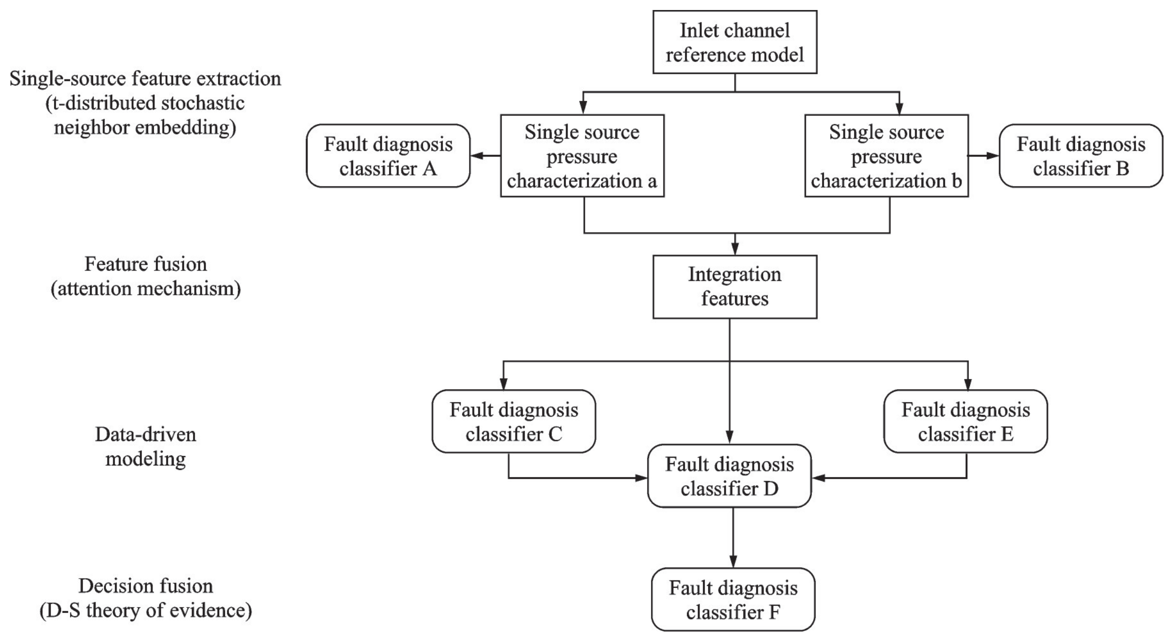


Fig.2 Intelligent diagnosis flowchart of intake tract faults

2 Data-Driven Modeling of Supersonic Air Intakes

In the context of modeling supersonic air intakes with instability mechanisms across a wide speed range, the inherent complexity and intricate flow details of the intake system present significant challenges. To efficiently and rapidly create a high-accuracy model of the intake, this paper proposes a data-driven modeling approach. This method circumvents the detailed internal flow mechanisms by utilizing data-driven techniques to uncover the mapping relationships between input data and system behavior. Through advanced big data analysis, this approach constructs a mathematical model that accurately represents the real-time operational state of the system, embodying the dynamic advancements in modern data science at the intersection of fundamental and applied sciences. Compared to traditional physics-based mechanism modeling, this data-driv en method offers distinct advantages in terms of speed, efficiency and accuracy. It is particularly well-suited for developing predictive and control models for manufacturing processes, where timely and precise modeling is essential.

2.1 Benchmark modeling of supersonic air intakes

A supersonic inlet model with instability mechanism in wide speed domain is designed with fixed geometry and mixed compression axisymmetric inlet structure[20]. The inlet adopts a two-stage cone compression and is designed for an incoming Mach number of 4.5. The inlet parameters are based on the incoming flow at 27 km altitude flight. The inlet angles are 10° and 8°. The inlet length is 910 mm. The capture radius is 160 mm. The throat height is 12.2 mm. And the internal/total constriction ratio is 1.64/6.21.

The 2D computational domain mesh is shown in Fig.3, where intensive mesh refinement is implemented for the adjacent wall region in order to finely capture the subtle fluid dynamics within the adherent layer, and additional mesh enhancements are applied where significant changes occur in the flow characteristics. A pressure remote field model, a non-sliding adiabatic wall setup, and pressure-set outlet boundary conditions are utilized in the numerical calculations.

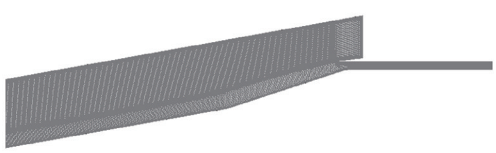


Fig.3 Axisymmetric mixed-pressure supersonic inlet mesh model

2.2 Instability feature signal extraction

The performance of an aero-engine intake is evaluated through a range of parameters, with vibration indicators playing a central role, as they reflect the stability characteristics of the system. When an engine experiences surge, typical indicators include significant fluctuations in compressor outlet pressure, pronounced instability in air flow, sudden drops in both high-pressure and low-pressure rotor speeds, a sharp rise in low-pressure turbine outlet temperature, a sudden spike in engine inlet pressure , and abrupt changes in thrust.

To assess engine instability, key parameters such as inlet and outlet pressures, the turbine outlet temperature, and high-pressure and low-pressure rotor speeds are closely monitored. The primary objective is to capture the immediate initial fluctuations in the engine's compression components, as these are critical to identify the onset of instability. While pressure, temperature, and rotor speed parameters exhibit significant dynamics during vibration events, pressure changes are often gradual and exhibit long periods, and thus less effective for real-time analysis of engine states. Temperature signals are slow to respond and not intuitive for identifying instability. Rotor speed fluctuations, though related to fuel control, offer an indirect correlation. Transient pressure changes are more easily detectable and can be a reliable indicator of instability. Therefore, inlet pressure data, in the form of pressure pulsations, is selected as a key characteristic parameter for determining engine instability.

3 Decision-Making Fusion Diagnosis Method for Intake Tract Faults Based on Feature Fusion of Attention Mechanisms

3.1 Attention mechanism-based fusion method for inlet wall pressure features

The expressive power of the fault characteristics of intake tract instability is weak. Although advanced detection techniques for individual signals have been optimized in a variety of ways, their progress in improving diagnostic accuracy is still significantly constrained. Therefore, this study focuses on the analysis using an approach with multiple characteristics. Inlet wall pressure feature fusion refers to the combination of features from different information sources or feature spaces, in order to provide more information content and a more detailed presentation. In the field of machine learning as well as data analytics, feature fusion is often used to improve the overall performance of a model, increase the accuracy of predictions or simplify the way that a model is described. The core goal of feature fusion is to integrate data from different sources with the aim of obtaining a more complete presentation of the features. This strategy helps the model to effectively understand the intricate connections between multiple sources of data, which improves the model's generalization performance and enables more accurate expectations for different kinds of data.

3.1.1 Attention mechanisms characterizing integration basic theory

In the field of modern AI, the attention mechanism is widely used and has a large number of application scenarios. The attention mechanism can be described by using some kinds of regression models, where the training data of n instances and their corresponding target values are known to contain the features$\{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$, to solve the target value y for a new query instance x. This model uses a weighted average technique as the estimator result, where the weights correspond to the correlation between the training cases and the query are respresented as

$$\hat{y}=\sum_{i=1}^{n}\alpha(x,x_i)y_i \tag{1}$$

where the weight function α represents the computation of the predictive relevance of instance x_i for x. Eq.(1) can accurately summarize the thinking underlying the mechanisms of attention. Modern models of attention depends on the domain of attentional focus and have progressed at an impressive rate. Attention mechanisms can be categorized into several areas such as channel attention, spatial attention, or temporal attention. The mechanism of channel attention is modeled by assigning specific weights to each channel, which helps to adaptively acquire samples related to channel fusion. The squeeze and excitation (SE) module is the most typical one. This module aims to enhance the global representational function of the feature map by constructing correlations between channels, which in turn enables a greater focus on emphasizing the strong features in data messages, while suppressing the weak features.

In the adaptive weighted fusion process, a channel attention strategy is utilized to determine the criticality of each single channel within the multichannel feature matrix. First, a feature embedder is used to integrate the features of each channel. Considering the significant differences between different channels, trained parameters are used to precisely control the weights of each channel. In order to improve the module robustness, the Euclidean norm (L2 paradigm) is chosen to compute the global features, Let the embedding weight $\boldsymbol{\alpha}=[\alpha_1, \alpha_2, \cdots, \alpha_m]$, then the global feature is defined as

$$s_{mn}=\alpha_m\left[\left(\sum_{i=1}^{W}\sum_{j=1}^{W}f_{mn}(i,j)^2\right)+\varepsilon\right]^{\frac{1}{2}} \tag{2}$$

The L2 paradigm is chosen as a means of standardizing the channel ensemble information, so as to make the description of the channel information more clear and intuitive. In order to clarify the cooperation between the channels and how to confront each other, the feature matrix of multiple channels is investigated in this study, and a gated adaptive strategy is adopted. In view of the insufficient generalization ability of traditional channel normalization methods, trainable weights $\boldsymbol{\gamma}$ and deviations $\boldsymbol{\beta}$ are added to this method to simulate the activation status of channels. Let the gating weight $\boldsymbol{\gamma}=[\gamma_1, \gamma_2, \cdots, \gamma_m]$, the gating bias $\boldsymbol{\beta}=[\beta_1, \beta_2, \cdots, \beta_m]$, then the final obtained channel attention output is represented as

$$\hat{f}_{mn}=\sigma(\gamma_m\hat{s}_{mn}+\beta_m)f_{mn} \tag{3}$$

where σ denotes the Sigmod function. Relying on the aforementioned gating mechanism, the model shows that the performance competitiveness of a particular channel is positively enhanced when the channel's gating weight is enabled. Conversely, when the control weights of a particular channel are restricted, the model enhances the synergy and integration between that channel and other channels. Meanwhile, the gating mechanism ensures that the channel's original information can be conveyed securely, which is achieved by selecting the appropriate activation function.

3.1.2 Fusion algorithm for supersonic inlet features based on attention mechanism

In some data-level multi-sensor data fusion methods for supersonic air intakes, multi-sensor measurements are processed without considering their respective sensitivities to different types of data. In order to better improve the quality of the fused data, this study designs a multi-source data fusion method based on the SE-block protocol to distinguish the importance of various intake sensor data more clearly.

The SE module acts as a shallow computational unit that mainly performs feature reorganization for any transformation F_{tr} from input $\boldsymbol{X}$ to feature mapping $\boldsymbol{U}$, where $\boldsymbol{U}$ denotes the feature map with the width W, the height H and the number of channels C after feature dimensionality reduction. $\boldsymbol{u}_c \in \mathbf{R}^{H\times W}$ indicates the corresponding characteristics of each channel. A typical scenario in this application setting is the convolutional transform by introducing the SE module. Feature $\boldsymbol{U}$ first performs dimensionality reduction for each channel feature to generate a global distribution characterization of the channel features. Then, with the help of the adaptive gating strategy, the distributional characterization of the channels is transformed into weights and embedded into the relevant feature channels, as shown in Fig.4. The detailed operation flow of the SE module is described below.

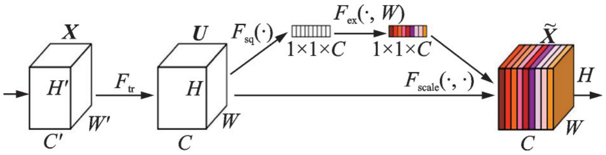


Fig.4 SE-block fundamentals

For example, in the convolutional transform, the input to the convolutional layer is $\{\boldsymbol{x}^1, \boldsymbol{x}^2, \cdots, \boldsymbol{x}^{C'}\}$, where C' denotes the input channel. The resulting output is $\{\boldsymbol{u}_1, \boldsymbol{u}_2, \cdots, \boldsymbol{u}_C\}$. Then the convolutional layer transform can be represented as

$$\boldsymbol{u}_c = \sum_{i=1}^{C'} \boldsymbol{v}_c^i * \boldsymbol{x}^i \tag{4}$$

where $*$ denotes the convolution and $\boldsymbol{v}_c^i$ the single-channel 2D spatial kernel acting on the corresponding channel. Since the output is formed through the sum of all channels, it results in channel dependencies are only masked in the characteristics captured by the learner, and this dependency is tightly linked to local spatial relationships. The goal of the SE module is to extract channel dependencies through explicit modeling in order to improve its sensitivity to key information properties. In order to find a channel identity with statistical expression properties, the local spatial information of the transformed output $\boldsymbol{U}$ is aggregated into $\boldsymbol{z} \in \mathbf{R}^{C\times 1}$ using global average pooling.

$$\boldsymbol{z}_c = F_{sq}(\boldsymbol{u}_c) \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} \boldsymbol{u}_c(i,j) \tag{5}$$

where $\boldsymbol{z}_c$ denotes the characteristics of each channel after aggregation. In order to fully capture channel dependencies using aggregated information, network configurations that can flexibly learn nonlinear soft interactions need to be chosen, and thus a simple gating strategy based on the sigmoid activation function is selected. In order to enhance the accuracy of the SE-block model while reducing its complexity, the channel dependencies of the aggregated information are learned through an intermediate layer consisting of a reduced-dimensional fully connected layer and an incremental fully connected layer. The weight vector is derived as

$$\boldsymbol{s} = F_{ex}(\boldsymbol{z}, W) = \sigma(g(\boldsymbol{z}, W)) = \sigma(W_2\delta(W_1\boldsymbol{z})) \tag{6}$$

where δ denotes the ReLU function; and W_1 and W_2 are the fully connected layer weight coefficients from model optimization. The weight vector $\boldsymbol{s}$ computed by the activation operation is utilized to adjust the weights of the transformed output $\boldsymbol{U}$ to produce the final output data of the SE module, which is represented as

$$\tilde{\boldsymbol{x}}_c = F_{scale}(\boldsymbol{u}_c, \boldsymbol{s}_c) = \boldsymbol{s}_c\boldsymbol{u}_c \tag{7}$$

where $\tilde{\boldsymbol{x}}_c$ indicates the final output of the SE module and F_{scale} the multiplying of the weight vector along the channel with the feature map. This algorithm mainly consists of data preprocessing and fusion steps for adaptive weighting. In the link of data preprocessing, the collected data from various air intake sensors are firstly processed for noise reduction and normalization. After short-time Fourier transform, the sample information is transformed into different frequency images, and the spatial attributes of the image samples are mined from them to obtain a comprehensive multi-scale feature map.

During the adaptive weighted fusion stage, a channel attention mechanism is employed to quantify the criticality of individual channels within the multi-channel characteristic matrix. The adaptive attention framework utilizes learnable weight matrices to dynamically allocate weights across temporal, frequency, and spatial domain features. For inlet fault diagnosis applications, this approach specifically enhances the weighting coefficients for abrupt pressure transients, as these signatures are particularly discriminative for detecting incipient instability phenomena. First, the global attributes within each channel are pooled by using a global feature embedding component. Second, a gating adaptive strategy is adopted to determine the competition and cooperation patterns among the channels with respect to the original multichannel feature matrix. At the same time, the gating strategy ensures the efficient transmission of raw information within the channels by selecting appropriate activation functions. Utilizing lightweight spatial attention and channel attention control techniques, the feature images of multiple source fusion are successfully acquired, and then the inception module is deployed at the backend of the network to accomplish the fault classification task.

The structure of a complete feature fusion diagnostic algorithm consists of several parts: An input layer, a single spatial feature extraction layer, integrative multi-channel features and an output layer for specific classification. The framework of this algorithm is shown in Fig.5. In this method, multiple input data are first obtained from a single source of features through a spatial feature extraction layer. This information is fed into the channel fusion processing layer for information aggregation, and finally classified with the help of a network of inception modules to derive their corresponding fault types.

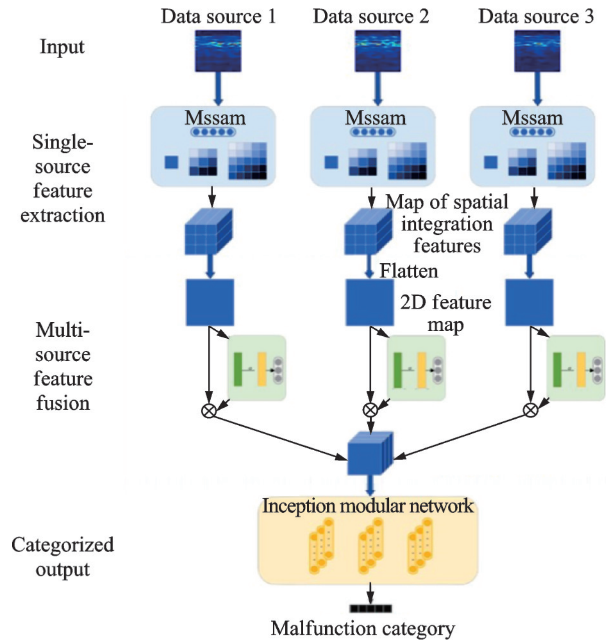


Fig.5 Attention mechanism-based feature fusion intake tract fault diagnosis algorithm

3.2 Fault decision fusion diagnosis method based on D-S evidence theory

For the diagnosis of instability faults in supersonic air intakes, despite the widespread use of advanced intelligent algorithms, most fault diagnosis still relies on a single intelligent classifier, i.e., only one specialized algorithm is used for identifying the type of fault. Given the differences in the working principles, characteristics and advantages of various classification tools, they are likewise accompanied by their own shortcomings, which leads to the difficulty of a single classifier model in detecting and diagnosing supersonic air intakes comprehensively and reliably in a variety of scenarios. How to fully utilize the strengths and capabilities of multi-intelligent diagnostic algorithms, bypass the inherent limitations of the algorithms, and continue to enhance the accuracy and reliability of the fault diagnosis is an innovative topic, and also coincides with the basic concepts and goals of information fusion.

3.2.1 Fundamentals of D-S evidence theory

The D-S evidence theory is widely used in information fusion as a method to deal with uncertain logical inferences. The system has the function of combining information from multiple sources of evidence and can quantitatively analyze the uncertainty of things. It has certain application prospects in the field of intelligent diagnosis of mechanical equipment faults[21].

Research methods based on the D-S evidence theory are divided into three main categories: Data fusion, feature fusion, and decision fusion. A hybrid intelligent diagnostic model for intake tract instability faults based on decision-level fusion is proposed.

The basic principle of the D-S evidence theory consists of the following three parts.

(1) Identification framework

The D-S evidence theory defines that the recognition structure is based on all potentially occurring hypothetical datasets $\Theta=\{A_1, A_2, \cdots, A_n\}$, and that all hypothesis sets are scalable to each other and are not dependent on each other, for a total of $2n$ hypothesis sets.

(2) Basic probability distribution

When a mapping function h with a power set of $2^{A_i} \in [0,1]$ satisfies Eq.(1), h is said to be a basic probability distribution, also known as a mass function or evidence. where the $h(A_i)>0$, the subset A_i is called a focal element.

$$\begin{cases} \sum_{i=1}^{n} h(A_i)=1 \\ h(\varnothing)=0 \end{cases} \tag{8}$$

A piece of evidence is shown as $h_1(A_1)=0.6$, $h_2(A_2)=0.5$, and $h_3(A_3)=0.2$. Then A_1, A_2, and A_3 are the possible sets of all hypotheses, and the magnitude of the evidence's support for each subset is expressed by the magnitude of the value of h.

(3) Synthesis rules

The fusion approach for multiple evidences in the D-S evidence theory is shown in Eq.(9), where $A_1, A_2, \cdots, A_n$ are the focal elements. k is the conflict coefficient and calculated by Eq.(10).

$$\begin{aligned} h(A) &= (h_1 \oplus h_2 \oplus \cdots \oplus h_n) A = \\ &\frac{1}{1-k} h_1(A_1)+h_1(A_1)h_2(A_2)+ \\ &h_1(A_1)h_2(A_2)h_3(A_3)+\cdots+ \\ &h_1(A_1)h_2(A_2)\cdots h_n(A_n) \end{aligned} \tag{9}$$

$$\begin{aligned} k &= h_1(A_1)+h_1(A_1)h_2(A_2)+ \\ &h_1(A_1)h_2(A_2)h_3(A_3)+\cdots+ \\ &h_1(A_1)h_2(A_2)\cdots h_n(A_n) \\ &A_1 \quad A_2 \quad \cdots \quad A_n=\phi \end{aligned} \tag{10}$$

where $\oplus$ denotes the orthogonal product. When $k=0$, this indicates complete compatibility between the different pieces of evidence; when $0<k<1$, it proves that there is certain degree of compatibility between the pieces of evidence and that the synthesis criterion has a fairly high degree of validity; when $k=1$, this synthesis rule will not be used because the evidence is completely untrue.

3.2.2 Fusion algorithm for decision making on supersonic intake failures

The underlying probability distribution is a central part of the decision level integration in the framework of the D-S evidence theory to fully explore the working principle and unique characteristics of each classification tool[22], and a probability-based basic distribution scheme based on the principles and uniqueness of various classifiers is proposed. The inlet pressure data exhibit high-dimensionality with limited samples, making support vector machine (SVM) the optimal choice. Multi-layer perception (MLP) is selected to perform deep nonlinear mapping of pressure data for capturing transient dynamic characteristics, while the random forest (RF) is employed for feature importance analysis. Therefore, this study adopts SVM, MLP and RF algorithms for fault diagnosis.

SVM: In order to assign appropriate probability values to the data results of the SVM, a geometric distance-based approach is introduced. The quantification of the probability is performed by analyzing the relative distance between the sample points and the hyperplane[23]. As the distance between the sample and the hyperplane increases, the trustworthiness of the sample for the current classification increases. This relationship is further normalized using the Softmax function to obtain the probability that sample P belongs to category i.

$$h_1(P)_i = \frac{\exp(R(P)_i)}{\sum_{l=1}^{k} \exp(R(P)_l)} \tag{11}$$

where $R(P)$ denotes the distance function between sample points.

MLP: The Softmax layer is widely used in neural network based classification systems and mainly used to estimate the likelihood that an example belongs to the same category. In the output module, a Softmax module is incorporated to narrow down the input data of the previous layer. When the value of the output is positively correlated with the ratio of the input elements and totals to 1, this output can be used as the likelihood of whether a sample P belongs to category i or not, namely

$$h_2(P)_i = \frac{\exp(z_i)}{\sum_{i=1}^{g} \exp(z_i)} \tag{12}$$

where g indicates the number of categories; and z_i the ith element of the input softmax layer.

RF: When discussing probability assignment methods in random forests, the voting method is the widely used strategy. The core method is to calculate the voting frequency of a decision tree and assign a probability value under the comprehensive consideration of the classification status inside and outside the decision tree. Assuming that the number of decision trees in a random forest is t, the probability that a sample P is determined as

$$h_3(P)_i = \frac{\sum_{j=1}^{t} p_j}{t} \tag{13}$$

To enhance diagnostic accuracy and credibility, the sub-model for inlet instability faults can adopt decision-level fusion techniques to integrate diagnostic data from multiple models after outputting preliminary diagnostic results, thereby fully leveraging the complementary advantages among different models. The D-S evidence theory, a mature algorithm for decision-level fusion, has been systematically applied to this sub-model in this study, successfully yielding diagnostic conclusions with significantly improved robustness. The overall logic and workflow of the algorithm are illustrated in Fig.6.

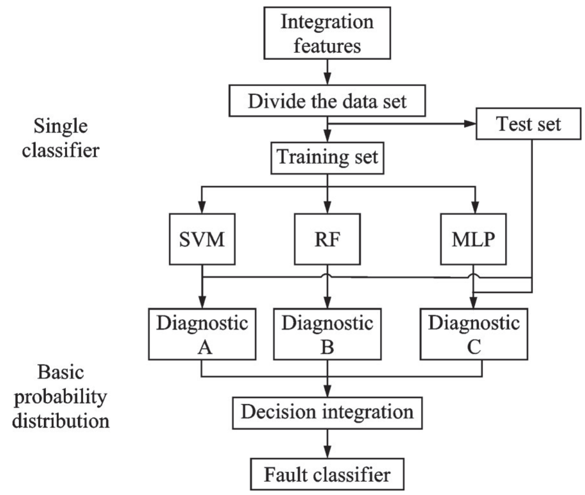


Fig.6 Decision fusion diagram for inlet instability faults based on D-S evidence theory

4 Simulation Verification

4.1 CFD simulation results and analysis of supersonic inlets

The design point for the wide-speed-range supersonic inlet model is set at a flight altitude of 27 km, a Mach number of 4.5, and standard atmospheric pressure. The computational domain is solved numerically by the Navier-Stokes (N-S) equations using the Roe-FDS scheme. A standard k-ε turbulence model is employed, and the governing equations are discretized using a second-order upwind scheme. Throughout the simulation, residuals and flow rates at the inlet and outlet are continuously monitored. Convergence is achieved when all residuals are reduced by three orders of magnitude, or when the residuals no longer decrease and both inlet and outlet flow rates stabilize.

At a flight speed of Mach 4.5, the inlet operates in a critical state. However, when the flight speed drops to Mach 3.2, the hybrid intake system fails to establish a complete and stable shockwave system, resulting in a turbulent flow field. The total pressure recovery coefficient is reduced, and the mass flow rate of the geometric intake exceeds the engine's required intake flow at startup, rendering the inlet in a non-starting state. For the hypersonic aero-engine's hybrid intake system, pressure signal sampling points are placed along multiple modal channels, with pressure acquisition points distributed along the walls. A set of counterpressure multipliers is used at typical operating points to simulate combustion chamber pressure conditions, yielding current intake pressure sample data. The pressure data from the upper and lower wall surfaces of the intake throat are extracted for feature fusion and instability fault diagnosis, as highlighted in Fig.7.

In order to obtain the sample data of intake

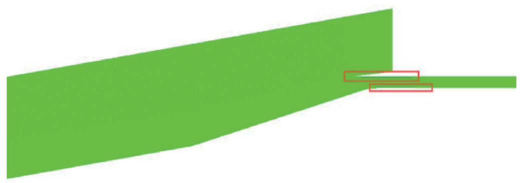


Fig.7 Inlet pressure data extraction along the course of the wall

tract under different working conditions, the intake conditions are changed including the intake temperature, the humidity, the flight altitude, and the intake angle of attack, etc. Then the anomalies and missing values of pressure sample data collected from numerical simulations are processed, merged, and organized. Fig.8 displays the pressure distribution along the upper wall surface for different channel locations, where each pressure distribution includes 91 data points. The total pressure recovery coefficient is calculated for the obtained pressure data, and labels are assigned using a clustering algorithm based on flow conditions and pressure pulsations. Stable samples are labeled as "2", while unstable samples are categorized as "−2" "−1" and "1" based on the severity of instability.

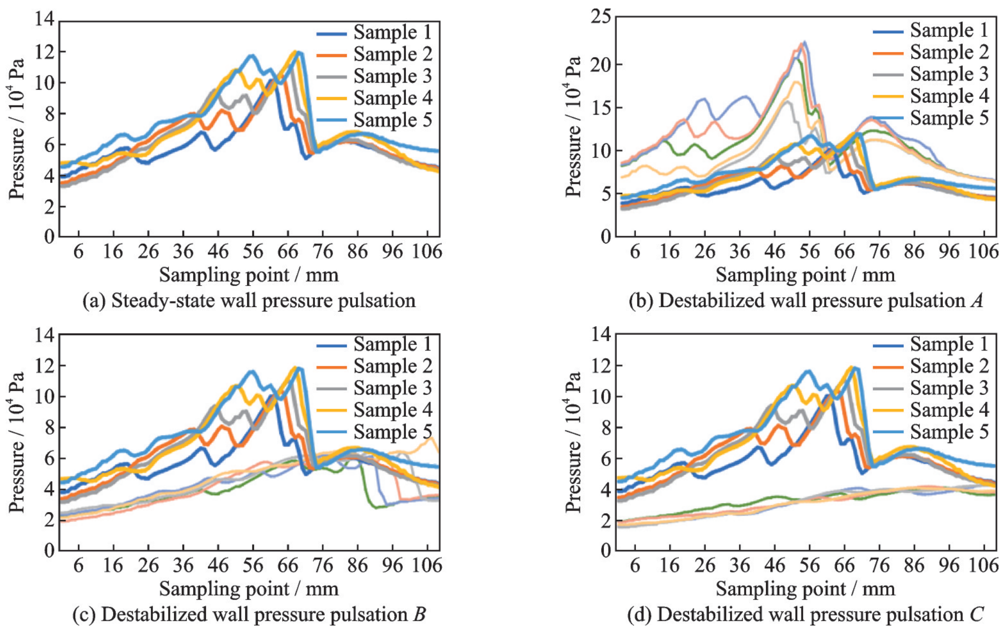


Fig.8 Wide velocity domain inlet wall pressure pulsation

4.2 Data-driven modeling of supersonic inlets with instability mechanisms in wide-speed domains

The process of data fusion-driven modeling for supersonic inlets can be outlined in the following steps.

(1) Data preparation: The initial task is to prepare a pre-labeled dataset, where each sample includes a feature set and corresponding category labels. These samples will be used to construct a SVM model.

(2) Finding the optimal hyperplane: The primary objective of SVM is to identify the optimal decision hyperplane that maximizes the margin between classes, thus ensuring effective separation of data points. The hyperplane is essentially a $(d-1)$ dimensional linear space, where "d" represents the dimensionality of the feature space. SVM performs classification by maximizing the margin between classes, improving the model's generalization ability.

(3) Kernel function transformation: When the data is not linearly separable in the original feature space, SVM employs kernel functions to map the samples to a higher-dimensional space, making the data linearly separable. Common kernel functions include linear, polynomial, and Gaussian kernels.

(4) Solving the optimization problem: SVM solves a convex optimization problem to determine the optimal hyperplane, aiming to maximize the inter-class margin and ensure that correctly classified samples are as far as possible from the decision boundary.

(5) Output result: Based on the position of the hyperplane, unclassified samples are assigned to a category. Samples on one side of the hyperplane are classified as one category, while those on the other side belong to a different category.

Based on the data of the pressure feature signals of the upper and lower wall surfaces of the supersonic air intake channel, the program is written to find the optimal hyperplane, and then the kernel function is transformed and the optimization problem is solved to achieve the output. The model is obtained based on SVM classification. It can be concluded that the accuracy of the mathematical model obtained from the upper wall pressure signal training is 0.819 7, the training set accuracy (ACU) is 0.956 79, the validation set ACU is 0.852 38, and the test set ACU is 0.8. The accuracy of the mathematical model obtained from the lower wall pressure signal training is 0.854 2, the training set ACU is 0.969 14, the validation set ACU is 0.857 14, and test set ACU is 0.85. Training, validation, and test set results show varying performances, indicating some limitations, including issues with misclassifications such as falsely predicting unstable samples as stable ones (false negatives) and vice versa (false positives).

4.3 Decision fusion diagnosis of intake faults based on attention mechanism feature fusion

The data fusion is based on isomorphic signals where pressure pulsation data of the upper and the lower wall surfaces are selected as the input data for the information feature fusion algorithm. Prior to data input to the network, these pressure pulsation data are converted into time-frequency maps by short-time Fourier transform (STFT). These images are used to extract the spatial properties of the RGB image samples using the self-attentive network described above, resulting in a comprehensive multi-scale feature map $\{f_{1n}, f_{2n}, \cdots, f_{mn}\}$ with the same width and height which value is Q' and number of channels C'. In order to complete the feature fusion, the synthesized feature maps are firstly simplified into the related independent channel gray matrices $\{f_{1n'}, f_{2n'}, \cdots, f_{mn'}\}$ with the same width and height which value is W. The single-channel grayscale matrices are further superimposed into multiple-channel attribute matrices. The above operation permits the transformation of data from multiple sensors into multichannel sample data, cleverly transforming the multisource idea into a multichannel structure, which in turn allows effective weighted integration with the help of a lightweight attention strategy.

To evaluate the quality of the fused features, a t-distributed stochastic neighbor embedding (t-SNE) clustering method is used for dimensionality reduction and the features are mapped into a two-dimensional image. The resulting feature clusters are shown in Fig.9. The sample set can be clearly grouped into four distinct clusters, as indicated by the four different colors of sample points. By combining the total pressure recovery coefficient of the sample's inlet duct and the flow capture status, it is determined that the blue sample cluster in the lower left corner in Fig.9 represents the steady-state data

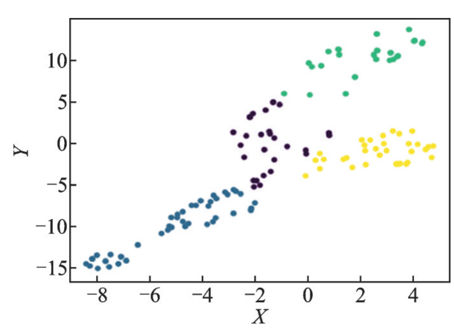


Fig.9 Clustering of inlet channel wall pressure characteristics

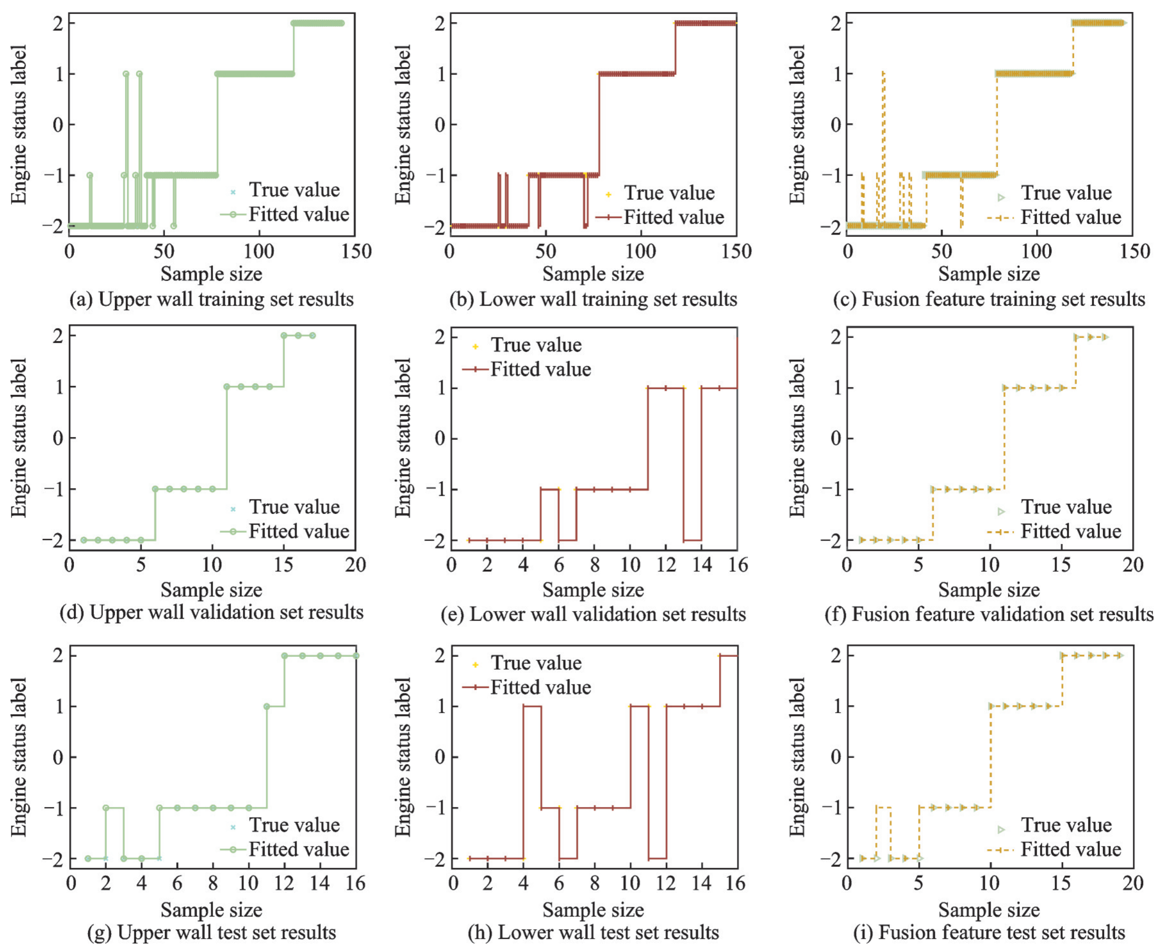
cluster, while the remaining three colored data clusters correspond to the three different instability data clusters. The boundaries between these clusters are clear. Although the number of feature samples in other categories is smaller, most of the feature clusters are concentrated near their respective geometric centers. This indicates that the feature distribution extracted by this synthesis algorithm shows significant differences across the various categories.

Following the acquisition of fused features, the effectiveness of the fusion algorithm in enhancing fault diagnosis is validated by training a mathematical model using SVM algoithms. Diagnostic outcomes are rigorously compared with single-feature model results from Section 3 (Table 1). The fused-feature model achieves an accuracy of 90.123%, with the training, the validation, and the test set accuracies of 0.944 44, 1.0 and 0.9, respectively, representing improvements of 8.153% (vs. upper wall pressure feature) and 4.703% (vs. lower wall pressure feature). Comparative classification results (Fig.10) and confusion matrices (Fig.11) demonstrate effective mitigation of misjudgments and missed detections.

Table 1 Comparison of fusion feature accuracy %

Indicator	Upper wall feature	Lower wall feature	Integration feature
Correct rate	81.97	85.42	90.12
Training set ACU	95.67	96.91	94.44
Validation set ACU	85.23	85.71	100.00
Test set ACU	80.00	85.00	90.00

However, although the surge detection accuracy of the fused-feature model reaches 90.123%, this remains insufficient for safety-critical engine applications. Misclassifying unstable states risks catastrophic flow separation and aerodynamic stall within the inlet. To meet aerospace-grade reliability standards, further optimization of feature fusion weighting coefficients and D-S evidence conflict resolution thresholds is imperative.



(a) Upper wall training set results (b) Lower wall training set results (c) Fusion feature training set results

(d) Upper wall validation set results (e) Lower wall validation set results (f) Fusion feature validation set results

(g) Upper wall test set results (h) Lower wall test set results (i) Fusion feature test set results

Fig.10 Classification results of the training, the validation, and the test sets for inlet destabilization trouble shooting

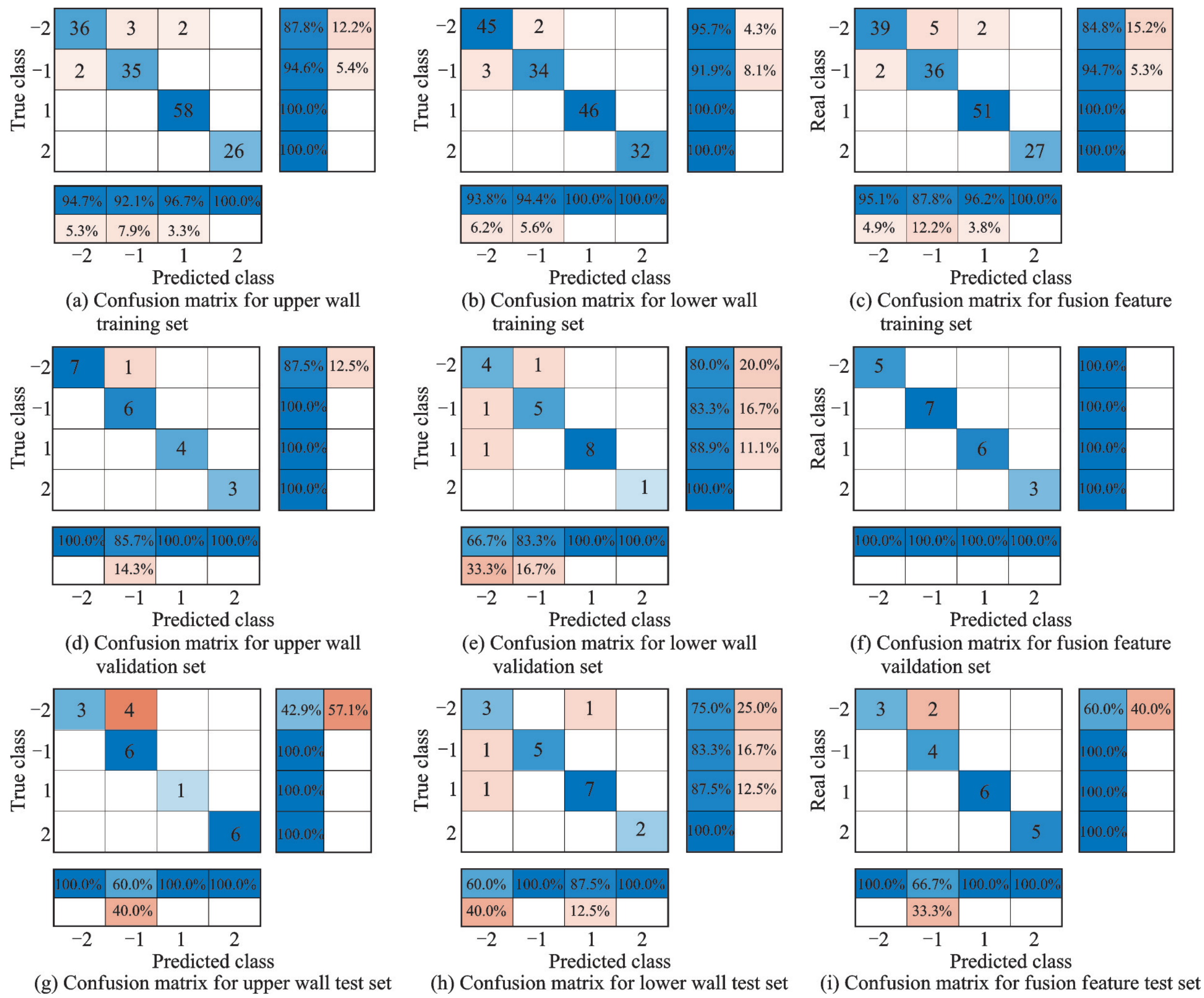


Fig.11 Confusion matrices of the training, the validation, and the test sets for inlet destabilization fault diagnosis

The decision fusion optimization model is used to enhance the accuracy of the baseline model. As previously mentioned, the supersonic inlet duct has four possible states: One steady-state and three instability states. These states are described by their respective labels: 2, 1, −1, and −2, representing the fault types. These four inlet duct states are treated as fault hypotheses, forming the recognition framework of the D-S evidence theory, $\Theta'=\{2,1,-1,-2\}$. After multiple experiments, the basic probability assignment is determined to be $\{0.5,0.3,0.1,0.1\}$, and decision fusion is performed based on the synthesis method in Eq.(9). Using the fused features as input, the SVM, RF and MLP algorithms are used to train the supersonic inlet duct mathematical model, which includes instability mechanisms over a wide speed range, for preliminary fault diagnosis. The training results and accuracy are shown in the Table 2. To best leverage the functions and characteristics of each classifier, the basic probability assignment plays a crucial role in the decision fusion using the D-S evidence theory. The base probability assignment strategy obtained is applied to the diagnostic outputs of the three different algorithms, and further integration of these outputs is carried out using formulas and synthesis rules. This results in a fault diagnosis model for the inlet duct, combining feature fusion and D-S decision fusion. Multiple inlet duct test sample points are used as input and the fault diagnosis accuracy rates of each model are shown in Table 2.

As shown in Table 2, the fault diagnosis accuracy of individual classifiers is concentrated around 90% while the fusion model achieves over 95% accuracy. The single-classifier model demonstrates

Table 2 Comparison of decision fusion accuracy %

Indicator	SVM	RF	MLP	Fusion model
Correct rate	90.12	89.27	91.35	96.31
Training set ACU	94.44	89.50	91.97	99.43
Validation set ACU	100.00	85.71	90.47	93.54
Test set ACU	90.00	100.00	90.00	100.00

limitations in providing comprehensive and reliable diagnosis across various inlet operating states, resulting in relatively lower accuracy. In comparison, the fusion model improves fault diagnosis accuracy to above 95%, exhibiting superior diagnostic capability. Analysis of Figs.10, 11 reveals that during training, single classifiers show erroneous deviations in some sample points within both validation and test sets, whereas the fusion model demonstrates more precise training results. From the confusion matrix perspective, single classifiers exhibit lower fault diagnosis accuracy with multiple misdiagnosed sample points, including issues of false positives and missed detections. The fusion model significantly improves diagnostic accuracy, effectively resolving misjudgment issues while enhancing model robustness. This improvement stems from the complementary strengths of individual classifiers. SVM excels in high-dimensional feature spaces. RF resists overfitting in multi-regime datasets. And MLP captures nonlinear instability precursors. By synthesizing these advantages, the fusion model enhances fault detection sensitivity while maintaining specificity, thereby enabling precise differentiation of inlet states (stable, incipient instability and surge). This approach safety-critical requirements for aero-engine systems, addressing the limitations of single-algorithm diagnostics in complex operational environments. Therefore, the feature fusion-based inlet fault decision fusion diagnosis algorithm achieves over 95% accuracy in inlet instability fault diagnosis, not only resolving false positive and missed detection issues but also demonstrating excellent robustness.

This work advances inlet fault diagnostics by harmonizing data-driven learning with evidence-based uncertainty management, offering a scalable solution for next-generation aero-engine health monitoring systems.

5 Conclusions

This study addresses the challenge of instability fault diagnosis in wide-speed-range supersonic inlets. Leveraging wall pressure data derived from CFD simulations, a data-component fusion-driven modeling approach is developed to construct an inlet mathematical model. To overcome the limitations of low diagnostic accuracy in single-signal methods and integrate the advantages of multiple intelligent algorithms, an inlet fault decision fusion diagnosis algorithm based on attention mechanism feature fusion is proposed, achieving efficient instability fault diagnosis across wide-speed regimes. This work fuses multi-source information to improve the accuracy of fault diagnosis and enhance the robustness of the system. Meanwhile, applying the D-S evidence theory to the intake tract fault diagnosis study improves the model accuracy, solves the leakage judgement problem and enhances the robustness of the system compared to other previous single fault diagnosis method. So this work advances inlet fault diagnostics by harmonizing data-driven learning with evidence-based uncertainty management, offering a scalable solution for next-generation aero-engine health monitoring systems. The key contributions are as follows.

(1) An attention mechanism and D-S evidence theory-based fusion diagnosis method. A hybrid framework combining attention mechanism-driven pressure feature fusion and D-S evidence theory-based decision fusion is developed. This method integrates the strengths of multiple algorithms (e. g., SVM, RF, MLP), resolving the low diagnostic accuracy (less than 85%) and limited optimization potential of single-signal approaches. The fusion algorithm achieves diagnostic accuracy exceeding 95%.

(2) Component-data-driven inlet modeling. A supersonic inlet mathematical model incorporating wide-speed-range operability and instability mechanisms is rapidly developed using SVM algorithms and CFD-extracted wall pressure data. The model

exhibits high computational efficiency and precision, enabled by mapping intrinsic relationships within multi-regime datasets.

(3) Axisymmetric supersonic inlet benchmark model and CFD validation. An axisymmetric inlet benchmark model is established, with CFD simulations extracting high-fidelity pressure data from hundreds of wall-mounted points under steady/unsteady conditions. Pressure datasets across multiple flight envelope points are generated, providing foundational training samples for data-driven modeling.

Future research directions: (1) Algorithm optimization. The current deep neural network-based algorithm demands significant computational resources, limiting real-time applicability. Future work will focus on reducing grid complexity while maintaining more than 95% accuracy to enhance computational speed. (2) 3D inlet model development. The 2D axisymmetric model will be expanded to a 3D mesh model for higher-precision wall pressure data acquisition, critical for improving inlet safety performance in hypersonic regimes.

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基于注意机制特征融合的进气道故障诊断

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摘要：为解决宽速域超声速进气道不稳定性故障诊断难题，提出了一种基于注意机制特征融合的进气道故障决策融合诊断算法，实现了跨宽速域不稳定性故障的高效诊断。首先，考虑到宽速域进气道数学建模中对壁压数据提取的要求，建立了用于计算流体动力学(Computational fluid dynamics, CFD)模拟的超声速进气道模型。其次，利用数据驱动的建模技术和支持向量机(Support vector machine, SVM)算法，使用CFD得出的入口壁压力数据，快速开发了一个涵盖宽速域并包含不稳定性机制的高精度数学模型。随后，提出了一种进气道故障决策融合诊断方法：通过注意机制融合压力特征，然后基于Dempster-Shafer(D-S)证据理论进行决策融合，综合了多种智能算法的优点，克服了单一信号诊断方法的局限性(精度低、优化潜力受限)。仿真结果验证了数据驱动的宽速度范围进气道模型在实现高精度和快速收敛方面的有效性。此外，融合诊断算法在检测不稳定性方面显示出达到超过95%的准确度，与其他单一故障诊断算法的准确度相比，代表了超过5%的改进。这种增强有效地消除了遗漏或错误诊断的发生，同时还在操作不确定性下表现出稳健的性能。

关键词：宽速域超声速进气道；数据驱动建模；注意力机制；Dempster-Shafer证据理论；故障诊断