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MMPD-Net: An Aircraft Deformation Prediction Network Based on Multimodal Fusion

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Abstract – In the assembly process of aircraft manufacturing, the aircraft structural is flexible, it is easy to deform under the influence of material factors and working condition factors. Therefore, it is necessary to propose a deformation prediction model to timely find deformation problems. In recent years, with the development of artificial intelligence technology, deep neural network has been widely used in intelligent manufacturing. This paper combines deep neural network with aircraft deformation prediction, and proposes an aircraft deformation prediction network that based on multimodal fusion (MMPD-Net). We consider both the aircraft structure data and the working condition data on aircraft deformation prediction. MMPD-Net extracts the features of aircraft structure mode and working condition mode respectively. We propose a multimodal fusion network to fuse features, which include the algorithm of average pooling and Bayesian decision. Compared with the mainstream point cloud classification network, MMPD-Net achieves higher classification accuracy on aircraft deformation dataset.

Keywords - Deep neural network; Multimodal fusion; Deformation prediction; Point cloud

1. **Introduction**

In the process of civil aircraft manufacturing and assembly, the requirements for assembly accuracy are very strict [1-3], but in the actual assembly process, because the aircraft structural material is a flexible material[4,5], the aircraft will be deformed when it is assembled in different environments or squeezed by external forces [17]. The deformation of aircraft structure will have a serious impact on the assembly acceptance and actual use, so it is very important to find the deformation of aircraft in time during the assembly process. The deformation of aircraft is usually small during the assembly process, so it is difficult to find the deformation of aircraft manually [6].

In recent years, the intelligent prediction of deep learning method has been widely used in various fields [7,8]. In the scene of aircraft assembly, the deep learning method can reduce human investment and intelligent prediction. In the process of aircraft assembly, the aircraft structure data is usually processed in the format of point cloud data [9]. However, in the prediction of aircraft deformation based on deep neural network, we find that structure data can extract the deformation characteristics and has strong nonlinear ability [10], but its data generalization ability is poor. In addition, it is very important to consider the influence of external factors on aircraft deformation in the actual scene. The processing of assembly working condition data can extract the deformation characteristics of external factors, it has strong generalization ability [11], but the accuracy not high. Therefore, the advantages of the two kinds of data modes should be complementary.

In this paper, we propose an aircraft deformation prediction network based on multimodal fusion. The network framework is shown as Fig.1. This network can classify the deformation degree of aircraft structure. Our method uses aircraft structure data and working condition factor data two kinds of datasets, and use two deep neural networks to extract features from the data of the two modes. For feature extraction of aircraft deformation structure data, considering the small difference between aircraft deformation data, we should pay more attention to the extraction of local features, so we integrate the attention mechanism into the current mainstream point cloud classification network PointNet [12], structure features can be obtained by feature extraction through the network. For the data of working condition factors, we use the deep neural network with residual mechanism [13] to extract the features, which can obtain the external physical features. After get the features of two modes, our model adds two different feature fusion mechanisms based on average pooling and Bayesian decision respectively [14]. The two feature fusion methods fuse the features of the two modes at the feature level and the score level respectively [15]. In addition, in order to evaluate the effect of our network, we also made the aircraft deformation datasets that is composed of aircraft deformation structure dataset and aircraft deformation working condition dataset, and these two kinds of datasets corresponding to the two feature extraction networks. On our dataset, our network has achieved good classification results.

The contributions of this paper are as follows:

1) We propose the MMPD-Net, which use two deep neural networks to extract features from deformation datasets of two modes for aircraft deformation prediction. We realizing the complementary advantages between the mechanism and data, and providing a new idea for the research of aircraft deformation prediction.

2) We make the aircraft deformation datasets, including aircraft deformation structure dataset (ADSD) and aircraft

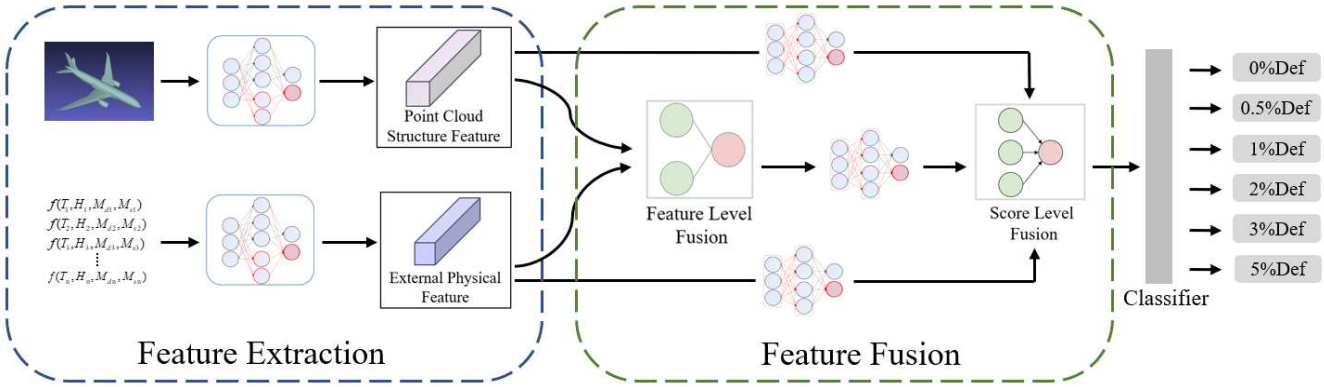


Fig.1 The framework of MMPD-Net. The network includes feature extraction and feature fusion two parts.

deformation working condition dataset (ADWD). The two datasets provide characteristic information for aircraft deformation prediction in different modes.

3) For feature extraction of aircraft deformation data, based on the mainstream point cloud classification network, and aiming at the characteristics of deformation classification and prediction, we add an attention mechanism suitable for point cloud data to enhance the extraction of local features.

4) For the extracted multimodal features, we propose a hybrid feature fusion method at feature level and score level, which improve the aircraft deformation classification accuracy.

2. **Related Works**

2.1 **Aircraft Deformation Analysis**

Deformation analysis is very important to the whole aircraft manufacturing process, so the research on aircraft deformation has also been paid special attention [16-18]. Wang et al. [19] based on the static mechanics equation of elastic beam, derived the assembly deformation prediction model, it lays a foundation for the prediction of aircraft deformation deviation analysis. Huang et al. [20] studied the influence of initial stress on deformation in aircraft assembly, and established a mathematical model for analyzing assembly deformation, which provides a new theoretical method for aircraft deformation analysis. Liu et al. [21] proposed new cross-scale method to predict the structural deformation of aircraft materials, and the method has been applied to multiple stages of multiple assembly and achieved good results. Dvurecenska et al. [22] use image decomposition analyzed the feature vectors of different aircraft deformations, and evaluated the relationship between the curvature of deformations. Sagadeev et al. [23] proposed a method for monitoring the deformation of aircraft structure using optical fiber sensing and measurement technology.

2.2 **Point Cloud Data Processing**

The aircraft structure dataset is composed of point cloud data. Compared with image data, point cloud data has many unique properties. Point cloud data is irregular and unstructured, so the processing of point cloud data is more complex, especially in the field of point cloud classification. There are two kinds of point cloud data classification methods based on deep learning, which are projection-based point cloud classification network and network classified by original point cloud data.

For projection-based network, Maturana et al. [24] proposed VoxNet, VoxNet use volumetric occupancy grid to represent the environment state of data with three-dimensional grid. This method uses the voxelization of point cloud, and can generate global labels of different categories through the superposition of multiple levels to complete the classification. Wu et al. [25] inspired by the convolution depth belief network, proposed a 3D Shapenets model. In this model, the geometric features of the point cloud are represented by the binary probability distribution in the voxel grid, which further improves the training efficiency of the model. Relevant researches have used multi perspective projection to project point clouds. Su et al. [26] proposed MVCNN suitable for point cloud data. Feng et al. [27] proposed GVCNN model, based on MVCNN, this model adds the information features between learning views to generate descriptors of different levels.

For the classification network based on original point cloud data, PointNet [12] first time proposed this method. Qi et al. [28] Added a series of abstraction layers to further optimize PointNet. Li et al [29] first t applied convolution to point cloud data. They proved that the development of local structure is important for point cloud classification network. Wu et al. [30] proposed learning convolution kernel of approximate 3D with MLP. Yan et al. [31] divide the network into adaptive sampling module and local- nonlocal module.

2.3 **Multimodal feature fusion**

Multimodal feature fusion can provide more information for model decision-making, and further to improve the accuracy of the overall decision-making results. It has been widely used in video classification [32], event detection [33], emotion analysis [34] and other scenarios. The methods of multimodal feature fusion can be divided into early fusion and late fusion. Murphy et al. [35] research on feature level fusion, proposed a variety of methods to solve the synchronization problem for the early fusion methods. Kahou et al. [36] proposed the post fusion method, that is, the method of determining rules, such as maximum value fusion and average value fusion, which laid a foundation for subsequent research on post fusion. Wang et al. [37] proposed a method to deal with multiple modes at different time resolutions, this method greatly improves the fusion efficiency. Lan et al. [38] realized the detection of multimedia event detection by using the hybrid fusion method, which is a successful attempt of multimodal feature fusion in the application of actual scenes. This method captures the feature

relationship and handles the over fitting problem through early fusion and late fusion.

3. **Proposed Method**

In this section, we introduce our proposed method on MMPD-Net. For aircraft deformation prediction, our method mainly includes the following three parts: (1) aircraft deformation dataset, (2) feature extraction, (3) feature fusion. The following subsections will introduce the implementation details of our methods.

3.1 **Aircraft Deformation Dataset**

ADSD： aircraft deformation structure dataset (ADSD) is used to extract the deformation characteristics of aircraft structure. We collected aircraft point cloud data from ModelNet40 [25] and other aviation agencies, and use these original data as the class without deformation, which also is the class of 0%def. The average variation of Euclidean distance from each point to the geometric center in the aircraft structure is used as the standard to judge the degree of deformation. For each aircraft point cloud data, we should first determine its geometric center, like Fig.2.

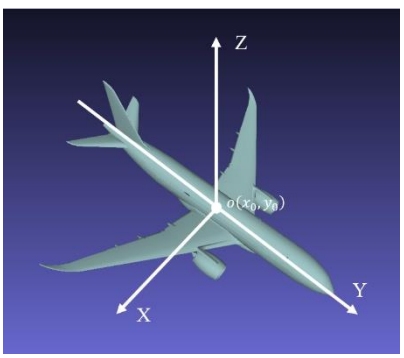


Fig.2 Geometric center of aircraft point cloud data

The average Euclidean distance from each point in the raw data to the geometric center is shown in (1), the average Euclidean distance from each store in the deformed data to the geometric center is shown in (2), and formula (3) is the calculation method of deformation variables.

$$d_0 = \frac{1}{M}\sum_{i=1}^{M}\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (y_i - y_0)^2} \quad (1)$$

$$d_1 = \frac{1}{M}\sum_{i=1}^{M}\sqrt{(x_{di} - x_0)^2 + (y_{di} - y_0)^2 + (y_{di} - y_0)^2} \quad (2)$$

$$\delta_{def} = \frac{d_1 - d_0}{d_0} \quad (3)$$

According to this deformation degree judgment standard, there are six classes of aircraft point cloud deformation dataset, which are 0%Def, 0.5%Def, 1%Def, 2%Def, 3%Def, 5%Def. We sample all the points in the raw point cloud data according to the deformation class, so that the spatial position of different numbers of points in the point cloud changes to get different degrees of deformation. Visualization of some aircraft point cloud deformation dataset is shown as Fig.3.

ADWD： aircraft deformation working condition dataset (ADWD) is composed of external environmental factors that affect the deformation of aircraft structure. We get the relevant

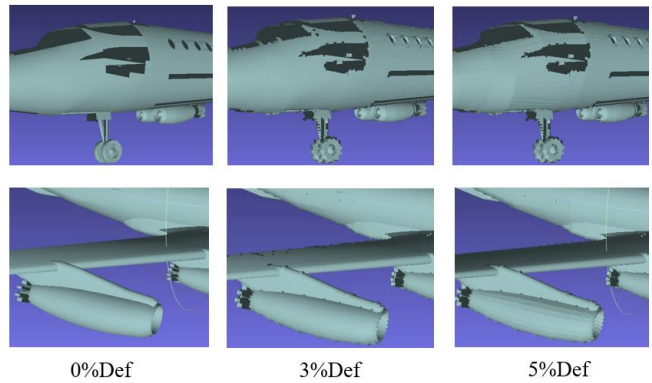


Fig.3 Visualization of different deformation classes of aircraft structure data

characteristic indexes that affect aircraft deformation and the environmental parameters corresponding to different deformation levels from aviation agencies. The most important factors causing deformation are Ambient temperature, ambient humidity, assembly time and assembly stress, and these factors can be summarized as follows:

$$F_{phy} = f(T, H, M_d, M_s) \quad (4)$$

Where T is ambient temperature, H is ambient humidity, M_d is assembly time and M_s is assembly stress. Each data in ADWD is corresponding to one point cloud data of the same class in ADSD.

3.2 **Feature Extraction**

In MMPD-Net, the feature extraction network is divided into two parts: structure feature extraction network and external physical feature extraction network. The structure feature extraction network model trains and extracts feature from the aircraft deformation structure dataset, and the external physical feature extraction network extracts features from the aircraft deformation working condition dataset.

Considering the particularity of point cloud data, the structure feature extraction network is different from the ordinary image feature extraction network, it needs to consider the disorder of point cloud data and the invariance of spatial transformation. For aircraft deformation structure data, the feature differences between various categories usually only exist in local locations. In order to extract local useful features, our network adds an attention mechanism suitable for point cloud to the popular point cloud classification network PointNet, which can improve the extraction of local features in data. The network framework is shown in the Fig.4.

For the input point cloud data, an affine transformation module (T-Net) is used to perform affine transformation on the data. T-Net can rotate the point cloud by lead into another matrix to obtain the best recognition state. In T-Net, the point cloud data is mapped to 1024-dimensional space through three convolution layers. For each point, there is a 1024-dimensional vector representation, but this vector representation has some redundancy. Therefore, the maximum pooling operation is to keep only the largest points in the 1024-dimensional channel. The vector of 1×1024 is the global feature of the point cloud

data. Input this global feature to two full connection layers, can get 256-dimensional feature, reshape the feature, and finally output a 3×3 rotation matrix. By multiplying the rotation matrix

Where σ denotes the sigmoid function, $W \in ¡^{C}$ note that the MLP weights. The attention mechanism is shown as Fig.5.

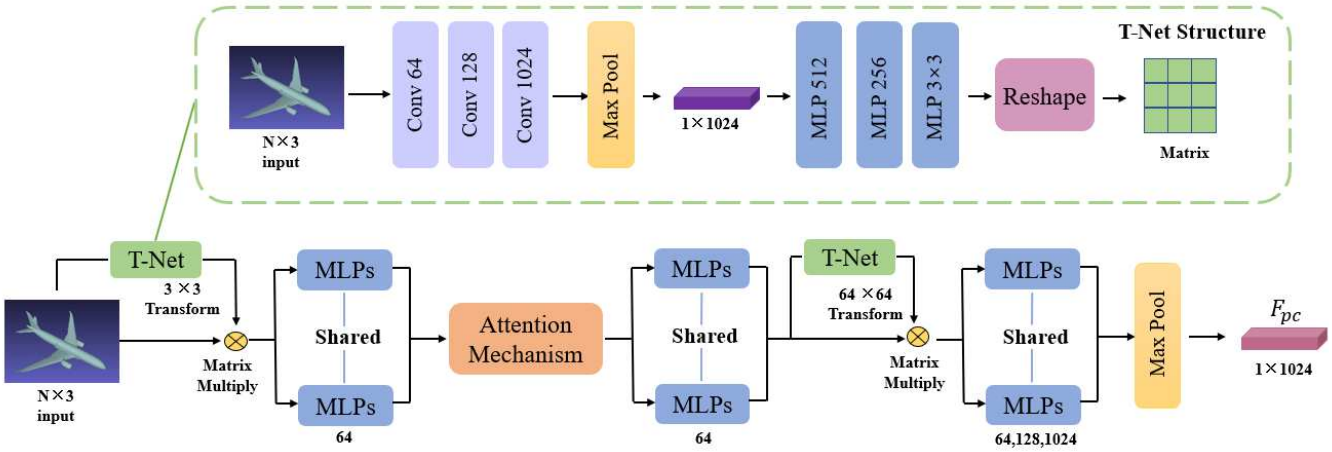


Fig.4 Aircraft structure feature extraction network. We add the attention module that suitable for point cloud data between the shared MLPs, which improves the performance of extracting local features from aircraft deformation point cloud data.

with the original point cloud input, the best recognition state of the current point cloud can be obtained. The main network is like T-Net to extract feature through shared MLP, then the 1024-dimensional global vector F_{pc} is obtained through max pool fusion. F_{pc} is used as the input of feature fusion.

We note that in feature extraction for deformation dataset, feature differences between different classes often exist in local parts of the data, so we lead into the attention module to improve the accuracy of feature extraction. The attention mechanism module generates different weights for each channel, and allows the network to spontaneously adjust the weights during training, it can make the network pay more attention to the more important features when extracting features. Based on the image domain attention mechanism method, point cloud input feature F aggregated by using parallel average pooling and maximum pooling , and generate feature descriptors F_{avg} and $F_{\max}$ from different angles, and next use a single hidden layer MLP with shared parameters to train the feature channel number dimension of aggregated features to generate attention weights. Finally, the activation function σ is used to activate weights. Different from the attention mechanism of image data, the input of point cloud data is shown as $F \in ¡^{1\times N\times C}$, where the N is the number of point cloud, and the C is the number of channels. The algorithm of the point cloud attention mechanism can be summarized as follows:

$$F_o = M_c(F) \otimes F \tag{5}$$

Where the M_C is the point cloud attention structure. The process of M_C is:

$$\begin{aligned} M_c(F) &= \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \\ &= \sigma(W(F_{\text{avg}}) + W(F_{\max})) \end{aligned} \tag{6}$$

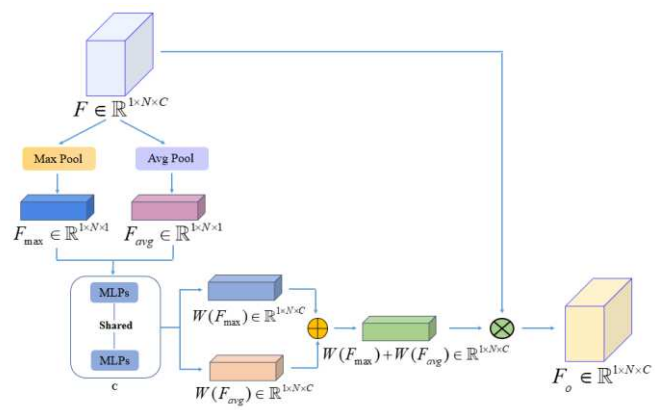


Fig.5 Structural details of point cloud attention mechanism

To extract the external physical features of aircraft, we construct a depth neural network with depth residual module. The residual module can jump to connect different layers, that is, the input of the unit is directly added with the output of the unit, it can solve the problem of network accuracy saturation and gradient disappearance. The network structure is composed of six layers neural network and two residual modules. Each residual module includes three layers neural network, and the number of output channels is 12, 24 and 4. After the network feature extraction, we get the external physical feature F_{phy}, which can as the input variable in the feature fusion stage. The network structure is shown in the Fig.6.

3.3 **Feature Fusion**

There are two methods of feature fusion: early fusion and late fusion, they can also be called feature level fusion and score level fusion respectively. Early fusion refers to extracting the representation of features from each mode, and then fusion at the feature level. The advantage of feature level fusion is that each independent mode can train independently, so it is helpful for cross modal transfer learning. In late fusion method, the

deep learning model first trains different modes, and then fuses the output results of multiple modes. The process of late fusion is independent of features, and there is no correlation between

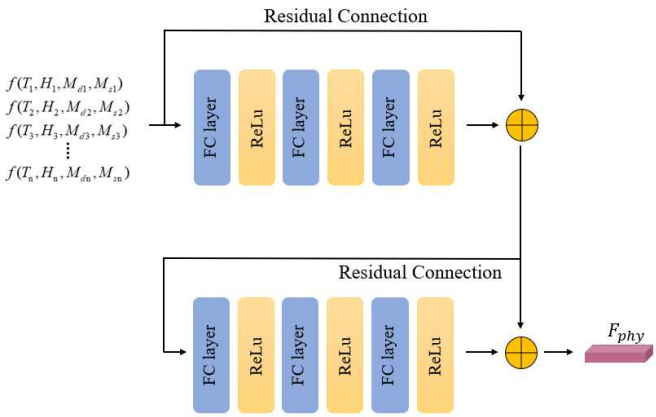


Fig.6 The extraction network framework of external physical feature.

misclassifications from multiple models, so late fusion is applicable to a wider range of scenarios.

Our feature fusion network framework is shown as Fig.7.

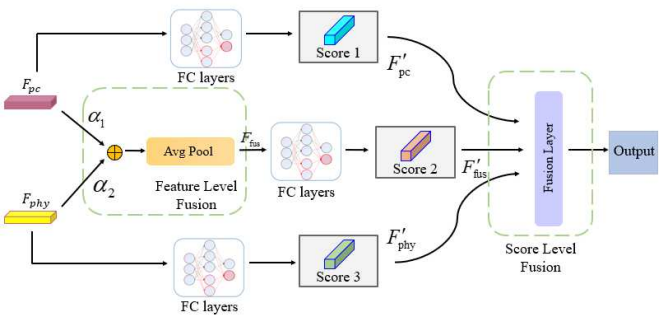


Fig.7 The network framework of feature fusion, which includes feature level fusion and score level fusion.

Through point cloud feature extraction network, we get the point cloud feature F_{pc}; and we get the external physical feature F_{phy} through a depth neural network with depth residual module. The whole fusion process is divided into two parts. First, F_{pc} and F_{phy} fuse at the fusion level, we can get the preliminary fusion features F_{fus} .We use statistical method and average pooling method for this fusion. We give different weights α_1 and α_2 to F_{pc} and F_{phy} respectively, in this way, the proportion of different modes can be weighed to achieve better fusion effect. The process of feature level fusion can be summarized as follows:

$$F_{\text{fus}} = AvgPool(\alpha_1 F_{pc} + \alpha_2 F_{\text{phy}}) \tag{7}$$

After the feature level fusion, we get three different kinds of features F_{pc}, F_{phy} and F_{fus}. All these feature input to a certain number of full connection layers respectively can reduce the dimension and get the classification scores, which are F'_{pc}, F'_{phy} and F'_{fus}. These scores include not only the prediction scores of aircraft deformation by each single mode, but also the prediction score that after feature level fusion. Bayesian decision theory is a classical pattern recognition method. The Bayesian decision model sample space Ω include C kinds of model classes. When we input a sample x, according to Bayesian decision theory of minimum error rate, if sample x is classified as class, the class j is the model category with the largest posterior probability under the condition of input sample x.The decision process can be shown as:

$$x \to \omega_j, \quad if \ F(\omega_j) = \max_{k=1,\ldots,C} P(\omega_k \mid x) \tag{8}$$

Where $P(\omega_k \mid x)$ is the posterior probability of the class k. Our score level fusion method adopts the feature fusion method that based on Bayesian decision. For the features that we have gotten F'_{pc}, F'_{phy} and F'_{fus}. We need to normalize them in the score level fusion process. Here we use the logSoftmax function for normalization. The logSoftmax function is a variant of Softmax and has better numerical stability. The logSoftmax function is shown as:

$$\log Soft\max(x_i) = \ln\left(\frac{\exp(x_i)}{\sum_j \exp(x_i)}\right), i = 1,2,\ldots,j \tag{9}$$

For our score level fusion method, based on Bayesian theory, the fusion process can be summarized as:

$$x_1 = \log Soft\max(F'_{pc}) \tag{10}$$

$$x_2 = \log Soft\max(F'_{phy}) \tag{11}$$

$$x_3 = \log Soft\max(F'_{fus}) \tag{12}$$

$$F = \max_{k=1,\ldots,C} P(\omega_k \mid x_1, x_2, x_3) \tag{13}$$

From (10), (11) and (12) we can get that $P(\omega_k \mid x_1, x_2, x_3)$ is the posteriori probability that the output result is class k after score level fusion. And because each classifier is independent of each other, combined with (14), we can express the joint conditional probability in the form of multiplying the classification probabilities of each classifier, and shown as (15).

$$P(\omega_k \mid x_1, x_2, x_3) = \frac{P(x_1, x_2, x_3 \mid \omega_k) P(\omega_k)}{P(x_1, x_2, x_3)} \tag{14}$$

$$F = \max_{k=1,\ldots,C} P^{-(M-1)}(\omega_k) \prod_{i=1}^{M} P(\omega_k \mid x_i) \tag{15}$$

Where the $P(\omega_k)$ is the prior probability of class k. Each classifier is independent of each other means the probability distribution of the output of each classifier is independent of each other. In aircraft deformation prediction, the classifier with different modal features may have a situation that the posterior probability of class k of a certain classifier $P(\omega_k \mid x_i)$ may be is 0. This will make the classification error after feature fusion. To solve this problem, we lead into the assumption that prior probability and posterior probability are approximately equal. This assumption assumes that the posterior probabilities under each classifier condition will not deviate significantly from the prior probabilities of this class, which can be shown as:

$$P(\omega_k \mid x_i) = P(\omega_k)(1 + \theta_{ki}) \tag{16}$$

Table.1 Comparative results of classification accuracy between MMPD-Net and mainstream point cloud classification network on aircraft deformation prediction dataset

Method	Classification Accuracy/%					
	0%Def	0.5%Def	1%Def	2%Def	3%Def	5%Def
PointNet	78.25	54.25	62.09	75.63	77.25	80.06
PointNet++	79.40	56.80	64.23	78.94	75.34	83.64
PointCNN	80.00	62.00	72.00	73.00	74.00	76.00
PointWeb	76.60	60.40	**77.50**	70.50	81.40	81.70
PointASNL	62.10	64.60	70.60	76.85	82.50	83.55
MMPD-Net (Ours)	**82.46**	**75.30**	76.67	**80.55**	**84.69**	**86.25**

Where θ_{ki} can be regarded as a minimal variable. According to this assumption, and combine (10), (11), (12), (16), we can get the final representation of score level feature fusion:

$$P = \max_{k=1,\mathrm{L},C}\{(1-M)P(\omega_k) + \lambda_1 P[\omega_k \mid \log Soft\max(F'_{pc})] + \lambda_2 P[\omega_k \mid \log Soft\max(F'_{phy})] + \lambda_3 P[\omega_k \mid \log Soft\max(F'_{fus})]\} \quad (17)$$

In the fusion process, we also give different weights to each input feature, it is proved by experiments that when $\lambda_1 = 0.5$, $\lambda_2 = 0.2$ and $\lambda_3 = 0.3$, the best effect is achieved.

4. **Experiments**

In this section, we evaluate the performance of MMPD-Net on ADSD and ADWD, and compared it with the performance of current mainstream point cloud classification network on ADSD. And we evaluate the influence of different external factors in ADWD on aircraft deformation.

4.1 **Datasets**

We tested the performance of MMPD-Net on aircraft deformation datasets, the ADSD and ADWD include six classes respectively. Each class contains 726 pieces of data, which are divided into training set and test set in a ratio of 4: 1. At the same time, we selected the mainstream point cloud classification networks for comparative experiments, and trained and tested them on the ADSD. The dataset division is the same as MMPD-Net.

4.2 **Implementation**

In our experiments, we used a PC equipped with an i7-11700, 2.9GHz CPU and a NVIDIA RTX 3080 GPU. We use the PyTorch as the developing environment.

For the training of point cloud feature extraction network, we set 200 training epochs, and set the original learning rate as 0.002, 10-fold decrease per 30 epochs. For the external physical feature extraction, we set 100 training epochs, and set the original learning rate as 0.0001.

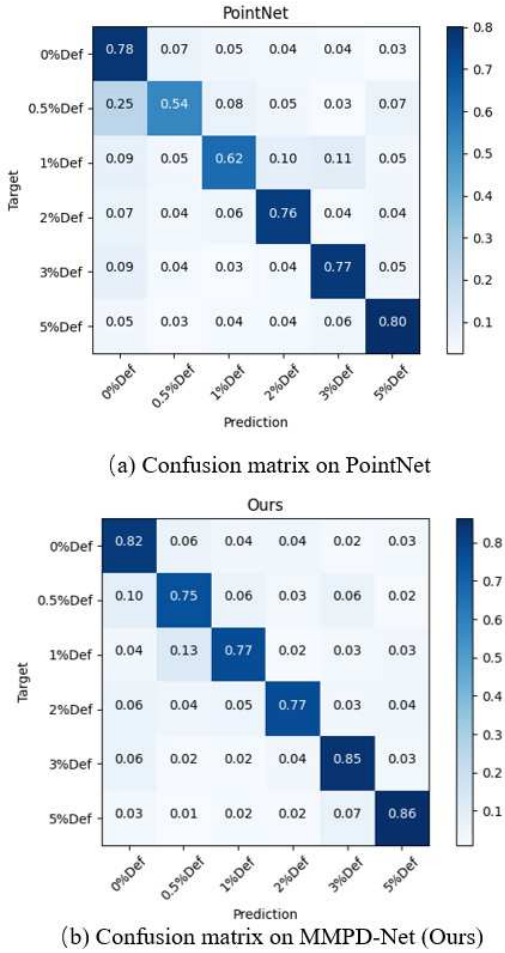
4.3 **Experimental analysis**

In order to evaluate the effect of MMPD-Net in aircraft deformation prediction, we selected five mainstream point cloud classification networks for comparison. The experimental results are shown in Table 1. Comparative results show that MMPD-Net is superior to the current mainstream point cloud classification network in the classification accuracy of each class in aircraft deformation prediction. Among them, the effect of 0.5% Def is 10.7% higher than that of the current mainstream point cloud data classification methods. In addition, from the experimental results, we note that the classification accuracy of class 0.5 %Def and class 1%Def is lower than that of other classes. Therefore, we conducted a confusion matrix experiment to demonstrate, the experimental results are shown in Figure 8.

In order to facilitate comparison, we also conducted a confusion matrix experiment on the experimental results of PointNet. From the confusion matrix, we can find that for class 0.5 %Def and class 1%Def, the correct classification probability of PointNet and MMPD-Net is both lower than that of other classes, but MMPD-Net is still higher than PointNet, and MMPD-Net is easy to misclassify class 0.5 %Def to class 0%Def and misclassify class 1%Def to class 0.5 %Def. We conduct t-SNE experiments on the fused features to further verify our conclusions, which is shown as Fig.9.

From the Fig.9, we can see that the feature distribution of class 2%Def, 3%Def and 5%Def is relatively independent, while the dispersion degree of 0%Def, 0.5%Def and 1%Def is relatively small. According to the experimental results, the deformation degree difference between 0%Def, 0.5%Def and 1%Def is smaller than others, and the features are relatively similar, so there will be a certain probability of misclassification.

In order to evaluate the accuracy of our model more intuitively, we selected two common evaluation indicators of data average accuracy (MA) and overall accuracy (OA) in the current point cloud classification evaluation standards to analyze the classification effect of the model. The experimental results are shown in Table 2.



(a) Confusion matrix on PointNet

(b) Confusion matrix on MMPD-Net (Ours)

Fig.8 Confusion matrix of PointNet and MMPD-Net

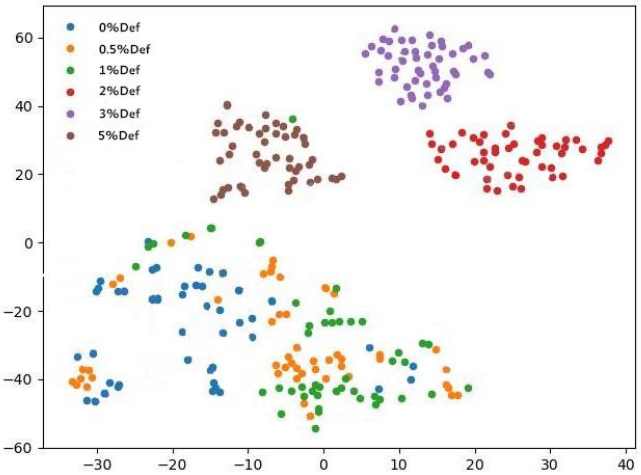


Fig.9 T-SNE of MMPD-Net

From the MA and OA data of different models, we can see that our model has achieved 80.98% MA and 84.23% OA compared with the current mainstream classification models, both of which have achieved better classification accuracy. This shows that MMPD-Net has achieved good results in aircraft deformation prediction.

MMPD-Net adopts the combination of feature level fusion and score level fusion in the feature fusion stage. In order to prove that our hybrid fusion method has more advantages, we

Table.2 Comparative results of MA and OA

Method	MA /%	OA /%
PointNet	71.25	73.63
PointNet++	73.05	74.48
PointCNN	72.83	75.26
PointWeb	74.68	75.57
PointASNL	73.36	77.32
Ours	**80.98**	**84.23**

conducted experiments and compared it with only feature level fusion and only score level fusion. The experimental results are shown in Table 3. From the experimental results, we can see that MMPD-Net use all level fusion increased by 4.74% MA and 5.95% OA compared to only use feature level fusion, increased by 2.45% MA and 1.73% OA compared to only use score level fusion, so our hybrid fusion method is effective.

Table.3 Comparative results of different fusion method

Method	MA /%	OA /%
Feature level fusion	76.24	78.28
Score level fusion	78.53	82.50
All level fusion	80.98	84.23

In order to evaluate the impact of various external physical factors on ADWD, we remove one kind of environmental data in ADWD each time and conduct experiments respectively. According to the experimental results, we can evaluate the impact of different external environmental factors on aircraft deformation, the experimental results are shown in Table 4.

Table.4 Comparative results of different data on ADWD

Data on APED	MA /%	OA /%
$H+M_d+M_s$	79.75	81.46
$T+M_d+M_s$	80.15	83.28
$H+T+M_s$	76.83	79.67
$H+T+M_d$	74.64	76.48
$H+T+M_d+M_s$	80.98	84.23

When the environmental temperature factor (T) is not included in the ADWD, the average accuracy of our model is 79.75%, and when the environmental humidity factor (H) , assembly time factor (M_d) and assembly stress factor(M_s) is not included respectively, the average accuracy of our model is 80.15%, 76.83% and 74.64% respectively. Therefore, we can conclude that the assembly stress factor (M_s) has the greatest impact on the deformation classification, while the environmental humidity (H) has the least impact.

5. Conclusion

In this paper, we propose an aircraft deformation prediction network based on multi-modal feature fusion: MMPD-Net. This network considers aircraft structure and aircraft working condition two kinds of mode data that would affect the aircraft deformation. We make aircraft deformation datasets for two modes ADSD and ADWD, and design two feature extraction networks to extract the features of the two modes. In the feature fusion stage, we propose a method combining feature level fusion and score level fusion. It has been proved by experiments that MMPD-Net achieved considerable results. The classification accuracy of MMPD-Net on aircraft deformation dataset achieved 80.98% MA and 84.23% OA, it is much higher than other point cloud classification networks in the field of aircraft deformation prediction.

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Declarations

Ethical Approval
not applicable.
Competing interests
We have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Authors' contributions
Zhihao Kong, JianHua Mao and Xiaofeng Lu wrote the main manuscript text and Jun Wang prepared all figures and tables. All authors reviewed the manuscript.
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Availability of data and materials
We proposed aircraft deformation structure dataset and aircraft deformation working condition dataset in this paper. The aircraft deformation structure dataset is composed of ModelNet40 and the aircraft deformation data from Aviation Agencies of China. The aircraft deformation working condition dataset is supported by Aviation Agencies of China.

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