[[1]](#footnote-1) **Real-time hierarchical risk assessment for UAVs based on recurrent fusion autoencoder and dynamic FCE: A hybrid framework**

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***Abstract*—**Effective risk assessment is critical for unmanned aerial vehicles (UAVs) to ensure their safety and reliability. Up to now, the researchers have proposed quite a few methods for the above target. However, these methods are mainly based on path planning and collision theory, the risk caused by the abnormal status of UAVs themselves is generally ignored, which limits the further improvement on their performance. In practice, due to factors such as complicated compositions, variable condition monitoring (CM) data, and scarce failure records, etc., it is always a great challenge to implement the complete information fusion and accurate risk assessment for UAVs based on their real-time status. In this regard, a novel hybrid framework is proposed in this paper, which integrates the qualitative knowledge and the quantitative CM data, to evaluate the real-time hierarchical risk of UAVs. Specifically, the complicated UAV is firstly abstracted as a multi-level evaluating index system considering its qualitative logic compositions. Then, for each low-level index, given its multivariate CM data of several time instants, recurrent fusion autoencoder (RFA), a novel unsupervised neural network architecture, is proposed to extract their robust and complete feature embeddings automatically, where not only the information of variate dimension but also the information of time dimension can be fully fused. Furthermore, the risk of each low-level index is quantified by the adaptive Gaussian mixture model in a probabilistic way, which is truly data-driven with the help of the Bayesian hyperparameter optimization. Finally, the dynamic fuzzy comprehensive evaluation is utilized to evaluate the hierarchical risk of UAVs level by level, it should be noticed that our method can dynamically adjust the weights of each index employing the variable weight coefficients, which can capture the preliminary risk of UAVs more timely compared with the traditional methods. The proposed framework is validated on two typical datasets: the turbofan engine datasets (simulation) and the UAV flight datasets (real). The experimental results demonstrate the effectiveness and superiority of the hybrid framework on robust information fusion and accurate hierarchical risk assessment.

***Key words—***Hybrid framework, Hierarchical risk assessment, Recurrent fusion autoencoder, Dynamic fuzzy comprehensive evaluation, Unmanned aerial vehicles

# INTRODUCTION

UAVs are one of the rapidly growing sectors in the aviation industry [1], which are applied to the various civilian and commercial fields, such as crop and infrastructure management, emergency management, search, and rescue, etc. [2]. In this regard, ensuring flight safety is critical to the mission capability and security of UAVs, and it is thus an increasing need to develop and improve the technique of risk assessment for UAVs.

In recent years, quite a few safety risk assessment methods for UAVs have been derived from the risk assessments for manned aircraft [3]. Considering the population density, the sheltering ant the obstacles factors, [4] generates a risk map to quantify the risk and estimate the risk optimum path for UAVs. Similarly, given the environmental factors, [2] proposes a Gaussian process model to measure the operational risk and minimizing the risk through the path-integral formulation. In addition to the above-mentioned risk assessment methods based on path planning, the risk assessments for UAVs combining the collision methodology have also received widespread attention [5]. Using the time rates of the bearing and collision core angles, [6] proposes a simplified model to calculate the probability of collisions for UAVs. Furthermore, taking the flight speed, flight direction and some environmental factors as inputs, [7] construct a more complicated deterministic model to calculate the safety flight bound for UAVs to avoid the potential conflict. Besides that, the Bayesian network is also a commonly used method to model the interdependencies between the failure modes and the external factors, and thus achieving the probabilistic risk assessment for UAVs [8].

These above-mentioned methods provide various ideas with the UAVs risk assessment from different perspectives. However, they mainly consider the environment, personnel, and other external factors to conduct the risk assessment, while generally ignore the real-time status of UAVs themselves that affects flight safety heavily. In these above literature, the status of UAVs is either assumed to retain the normal during the flight period or represented by some static failure rates that are usually hard to obtain in practices. In such circumstances, the complex UAV is overly idealized and may bring about an inaccurate risk assessment. Therefore, our target is to propose a more systematic and objective framework considering the internal factors of UAVs, i.e., CM data and logical compositions, that can evaluate the UAVs’ hierarchical risk related to the status of their key component.

However, since UAVs are composed of multiple subsystems and equipment, and there is massive CM data collected from these elements during the flight period, the evolution of UAVs’ status is a dynamic, multivariate, and complex system. In this context, there are two troublesome points needed to be addressed for the effective hierarchical risk assessment of UAVs.

The first one is how to fuse useful information from the multivariate CM data. The CM data can reflect the real-time status of UAVs and their potential risk, while they also inevitably contain much interference such as redundancy, noise, and outliers, etc. Therefore, the effective information fusion is critical for the accurate risk quantification. Up to now, there are two mainstream methods applied to information fusion: the statistic-based ones and the neural network-based ones.

The statistic-based methods generally apply the matrix factorization technique to fuse the effective components from high-dimensional data, where the common methods include the principal component analysis (PCA) [9], kernel PCA [10], and independent component analysis (ICA) [11], etc. Because of the relatively simple calculation and clear mechanism, these methods had been widely utilized in many fields of condition-based maintenance [12-14]. However, the common problem is that they all need to make some idealized assumptions of input data, like the Gaussian distribution, linear correlation, independence of variables, etc., which limits their performance in some complex systems like UAVs.

In comparison, with the help of the powerful capabilities on feature mining, the neural network-based methods can fully extract the intrinsic distribution characteristics from the multivariate input data without too much data assumption, which are thus gaining more and more attention. The stacked autoencoder (SAE) [15] based on the fully-connected layer and encoder-decoder architecture is the most typical one. However, for the hierarchical risk assessment of UAVs, not only the distribution characteristics among variates, but the temporal characteristics among adjacent time instants also contain the potential risk-related information. Unfortunately, these existing mainstream autoencoders [16, 17] are not good at processing the temporal relationships due to the limitation of their non-recurrent architectures. Aiming at this limitation, in recent years, some scholars have tried to replace the traditional fully connected layer with the recurrent cell structure (like the long short-term memory), and then proposed a new architecture, namely the recurrent autoencoder (RA) [18]. In theory, thanks to the capability on depicting the temporal characteristics, the recurrent architecture can achieve more complete information fusion compared with the nonrecurrent ones. However, in practice, due to the ‘hard’ fusion strategy, the existing recurrent architectures generally suffer from the vanishing gradient and cannot achieve the satisfied performance on temporal fusion, which is also a key issue that needs to be addressed.

The second one is how to evaluate the preliminary hierarchical risk timely for complicated UAVs.

The UAV is a complex system with various components, and it is almost impossible to directly describe the relationships between the massive CM data and the hierarchical risk of UAVs through a precise mathematical model. In such circumstances, fuzzy comprehensive evaluation (FCE) [19] developing from the fuzzy theory provides new ideas. It is suitable to describe the complex objects by using the multi-level evaluating index (EI) system under the vagueness and uncertainties, which has been widely applied to implement risk assessment for many complex objects, such as the autonomous underwater vehicles [20], ocean observing equipment [21], traffic [22], construction project [23], and seawater desalination project [24], etc. However, as a key step, the weight definition [25-27] in existing FCE is usually static, which means that once the weights are pre-defined, they will not be adjusted even with the real-time changing risk of each EI. In this regard, the risk of the index with small pre-defined weights is easy to be ignored due to the static weighting mechanism, which makes staffs hard to capture the preliminary hierarchical risk of UAVs and cannot take the corresponding effective manners in time.

TABLE I Summary of the literatures on the key steps in the status-related risk assessment approach

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Step | ID | Reference | Year | Means | Characteristics |
| Information fusion | 1 | W. Sun et al. [12] | 2007 | Vibration feature fusion for rotating machinery with PCA | Linear & variate |
| 2 | J. Ni et al. [13] | 2011 | Feature fusion for power system with KPCA | Nonlinear & variate |
| 3 | Z. Ge et al. [14] | 2012 | Gaussian-type data fusion for complex system with ICA | Linear & variate |
| 4 | H. Shao et al. [16] | 2017 | Vibration data fusion for rotating machinery with SAE | Nonlinear & variate |
| 5 | Z. Xiang et al. [17] | 2019 | Frequency data fusion for rolling bearing with SAE | Nonlinear & variate |
| 6 | W. Yu et al. [18] | 2019 | Multi-sensor data fusion for complex system with RA | Nonlinear & variate and time |
| Comprehensive evaluation | 1 | Y. Liu et al. [20] | 2014 | Assess motion performance for underwater vehicles with FCE | Static weight |
| 2 | Y. Wang et al. [21] | 2015 | Assessment for ocean observing equipment with FCE | Static weight |
| 3 | Y. Liu et al. [22] | 2017 | Accident risk assessment for traffic with FCE | Static weight |
| 4 | T. Gebrehiwet et al. [23] | 2019 | Risk level assessment for construction project with FCE | Static weight |
| 5 | Y. Zhang et al. [24] | 2020 | Risk assessment for seawater desalination project with integrated FCE | Static weight |

In view of the above-mentioned issues (shown as TABLE I in summary), this paper aims at proposing a hybrid framework integrating the qualitative knowledge and quantitative data, which can achieve the complete information fusion and real-time hierarchical risk assessment for complicated UAVs. First, according to the qualitative logical compositions of UAVs, the complicated UAVs are firstly abstracted and transformed into the multi-level EI system with initial weights, where the risk of the lowest-level indices can be reflected by their multivariate CM data directly. Second, to extract the intrinsic feature embeddings from the CM data, we propose a novel information fusion method named recurrent fusing autoencoder (RFA), which is a direct improvement of the existing recurrent autoencoder architecture. By means of the proposed sequential fusion layer, our RFA can deal with the problem of vanishing gradients and achieve the ‘soft’ temporal information fusion, which means that not only the temporal information of the last recurrent cell but also all the others can contribute to the final feature embedding. Therefore, the proposed RFA can extract the more robust and complete feature embeddings from both two aspects of time dimension and variate dimension simultaneously. Third, on the basis of the robust embeddings of each lowest-level index, a truly data-driven method, the adaptive Gaussian mixture model (GMM), is applied to provide the quantitative risk indication with the probabilistic meanings, which is developed from the Gaussian mixture model and Bayesian hyperparameter optimization, and thus can effectively model the feature embeddings with various distributions and uncertainty without any manual operations. Finally, according to the real-time probabilistic risk indications of these lowest-level indices, the dynamic FCE is applied to evaluate the hierarchical risk comprehensively, where the initial weights are adjusted dynamically thanks to the variable weight coefficients and thus it can more timely capture the preliminary risk caused by the slight anomaly of UAVs’ status. To sum up, the main contributions of this paper are listed as follows:

1. A novel information fusion method named recurrent fusion autoencoder (RFA) is proposed in this paper. Thanks to the proposed sequential fusion layer, RFA can deal with the vanishing gradient better compared with the standard recurrent autoencoder, and thus achieving more complete information fusion and highlighting the intrinsic risk from both two aspects of the time dimension and variate dimension.
2. The adaptive GMM can quantify the real-time probabilistic risk indication from the feature embeddings with various distributions, which is truly data-driven with the help of the Bayesian hyperparameter optimization.
3. With the help of the variable weight coefficients, the dynamic FCE can flexibly adjust the weights of EIs according to their real-time risk indications, and thus it can evaluate the preliminary status risk of UAVs timely.
4. The proposed hybrid framework provides a systematic methodology to evaluate the hierarchical risk of complicated UAVs, where both the qualitative logic compositions and quantitative CM data are integrated and analyzed systematically.

The remaining of the paper is organized as follows. Section Ⅱ introduces the necessary background. Section Ⅲ describes the procedure and methodology of the proposed hybrid framework. Section Ⅳ implement the experiments and discussions through the two case studies: the first one is to compare the performance on information fusion between our proposed RFA and existing mainstream methods using the C-MAPSS simulation dataset, and the second one is to validate the entire procedure of the proposed hybrid framework using the real flight dataset of UAV. Finally, the conclusions and future prospects are given in Section Ⅴ.

# Preliminaries

In this section, the necessary background knowledge of encoder-decoder architecture and FCE is introduced, which is the theoretical basis of our proposed data-driven risk assessment.

## Encoder-decoder architecture

In the field of deep learning, the encoder-decoder architecture is a typical type of neural network that can extract the intrinsic feature embeddings in an unsupervised manner [28]. The architecture generally includes an encoder and a decoder, where the encoder is applied to compress a multivariate input data into a short code embedding, and the decoder is applied to un-compress the code embedding into an output that matches the raw input data closely. The compressed short code embedding represents the intrinsic characteristics of the input data.

According to the different components of encoder and decoder, the architecture can evolve various variants. If the fully-connected layers are applied to build the encoder and decoder, we will obtain the most common architecture, namely the stacked autoencoder. If the encoder and decoder are built by the recurrent structures such as recurrent neural network (RNN) [29], gate recurrent unit (GRU) [30], and LSTM [31], we will obtain the recurrent architecture, namely the recurrent autoencoder. The above-mentioned two architectures can be further illustrated in **Figure 1.**

Figure 1 Two existing typical architectures for information fusion: stacked autoencoder (up) and recurrent autoencoder (down)

As shown in **Figure 1**, for the existing stacked autoencoder, the input is a vector at a certain time instant, the encoder and decoder are respectively two groups of fully-connected layers, i.e.,  and . Its core operations can be described as follows:

|  |  |
| --- | --- |
| , | (1) |

where  is the loss function of the stacked autoencoder,  is the feature embedding fused from the vector at a time instant. To sum up, the information fusion of this non-recurrent encoder-decoder architecture mainly aims at the input data of single time instant and multivariate, namely, the fusion from aspect of variate dimension.

For the existing recurrent autoencoder published in recent years, the input can be extended into a vector sequence (), where each vector is a vector, the encoder and decoder are respectively two groups of recurrent cells such as RNN, GRU or LSTM, etc., namely,  and  (). Its core operations can be described as follows:

|  |  |
| --- | --- |
| , | (2) |

where , are respectively the cell variates and output of the encoder cell , , are respectively the cell variates and output of , the last output  is set as the feature embedding, which fuse the useful information of inputs at previous time instants. To sum up, the standard recurrent architecture can be viewed as an extension of the non-recurrent one, which can not only implement the information fusion of variate dimension, but also further consider the temporal relationship between several time instants from the time dimension.

For each EI of the UAV, given its multivariate CM data of several adjacent time instants, not only the data characteristics among the variates can reflect its real-time risk, but the temporal relationship among time instants can also be utilized to represent its more detailed risk status. In theory, compared with the non-recurrent architecture, the recurrent architecture is more suitable for the UAVs’ risk information fusion because of the stronger capability on temporal representation. However, in practice, this advantage will become weaker due to the problem of vanishing gradient [32] when the length of the input sequence grows up. Aiming at the above practical issue, we further improve the existing recurrent autoencoder, where a sequential fusing layer is proposed and added to the encoder block. Along with the bidirectional encoding mechanism [33], it will help us achieve more robust and complete information fusion and highlight the intrinsic risk status. The corresponding details will be described in subsection Ⅲ-C.

## Fuzzy comprehensive evaluation

The above-mentioned encoder-decoder architectures are mainly applied to implement the information fusion for the low-level EIs of UAVs. Furthermore, in order to achieve the hierarchical risk assessment for the entire complicated UAVs, we apply the theory of fuzzy comprehensive evaluation and its necessary background is described briefly as follows.

As the effective means to address the problems with uncertain and fuzzy boundaries, the FCE method obtains wide applicability, especially in the field of risk assessment. Generally, the FCE method contains the following steps.

First, establish the multi-level EI system and the grading levels for the evaluated objects. To facilitate understanding, we take the simplest form, the single-level EI system containing  EIs , as the example. For each index , it can be divided into  grading levels (e.g., health, sub-health, danger, and failure).

Second, define the initial weight set () for the EI system, which describe the relative importance between each EI. The most common method for weight definition is the analytic hierarchy process (AHP) [34].

Third, calculate the risk membership matrix for the EI system according to the membership functions and risk indications. For each EI, given its risk indication , we can obtain its risk membership vector  with elements. The above process can be expressed as follows:

|  |  |
| --- | --- |
| , | (3) |
| , | (4) |

where  is the -th membership function,  is the membership that reflects the likelihood that the index  belongs to grading level . Repeating the above operation for all  indices, there will be a membership degree matrix .

Finally, implement the fuzzy comprehensive evaluation. According to the principal of fuzzy arithmetic [20], the comprehensive grading vector  can be described as follows:

|  |  |
| --- | --- |
| , | (5) |

where  represent the likelihood that the entire object belongs to the grading level .

With the help of FCE, the complicated object will be objected represented by multiple EIs, where its vagueness and uncertainty are reasonably depicted by the comprehensive grading vector. However, there is a shortcoming in the existing mainstream FCE methods that the weight sets of the EI system are generally static, which means that even if some local EIs present serious risks, the FCE will not give them more attention. Therefore, the existing static weights-based FCE is easy to ignore the preliminary risks of systems. Aiming at this issue, we apply the dynamic weight mechanism to FCE by means of the variable weight coefficients, which is illustrated in subsection Ⅲ-E specifically.

# Proposed hybrid framework

In this paper, we propose a novel hybrid framework to implement the hierarchical risk assessment for UAVs, which integrates the qualitative knowledge of UAVs’ logical composition and quantitative real-time CM data. This section is composed of five key parts: procedure of the hybrid framework, EI system establishment, robust information fusion by RFA, probabilistic risk quantification by adaptive GMM, and comprehensive evaluation by dynamic FCE. In each subsection, the specific process, innovations, and related logic of the methodology will be introduced respectively.

## A. Procedure of the hybrid framework

In this subsection, a novel hybrid framework is proposed for the hierarchical risk assessment of UAVs, which is mainly composed of the following four key steps. The procedure of the proposed hybrid framework is illustrated in **Figure 2**.

Figure 2 The flow chart of the proposed hybrid framework

(1) First, according to the qualitative logical compositions, the complicated UAVs are abstracted and transformed into an EI system, where the corresponding initial weight sets and the grading level sets are also pre-defined.

(2) Second, given the quantitative CM data of each lowest-level EI (3rd-level EI in this paper), there will be an RFA model built to extract the feature embeddings that fuse the useful information from both two aspects of variate dimension and time dimension. The above operations are accomplished by two phases: offline phase and online phase. In the offline phase, given the historical normal CM data, RFA will be trained in an unsupervised manner using the gradient descent optimization, and the intrinsic characteristics of the CM data will be represented in the model parameters. In the online phase, given the real-time CM data, it will be fused and transformed into a feature embedding vector by the trained RFA. The feature embedding fuses and codes the risk-related information for each lowest-level EI.

(3) Third, given the fused feature embeddings of each lowest-level EI, the adaptive GMM is developed to quantify its risk in a truly data-driven way, which is also accomplished by two phases. In the offline phase, given the normal feature embeddings, there will be a GMM trained automatically to model their baseline distribution with the help of Bayesian optimization. Then in the online phase, given the real-time feature embedding, the trained GMM will calculation its risk quantification with the probabilistic meanings, which reflects the deviation between the baseline feature distribution and real-time feature in the form of likelihood.

(4) Finally, given the real-time probabilistic risk indications of all lowest-level EIs, the corresponding initial weights are adjusted dynamically and there will be a fuzzy risk vector evaluated to reflect the risk of the higher-level EI. Repeating the above operations level by level, we will finally achieve the real-time hierarchical risk assessment for complicated UAVs under uncertainty.

## B. EI system Establishment

Since the UAV risk assessment is a complicated issue with uncertainty and vagueness, it is quite difficult to accurately depict the quantitative relationship between the status risk of UAVs and the massive CM data through a precise mathematical model. Aiming at addressing this problem, a multi-level EI system is firstly established in this subsection, which avoids us directly designing an overly complex model to evaluate the overall status risk of UAVs.

### Establishing the EI system

The UAV is a complicated system with various subsystems and equipment, its overall status is comprehensively impacted by the status of key components, and the status of components can further be reflected by the real-time CM data. Therefore, we establish an EI system with three-level EIs to abstract and describe the complicated UAV system.

First, the UAV flight status is set as the 1st-level EI  in our 3-level EI system, as the highest-level index, it reflects the status risk of the overall UAV during the flight period. Second, according to the logic structure and the related function, five critical subsystems of UAVs are set as the 2nd-level indices , which are respectively the flight control subsystem, steering gear subsystem, engine subsystem, electrical subsystem, and landing subsystem. These five 2nd-level EIs jointly represent the status of the 1st-level EI. Third, ten key components of these subsystems are set as the 3rd-level indices , which are respectively the pitch control, roll control, flap, rudder, elevator, gas path, oil, main generator, 28V battery, and undercarriage. At last, for each 3rd-level EI, we choose several CM parameters to quantify its real-time status, which can be expressed as , where  is the number of sensitive CMs and the  is the sensitive CM parameter carrying the risk-related information of the EI .

Through the above-mentioned qualitative knowledge, the complicated UAVs hard to be described by a precise mathematical model are transformed into the 3-level EI system, which can be illustrated in **TABLE II**.

TABLE II The evaluating index system for status risk of UAVs

|  |  |  |  |
| --- | --- | --- | --- |
| Index set in the 1st level | Index set in the 2nd level | Index set in the 3rd level | Sensitive parameters |
| UAV flight status | flight control subsystem | pitch control | pitch command  pitch feedback |
| roll control | roll command  roll feedback |
| steering gear subsystem | flap | left flap surface position  right flap surface position |
| rudder | left rudder surface position  right rudder surface position |
| elevator | left elevator surface position  right elevator surface position |
| engine subsystem | gas path | cylinder head temperature-1  cylinder head temperature-2 |
| oil | oil pressure  oil temperature |
| electrical subsystem | main generator | main generator current  main generator voltage |
| 28V battery | battery voltage-1  battery voltage-2 |
| landing subsystem | undercarriage | gear up command  gear up feedback |

### Defining the initial weight set and grading level set

Defining the weights for EIs is another key step in the hierarchical risk assessment of UAVs, which determines how much each local EI can affect the overall evaluation of UAVs status risk. In this paper, the order relation method is applied to define the initial weight set, which requires no consistency checks in the analytic hierarchy process (AHP) method and is thus more suitable for complicated index systems. The procedure of defining weight set by the order relation method mainly consists of 3 steps: index importance ranking, index relative importance (RI) assignment, and weight calculation. The rules of the relative importance assignment are illustrated in **TABLE III**, and a more specific description of the order relation method can be found in the literature [27].

TABLE III The results of RI assignment in the order relation method

|  |  |
| --- | --- |
| **RI** | **Rule description** |
| 1.0 | is same as |
| 1.2 | is slightly important as |
| 1.4 | is obviously important as |
| 1.6 | is strongly important as |
| 1.8 | is extremely important as |

Given a 3rd level EI set consisting of  elements, we will obtain the corresponding weight set using the Order relation method.

In addition to the weight set, the grading level set is a hierarchical expression of evaluation results by fuzzy language, which can be expressed as , where  is the number of the grading levels. In this paper, we define  grading levels for the significance of the EIs. The grading level set can be expressed as, where the variables , , ,  respectively represents the Health, Sub-health, Danger and Failure.

## C. Robust information fusion by RFA

The architecture of the proposed RFA is illustrated in **Figure 3**, which is mainly consisted of 3 components, namely, recurrent encoder block, sequential fusion layer, and recurrent decoder block. In the offline training phase, after the operation of data pre-processing, the multivariate sequences will be utilized as the inputs to fuse the status information and train the RFA, all 3 components are involved in this phase. In the online testing phase, after the same data pre-processing, the multivariate sequence will be fused and transformed into the feature embedding vector employing the trained RFA, only the recurrent encoder block and sequential fusion layer will be involved in this phase and the decoder block is abandoned. The details of the above-mentioned procedure are described as follows.

Figure 3 The architecture of the proposed RFA

### Data pre-processing

In order to ensure the effect of information fusion under real data conditions, it is necessary to preprocess the raw input data and obtain the input sequence suitable for the RFA. In this paper, we apply three typical data-preprocessing steps, namely, data split, data transform and data standardization, which is illustrated in **Figure 4.**

Figure 4 Data processing for RFA

For each 3rd-level EI , its real-time risk can be reflected by the time series of its belonging  CM sensitive parameters , where each time series is a CM data record. Before the relevant data preprocessing, we utilize the common quartile-based method[35] to eliminate outliers in these time series, to avoid interference for the subsequent analysis. In practices, these time series are generally non-stationary, which means that each local time period of the time series exhibits different characteristics, namely, each local short time series has the different contribution for the risk indication. In order to capture the temporal information, firstly, each entire time series is split into  short series using a sliding window. Therefore,  raw time series of EI  are split into an input tensor of size , which can be viewed as  matrices and each matrix contains  short time series of  points.

In order to further highlight the data characteristics, 6 common time domain functions, namely, mean, standard deviation, root mean square, peak coefficient, margin coefficient and skewness coefficient, are applied to implement the data transform. Specifically, given a matrix of size , it will be transformed into a vector of size . Repeating the operations for all the  matrices, we can obtain the transformed input matrix :

|  |  |
| --- | --- |
| , | (6) |
| , | (7) |

where  are respectively 6 time domain values of -th short time series,  is the transformed input matrix of size .

Finally, in order to achieve the more stable training process for RFA, we use the classical z-score method [36] to implement data standardization for the input matrix .

### Offline training for RFA

In the training phase, given the input matrices preprocessed from the historical normal CM data, our purpose is to teach RFA how to achieve information fusion from the aspects of time dimension and variate dimension, where the fused feature embeddings can represent the intrinsic characteristics of these normal input matrices. Aiming at this target, we adopted a recurrent encoding and decoding architecture with the bidirectional encoding mechanism as the main body. Furthermore, in order to ensure the robustness and completeness of information fusion, we propose a novel layer, called sequential fusion layer, in each recurrent encoder block. The detailed procedure is described in the following.

* Recurrent encoder block

As shown in **Figure 3**, the recurrent encoder block contains a forward encoder layer and a backward encoder layer, and each encoder layer is consisted of several LSTM cells. The multivariate input  of each time instant completes the variable-level information fusion in each LSTM cell. After flowing through all LSTM cells in the forward or backward manner, these inputs complete the temporal-level information fusion.

Specially, given an input matrix  of size , each LSTM cell in the forward and backward encoder layer will implement the following operations:

|  |  |
| --- | --- |
| , | (8) |
| , | (9) |

where , are the hidden state and cell state of LSTM cell,  and  are the marks of forward encoder and backward encoder, and  is the operators of each LSTM cell in the encoder block that is mainly depended on the gate mechanism of LSTM [37].

Each hidden state  is a vector of size 1\***ℱ** (ℱ is the dimension of feature embedding), which fuses the variate-level information in the current time instant  and temporal-level information in the previous time instants .

* Sequential fusion layer

After the above-mentioned encoder operations, we have completed the preliminary information fusion. The next core problem is how to obtain the final data representation, namely, feature embedding.

In existing mainstream recurrent autoencoders, researchers generally adopt a ‘hard’ fusion strategy: the last time instant’s output  containing the most information is directly set as the final feature embedding. It can be understood that the output at  the last time instant contributes 100% to the entire information fusion. However, due to the inherent problem of vanishing gradients in recurrent architectures, the data information of initial time instants will be difficult to be reflected in the final feature embedding when length  of input time instants grows up, which will cause the incomplete information fusion especially when the entire input sequence is non-stationary.

In such circumstances, the proposed RFA adopts a ‘soft’ fusion strategy, where a sequential fusion layer is proposed to perform the weighted fusion for the outputs  of all the input time instants. It can be understood that all the outputs have corresponding contributions to the final feature embedding. The above-mentioned operation can be achieved in many ways. In this paper, we chose an adaptive and simple method: a linear fully connected layer with the dropout trick [38]. The sequential fusion layer is illustrated in **Figure 5.**

Figure 5 Sequential fusion layer in RFA

Specifically, given all the outputs ,, of forward and backward encoder layer, we firstly concatenate them into the long vectors of size 1\*(*L*\***ℱ**):

|  |  |
| --- | --- |
| , | (10) |
| , | (11) |

Then a linear fully connected layer is applied to transform the long vector into the vector of size 1\***ℱ**:

|  |  |
| --- | --- |
| , | (12) |
| , | (13) |

where ,  are respectively the feature embedding of forward encoder layer and backward one, ∈(*L*\*ℱ)\*ℱ, ∈1\*ℱ, ∈(*L*\*ℱ)\*ℱ and ∈1\*ℱ are respectively the weight matrices and biases of the forward fully connected layer and backward one. These weights and biases can be updated automatically as the training process of RFA, which determine the contribution of each output to the fused feature embedding in a quantitative way. In addition, dropout, a common technique of deep learning, is applied in our sequential fusion layer, which avoids potential overfitting risks by resetting weight of certain node to zero randomly.

To sum up, sequential fusion layer fuses the outputs of each time instant in a *soft* strategy, which makes the fused feature embeddings more robust and complete. In addition, the parameters of the sequential fusion layer can be updated together with other ones in RFA, which is simple and adaptive.

* Recurrent decoder block

Similarly, the recurrent decoder block contains a forward decoder layer and a backward decoder layer. Its target is to decode the feature embeddings to the outputs that are closed to the inputs, and it needs to use backpropagation to update the parameters of the entire RFA.

Specifically, given the feature embedding of forward encoder layer and backward one, the operations of decoding are described as follows:

|  |  |
| --- | --- |
| , | (14) |
| , | (15) |
| , | (16) |
| , | (17) |

according to these decoded outputs, we can obtain the decoded matrices ∈*L*\*ℱ, ∈*L*\*ℱ of forward decoder layer and backward one.

Then, in order to calculate the reconstruction error, we increase the dimensionality of the decoded matrices as follows:

|  |  |
| --- | --- |
| , | (18) |

where ∈*L*\*6*H* is the decoded output matrix, RFA develops the loss function to calculate the reconstruction error between it and the input matrix , and utilizes back propagation to update the model parameters.

### Online information fusion

During the offline phase, the implicit mapping relationship between historical normal CM data and feature embedding was learned and represented by the trained RFA model.

During the online phase, we only keep the recurrent encoder block and sequential fusion layer of the trained RFA, the recurrent decoder block is abandoned. For each 3rd-level EI, given its real-time input matrix , the feature embedding can be fused as follows:

|  |  |
| --- | --- |
| , | (19) |
| , | (20) |

where ∈1\*ℱ is the final feature embedding of real-time input data, it represents the robust and complete characteristics of input data by taking into account of variate-level and local temporal-level information fusion.

## D. Probabilistic risk quantification by adaptive GMM

Through the RFA, the robust feature embeddings are extracted from the CM data. The potential risks of each EI can be reflected by the changing distribution of these feature embeddings. For each 3rd-level EI, the more the real-time feature embeddings differ from the distribution of its normal feature embeddings, the higher risk it may have. Therefore, the risk is defined as the deviation between the real-time feature distribution and the historical baseline one.

In fact, there are quite a few EIs for the complicated UAVs and they generally have various feature distributions. Aiming at this issue, we propose a truly data-driven method, namely, adaptive GMM, to model the feature baseline of these 3rd-level EIs and quantify their real-time probabilistic risk automatically, which is developed from the GMM and Bayesian optimization. Specifically, the above procedure contains two key steps: baseline modeling by adaptive GMM, real-time probabilistic risk quantification.

### Baseline modeling by adaptive GMM

As a widely applied probabilistic clustering algorithm, the GMM has superior capability on modeling the various data distribution [39]. For each 3rd-level EI, given its fused feature embedding , a finite mixture model  can be defined as follows:

|  |  |
| --- | --- |
| , | (21) |

where  is the number of the Gaussian components,  is the mixing proportion coefficient subject to , and  is the pre-defined hyperparameter set of GMM. For each Gaussian component in GMM, it can be denoted by the parameter , where ∈ℱ is the mean vector and ∈ℱ\*ℱ is the covariance matrix. The all parameters of  components in GMM can be grouped into a parameter set:

|  |  |
| --- | --- |
| , | (22) |

In the training phase, given the historical normal feature embedding sets  consisting of  samples (), our aim is to fit the optimal parameter set  that maximizes the likelihood function of GMM:

|  |  |
| --- | --- |
| , | (23) |

In this paper, the expectation-maximization (EM) algorithm [40] is applied to achieve the above target. Once the  converges to a local optimum, a relatively optimal GMM will be obtained given the hyperparameter set , and its optimal parameter set can be defined as .

Furthermore, in order to be truly data-driven, Bayesian information criterion (BIC) [41] is employed to select the optimal GMM from the candidate ones with different hyperparameter set . Specifically, the operation can be described as follows:

|  |  |
| --- | --- |
| , | (24) |
|  | (25) |

where  is the number of free parameters of the candidate GMM, it is used to penalize the overly complex hyperparameter set to avoid the overfitting. Among all the candidate GMMs, the one with the lowest BIC value  will be chosen as the optimal baseline model, which represents the historical baseline distribution of the EI .

### Real-time probabilistic risk quantification

In the online testing phase, the trained baseline model is applied to quantify the real-time risk with probabilistic meanings.

For a 3rd-level EI, given its real-time fused feature embedding , the normalized probability density  will be calculated by the corresponding baseline model, which quantifies and depicts the difference degree between the real-time status and the historical normal status. A real-time feature embedding from the same region of the baseline distribution will cause the normalized probability density  to approach 1, and the more it deviates from the baseline distribution, the closer the  will be to 0.

To be more intuitive, we calculate the deviation likelihood of range 0-1 using the operation , where the deviation likelihood is taken as the probabilistic indication reflecting the real-time risk of each EI . Repeating the above operations for each EI in the certain 2nd-level EI set , we will obtain the corresponding probabilistic risk indication set .

## E. Comprehensive evaluation by dynamic FCE

For the purpose on measuring the real-time hierarchical risk for UAVs and timely capture the slight risk that happened in the early abnormal status of UAVs, the dynamic FCE is utilized to perform the comprehensive evaluation level by level according to the real-time probabilistic risk indications in the 3rd-level, where the main three steps of the dynamic FCE are respectively described as follows.

### Dynamic weight adjustment by variable weight coefficients

According to the real-time probabilistic risk indications, the variable weight coefficients are utilized to adjust the initial weight set dynamically level by level, where the anomaly EIs will be adaptively assigned the greater weights so that the slight risk of UAVs will be captured timelier.

For a 2nd-level EI set, given its real-time probabilistic risk indication set , its initial weight set will be adjusted dynamically as follows:

|  |  |
| --- | --- |
| , | (26) |

where  is the initial weight of the 3rd-level EI ,  is the new weight adjusted by the variable weight coefficients, and the  is the sensitivity coefficient in the range of 0-1 that is applied to adjust the sensitivity to real-time quantitative risk. The closer the sensitivity coefficient  is to 0, the larger the new weight  will be reassigned to the index  with the same increasements in the corresponding risk indication , which makes that a slight low-level risk will be more easily reflected in the high-level risk of UAVs. Instead, the closer the sensitivity coefficient  is to 1, the weight adjustment is less sensitive to changes in the real-time risk indications. When the sensitivity coefficient  is equal to 1, the dynamic weights will degenerate into the static weights, which means that any changes in the real-time probabilistic risk indications cannot lead to the weight adjustment.

Through the variable weight coefficients, repeating the operations for all other 3rd-level EIs in the given 2nd-level EI set, we will obtain the dynamic weight set , which responses to the real-time changing probabilistic risk indications flexibly.

### Membership degree calculation

As for the UAVs with complicated components and massive CM data, there are vagueness and uncertainty involved in risk assessment. In such circumstances, one may sometimes feel more confident using the fuzzy evaluation than the precise evaluation [20]. Therefore, in this step, the probabilistic risk indications will be transformed into the membership degree to depict uncertainty by the membership functions.

Given the real-time probabilistic risk indication set  of a 2nd-level EI . For each real-time probabilistic risk indication , the rigid-type membership function [42] is employed to calculate its membership degree  for each grading level . Compared with the triangular and trapezoidal membership functions, the rigid-type membership function has a relatively smooth curve shape, which means that it is robust to the slight noise of risk indications and helps to implement the stable risk assessment. Since there are 4 levels in our grading level set , we apply 4 types of membership function as follows:

|  |  |
| --- | --- |
| , | (27) |
| , | (28) |
| , | (29) |
| , | (30) |

where - are the boundary values of 4 grading levels,  is the membership degree of the EI , which represents the likelihood that the EI  belongs to the grading level .

Repeating the above operations for all the other 3rd-level EIs, we will obtain the membership degree matrix  of given 2nd-level EI .

### Comprehensive evaluation for hierarchical risk

For each 2nd-level EI , given its dynamic weight set  and the risk membership matrix , we can evaluate its fuzzy risk vector  as follows[20], which can be understood as a weighted fusion of the risk membership probability:

|  |  |
| --- | --- |
| , | (31) |

where  is the real-time likelihood that the  belongs to the grading level , and  is also the next membership vector to support the comprehensive evaluation in the next level.

Repeating the above operations level by level, we will achieve the real-time hierarchical risk assessment for complicated UAVs. For each key EI of UAVs, there will be a fuzzy risk vector to describe its likelihood probability under each grading level quantitatively.

# Experiments and discussions

## A. Evaluation of the proposed RFA-based information fusion using the turbofan engines dataset

In this section, the simulation datasets of turbofan engines provided by the NASA prognostic data repository [43] are employed, where the targeted case study and metrics are developed to validate the performance on information fusion between RFA and other comparative mainstream methods.

### Data overview

In turbofan engine datasets, there are 100 complete run-to-failure records of engines, each record contains 21 sensor variables such as pressure at fan inlet, physical fan speed, and total temperature at fan inlet, etc., these variables reflect the continuous degradation of engines from different aspects. Furthermore, we abandon some useless variables without obvious degradation trends, and finally select 14 status-sensitive variables to represent the performance of entire engines. Taking an engine record as the example, the degradation data of its 14 selected variables is illustrated as follows:

Figure 6 14 selected variables in a turbofan engine records

Similar to the procedure described in subsection Ⅲ-B, we can regard the entire engine status as an EI with 14 sensitive parameters, which can be applied to verify the performance on information fusion of different methods.

### Information fusion among comparative methods

* Comparative information fusion methods

In addition to RFA, there are 5 existing mainstream information fusion methods employed as the comparisons that are respectively independent component analysis (ICA) [11], principal component analysis (PCA) [9], kernel component analysis (KPCA) [10], stacked autoencoder (SAE) [15], recurrent autoencoder (RA) [18].

In this paper, we choose the initial 15% data of each engine as the training dataset, the other 85% data of each engine is set as the testing dataset. Each sample is the vector of size , which is concatenated from the 14 variate points of each time instant. For the non-recurrent methods such as ICA, PCA, KPCA, and SAE, there is one sample of size  input for information fusion each time. For the recurrent methods like RA and our proposed RFA, there is 3 samples input for information fusion each time. For better visualization, the dimension of feature embedding is set as 3 for all the methods. All the data has been pre-processed by z-score standardization.

The above-mentioned definitions can be illustrated in **TABLE IV**.

TABLE IV Detailed definitions of all information fusion methods

|  |  |  |  |
| --- | --- | --- | --- |
| **Type** | **Method** | **Input size** | **Feature embedding size** |
| Non-recurrent | ICA |  |  |
| PCA |  |  |
| KPCA |  |  |
| SAE |  |  |
| Recurrent | RA |  |  |
| RFA |  |  |

* Visualization of information fusion

**Figure 7** exhibits the 3d-scatter plots of feature embeddings fused by the above-mentioned 6 methods: 3 axes of the figure represent 3 dimensions of the feature embeddings, the color represents the engine degradation status of each feature embedding, where the color mapping value=1 means that the engines are under the initial health status, and the color mapping value=0 means that the engines are under the end of failure status. Therefore, the ideal information fusion should ensure that the 3d scatter points between the similar status are as close as possible while the ones between the different status are separated as much as possible.

Figure 7 Scatters of feature embedding

According to the above analysis, in an intuitive way, it can be seen that the proposed RFA achieves the best performance on information fusion, RA and SAE that also employ the encoder-decoder architecture achieve slightly inferior results, while 3 other statistical-based methods, i.e., PCA, KPCA, and ICA, do not obtain the quite satisfied results. Especially for the ICA-based information fusion, its 3d scatter points present the obvious aliasing.

The above 3d scatter demonstrated the superiority of our proposed RFA for information fusion preliminarily. Furthermore, in order to compare the performance of the methods more comprehensively, we apply three typical distance functions, i.e. Mahalanobis distance [44], Euclidean distance [45], and standardized Euclidean distance [45], to convert these 3d feature embeddings into 1d health indicators (HIs). Specifically, the health indicator is defined as the distance between the testing feature embeddings and the normal ones:

|  |  |
| --- | --- |
| , | (32) |

where  is the distance function, ∈*3* , ∈*3*  are respectively the testing feature embedding vector and a normal one. Limited by the space, we only show the Euclidean distance-based HI results of 3 methods, namely, ICA, SAE and our proposed RFA, which can be seen in **Figure 8-Figure 10**.

Figure 8 ICA-based HIs of turbofan engines

Figure 9 SAE-based HIs of turbofan engines

Figure 10 RFA-based HIs of turbofan engines **(proposed)**

As shown in **Figure 8-Figure 10**, the overall trend of HI sequences and their local details among ICA, SAE, and RFA have been illustrated in a picture-picture way. Two subgraphs in each figure show part of the HI sequences in the two rectangular boxes of the total graph. In order to achieve a clear comparison, the subgraphs only show the HI sequences with the same length, that is, if some HI sequences in the box are interrupted, they will not be displayed in the subgraphs.

Since the chosen engine datasets are simulated under the continuous degradation status, a good information fusion method should be robust to the local data noise and highlight the degradation trend: the HI sequences should have good monotonicity and tendency. As shown in the above figures, RFA still achieves the best performance, which depicts good tendency overall and exhibits superior robustness to noise locally. The non-recurrent deep architecture, SAE, is slightly inferior. In comparison, the statistical method, ICA, has poor noise robustness and does not exhibit the satisfied results.

* Metrics of information fusion

Through the above visualization results, we have an intuitive understanding of the performance of the proposed RFA-based information fusion. In this subsection, we further introduce two common metrics [46], i.e. monotonicity (‘Mono’) and tendency (‘Tend’), to validate the performance of these methods quantitatively. ‘Mono’ quantitatively describes the robustness of an information fusion method under local disturbances, where the large ‘Mono’ means the better monotonicity, namely, the better robustness to local disturbances in CM data. ‘Tend’ quantitatively describes the completeness of an information fusion method for a continuous degradation system, where the large ‘Tend’ means the better correlation between the fused HI and the real degradation status of CM data.

which can be described as follows:

|  |  |
| --- | --- |
| , | (33) |
| , | (34) |
|  | (35) |

where  and  are respectively the HI value and time value (epoch of engines) of the *t*-th sample,  is the length of the samples of engines during the entire lifetime. The Score is the comprehensive indicator of 2 common metrics.

According to the above 3 metrics, the quantitative comparisons are detailly described in **TABLE V**.

TABLE V Detailed comparisons for HIs in a quantitative way

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Method** | **Distance** | **Mono** | **Tend** | **Score** |
| **RFA**  **(proposed)** | Mahalanobis | 0.6220 | 0.8923 | 1.5143 |
| **Euclidean** | **0.6473** | **0.8937** | **1.5410** |
| standardized Euclidean | 0.6347 | 0.8912 | 1.5259 |
| RA | Mahalanobis | 0.5560 | 0.8935 | 1.4534 |
| Euclidean | 0.5815 | 0.8926 | 1.4741 |
| standardized Euclidean | 0.5764 | 0.8870 | 1.4634 |
| SAE | Mahalanobis | 0.5429 | 0.8806 | 1.4235 |
| Euclidean | 0.5611 | 0.8786 | 1.4397 |
| standardized Euclidean | 0.5642 | 0.8788 | 1.4430 |
| PCA | Mahalanobis | 0.5478 | 0.8814 | 1.4292 |
| Euclidean | 0.5435 | 0.8691 | 1.4126 |
| standardized Euclidean | 0.5516 | 0.8695 | 1.4211 |
| KPCA | Mahalanobis | 0.5467 | 0.8856 | 1.4322 |
| Euclidean | 0.5416 | 0.8750 | 1.4165 |
| standardized Euclidean | 0.5562 | 0.8747 | 1.4308 |
| ICA | Mahalanobis | 0.5478 | 0.8814 | 1.4292 |
| Euclidean | 0.4000 | 0.8383 | 1.2383 |
| standardized Euclidean | 0.5453 | 0.8663 | 1.4116 |

As shown in **TABLE V**, the information fusion results based on the proposed RFA and Euclidean distance achieves the best monotonicity, tendency, and score (0.6473, 0.8937, and 1.5408), which respectively achieve 11.32%, 0.12%, and 4.54% improvement compared to the best existing method (RA-Euclidean), achieve 61.82%, 3.16%, and 9.17% improvement compared to the worst existing method (ICA-Euclidean). In general, with 3 different distance functions, the proposed RFA all achieves better results compared with the other 5 methods.

To sum up, the above-mentioned results demonstrate the superiority on robust information fusion of our proposed RFA, which brings about better robustness and completeness for information fusion by applying the novel sequential fusion layer. In addition, RA, the recurrent encoder-decoder architecture published in recent years, obtains slightly inferior but quite satisfied results (No.2 performance among the 6 methods), which also confirms the potential of the type of recurrent methods on information fusion.

## B. Evaluation of proposed risk assessment framework using the UAV’s real flight dataset

In this subsection, the real flight datasets of a UAV are applied to validate the proposed entire hybrid framework for hierarchical risk assessment.

### Data overview

In this subsection, the real CM data collected from a UAV during the flight period is utilized to verify the effectiveness of our proposed hybrid framework.

As shown in **TABLE II**, a three-level EI system is established that contains one 1st-level EI, five 2nd -level EIs, eleven 3rd-level EIs and twenty corresponding sensitive CM parameters. For each sensitive CM parameters , there are many time series with with  sampling points collected under the normal status, which are applied to the offline training for RFA and adaptive GMM. In addition, in order to test the performance of the proposed framework on evaluating the hierarchical risk under the different abnormality status of UAVs, four CM parameters , , ,  belonging to the two 3rd-level indices, oil , 28V battery  are injected 4 types of abnormality that are respectively named as the degradation status Ⅰ-Ⅳ. For the CM parameters under each type of abnormality, there are respectively 5 groups of time series samples utilized to test the risk assessment framework.

Due to lack of the sufficient real anomaly data of UAVs, we apply the anomaly injections to obtain the above-mentioned 4 types of anomaly CM data. Specifically, the anomaly data is conducted by respectively adding the 4 types of Gaussian random series and the time series under the normal status. Taking a time series sample  of CM parameter  as the example, this process can be expressed as follows:

|  |  |
| --- | --- |
| , | (36) |

where ,  are respectively the time series sample under the anomaly status and the normal status,  is a Gaussian random series that is composed of  Gaussian random numbers with  as mean and  as variance. , are the mean and variance of time series sample , , are the mean anomaly coefficient and the variance anomaly coefficient. In this paper, the anomaly coefficients  are respectively set as , , and  to reflect the 4 types of anomaly. The above anomaly injection simulates the abnormal symptoms of oil overpressure, oil overtemperature, and battery voltage increase that have been recorded in the historical flight of the UAV, which can be illustrated in **Figure 11** and **Figure 12**.

Figure 11 Anomaly injection of the CM parameters,  (local)

Figure 12 Anomaly injection of the CM parameters ,  (local)

### Real-time hierarchical risk assessment of UAVs

In this subsection, by means of the established EI system, we evaluate the real-time hierarchical risk of UAVs step by step.

* EI system establishment and initial weight definition

First, the order relation method is utilized to define the initial weight set  for each 2nd-level EIs . According to the logic components of UAVs and the respective function during the flight period, the importance ranking of these indices is set as follows: flight control subsystem > steering gear subsystem > engine subsystem > electrical subsystem, and their relative importance assignment is set as . Through the order relation method, the initial weight set of the 2nd-level EIs is obtained as . Similarly, we can define and calculate the initial weight sets of the other 3rd-level EIs as , , ,  and .

* Robust information fusion by RFA

As described in subsection C, for each 3rd-level EI, there is an RFA trained using the historical normal CM data in an unsupervised way, then given its real-time CM data, the trained RFA will extract its robust feature embedding for information fusion. Specifically, the detailed hyperparameters of RFA are illustrated in **TABLE VI**.

TABLE VI Detailed comparisons for HIs in a quantitative way

|  |  |  |  |
| --- | --- | --- | --- |
| **Hyperparameter** | **Value** | **Hyperparameter** | **Value** |
| Input size | 1\*6*H* | Dropout rate | 0.3 |
| Feature embedding size | 1\*2 | Loss function | Mean square error |
| Number of LSTM cells | 3 | Optimizer | Adam |
| Number of sequential fusion layers | 2 | Epochs | 40 |
| Bidirectional | True | Batch size | 16 |

Still taking the 3rd-level EIs ,  as the examples, the training loss of their RFAs is shown in **Figure 13**.

Figure 13 Training loss of RFAs related with , 

As shown in **Figure 13,** as the growth of the training epochs, the training loss of RFA gradually decreases, which means that the model gradually learns the implicit relationship between CM data and feature embeddings.

* Probabilistic risk quantification by adaptive GMM

For each 3rd-level EI, we apply the adaptive GMM to model its baseline distribution from the historical normal feature space automatically and then quantify its real-time probabilistic risk indication given the online CM data.

First, given the historical normal feature embeddings of each 3rd-level EIs, the adaptive GMM is utilized to model their baseline distribution automatically, where the parameters and hyperparameters of these adaptive GMMs are updated by the EM algorithm and Bayesian optimization algorithm. In this paper, the alternative hyperparameters of these GMMs are respectively pre-defined as follows: M-components =, covariance type =  and iterations = . Referring to the grid search technique [47], these hyperparameters are combined into  GMM candidates. Still taking the EIs  and  as the examples, their Bayesian information criterions (BICs) of 36 GMM candidates with different hyperparameter sets are exhibited in **Figure 14**.

Figure 14 The hyperparameter optimization of GMM candidates for the EIs , 

As shown in **Figure 14**, two optimal GMMs with the lowest BICs are chosen as the baseline models for EIs  and  respectively, which represent the characteristics of the baseline distributions quantitatively.

Second, for each 3rd-level EI, given its online feature embeddings fused from the online CM data, there will be a trained baseline model to quantify its real-time probabilistic risk indications (PRIs). To be more intuitive, still taking the EIs  and  as the examples, **Figure 15** and **Figure 16** exhibit the related results of risk quantification under the five statuses respectively, namely Health status, Degradation status-Ⅰ, Degradation status-Ⅱ, Degradation status-Ⅲ, and Degradation status-Ⅳ.

Figure 15 Baseline distribution modeling and probabilistic risk quantification of the EI  under different abnormal status

Figure 16 Baseline distribution modeling and probabilistic risk quantification of the EI  under different abnormal status

As shown in **Figure 15** and **Figure 16**, the baseline models are presented in the form of normalized probability density contours, which represent the historical feature spaces of two EIs under the Health status. In addition, when the abnormality degree of EIs increases, i.e., the anomaly coefficients increase from  to , it can be seen that the feature spaces under four anomaly statuses continuously deviate from the ones under the Health status. Meanwhile, the corresponding real-time PRIs of two EIs also increase continuously, which reflects the increasing potential risk caused by the anomaly status of EIs quantitatively and intuitively.

Through the adaptive GMM, we quantify the real-time risk for each 3rd-level EI using the offline and online feature embeddings effectively. It should be noticed that it is a truly data-driven risk quantification method with quite little manual intervention and the evaluation results can be well interpreted by the risk indications with the probabilistic meanings.

* Comprehensive evaluation by dynamic FCE

According to the real-time probabilistic risk indications of each 3rd-level EI, the dynamic FCE is applied to evaluate the hierarchical risk of other EIs level by level.

For all five 2nd-level EIs, given the real-time probabilistic risk indications and weights of their belonging 3rd-level EIs, we can obtain their real-time risk indications by means of the weighted average . Furthermore, given the real-time 2nd-level risk indications, the corresponding initial weights are dynamical with the help of the variable weight coefficients. The above process can be illustrated in **Figure 17** intuitively.

Figure 17 Quantitative risk indications and dynamic weights of 2nd-level EIs under the different status

As shown in **Figure 17**, the probabilistic risk indications of engine subsystem and electric subsystem increase continuously, which reflects their increasing anomaly degree objectively. Meanwhile, we can see that the larger weights are dynamically assigned to these two subsystems due to the increasing probabilistic risk indications, which means that the two subsystems are gaining more attention for the subsequent comprehensive evaluation.

According to the real-time probabilistic risk indications and the dynamic weights of these five 2nd-level EIs, the risk indications of 1st-level EI, namely the overall status risk of UAVs, are evaluated comprehensively at the same time. Furthermore, we obtain the real-time fuzzy risk vector of UAVs by using the membership functions, where the hyperparameters of these membership functions are set as , , , , , and . **Figure 21** and **Figure 22** present the results of the UAVs’ overall status risk evaluated by the existing mainstream FCE and our proposed dynamic FCE respectively.

Figure 18 Probabilistic risk indications and fuzzy risk vectors of UAVs’ overall status risk through the existing FCE

Figure 19 Probabilistic risk indications and fuzzy risk vectors of UAVs’ overall status risk through the dynamic FCE

As shown in **Figure 18** and **Figure 19**, the fuzzy risk vector describes the possibility that the overall UAV belongs to each grading level in the form of likelihood probability. Due to the static weight mechanism, the existing FCE is quite insensitive to the real-time anomaly of low-level EIs. Even when two critical subsystems (engine subsystem and electrical subsystem) show the serious anomalies, the existing FCE still classifies the UAV into the sub-health status with great confidence, which cannot reflect the practical status and risk of UAVs objectively.

With the help of the variable weight coefficients, our proposed dynamic FCE shows better sensitivity and flexibility to the local anomaly of UAVs. The UAV status is comprehensively evaluated in the danger or failure status with the highest membership when the critical subsystems locate in the Degradation status-Ⅳ, which exhibits a more reasonable conclusion than the results obtained by the existing mainstream FCE.

## C. Discussions

In view of the above experimental results, the four main conclusions are discussed as follows:

(1) The RFA employing the bidirectional recurrent architecture and the proposed sequential fusion layer, can achieve the robust and complete information fusion from both two aspects of variate dimension and time dimension.

Using the simulation datasets of turbofan engines, we compared the performance on information fusion between the proposed RFA and the other 5 existing mainstream methods, i.e., ICA, PCA, KPCA, SAE, and RA. As shown in **Figure 7** and **Figure 8-Figure 10**, whether in the form of 3d scatter plots or 1d HIs, the feature embeddings fused by the proposed RFA exhibit the better entire tendency and robustness to the local data noises compared with the other 5 ones. With the help of three quantitative metrics (‘Mono’, ‘Tend’ and ‘Score’), we further demonstrated the superiority of RFA: it all achieves the best results among the comparative methods under different distance functions. Specifically, compared with the best results (provided by RA) among 5 existing methods, the proposed RFA brings about 11.32%, 0.12%, and 4.54% improvement on the above 3 metrics respectively, brings about 61.82%, 3.16%, and 9.17% improvement compared with the worst ones (provided by ICA). The above experimental results prove the superiority of the recurrent architecture on information fusion compared with the non-recurrent ones, and then demonstrate that the proposed sequential fusion layer can further improve the robustness and completeness of information fusion.

(2) The adaptive GMM can quantify the real-time probabilistic risk from the various feature embeddings in a truly data-driven way.

Using the real flight dataset of a UAV, the multivariate CM data of each 3rd-level EI is firstly fused and transformed into the robust feature embeddings by RFA. According to these fused features, as shown in **Figure 15** and **Figure 16**, the adaptive GMM can model their historical baseline distributions accurately and quantify the real-time risk objectively even when they generally have various distribution characteristics. With the help of Bayesian hyperparameters optimization (shown in **Figure 14**) and probabilistic clustering, the adaptive GMM is truly data-driven and interpretable, where the entire procedure of the offline baseline modeling and the online risk quantification requires almost no manual intervention.

(3) The dynamic FCE can achieve the comprehensive evaluation for UAVs under uncertainty and timely capture the real-time slight risk.

As shown in **Figure 17** and **Figure 19**, the dynamic FCE implements the comprehensive risk evaluation level by level (1st-level, 2nd-level, and 3rd-level), which represents the real-time status risk of complicated UAVs quantitatively and hierarchically. In addition, as shown in **Figure 18** and **Figure 19**, compared with the existing FCE based on static weight mechanism, the proposed dynamic FCE depicts the real-time increasing risk of UAVs more reasonably. Thanks to the variable weight coefficients, our proposed dynamic FCE can adjust the weights of EIs dynamically and flexibly according to their real-time risk indications, which means that it is more sensitive to the slight anomaly of EIs and thus can capture the preliminary risk of UAVs timelier.

(4) The proposed hybrid framework provides a systematic methodology to integrate the qualitative knowledge and quantitative knowledge for the hierarchical risk assessment of complicated UAVs.

As shown in **TABLE II**, according to the qualitative knowledge of UAVs’ logic compositions, the complicated UAV is abstracted and transformed into a hierarchical system with weights (UAVs-subsystems-equipment-CM parameters), which is easy to operate and provide full consideration to each key risk-related factor. In addition, according to the quantitative CM data, the real-time hierarchical risk is quantified comprehensively with the help of RFA, adaptive GMM, and dynamic FCE. Through this hybrid framework, we integrate the qualitative knowledge and the quantitative knowledge systematically, and then implement the scientific and reasonable hierarchical risk assessment for complicated UAV, which can also be referred to by other similar scenarios.

(5) The hierarchical risk assessment results can provide quantitative support with the risk control of UAVs.

The risk management of UAVs can be broadly divided into two steps: risk assessment and risk control. This paper mainly focuses on the previous step to proposed a novel hybrid framework, and achieve the accurate risk assessment. Furthermore, in real situations, the above quantified hierarchical risk of UAVs can be referred to guide the risk control in overall and local perspectives. From the overall perspective, the quantified overall status risk can support the path planning and mission reconstruction of UAVs, e.g., if decision-makers find that a UAV is judged to serious risk, they can promptly terminate the preset mission and plan the optimal route to return the UAV. From the local perspective, the corresponding hierarchical risk can support the decision of critical components like function degradation and redundant switch, e.g., when the engine system is judged to high risk, decision-makers can reduce its load in advance to avoid safety accidents by reducing altitude, reducing engine speed, and other measures. Therefore, although the risk-related decision-making is not the focus of this article, we can still see that the assessed hierarchical risk can flexibly support the local and overall risk management of UAVs, which exhibits considerable research and application value in practical situations.

# Conclusion

In this paper, a novel hybrid framework is proposed for the hierarchical risk assessment of UAVs considering their logical compositions and real-time CM data. Our main contributions can be divided into 3 points. First, we emphasized the importance of information fusion for risk quantification. Therefore, a novel unsupervised deep model called RFA is constructed to highlight the intrinsic status representation from the multi-variate CM data. With the help of the proposed sequential fusion layer, our RFA model alleviates the issue of vanishing gradient in the existing recurrent architectures. The experimental results proved that it can achieve more complete information fusion and robust to the interference of data noise, compared with other mainstream methods. Second, the timely hierarchical risk assessment is achieved by the dynamic FCE. By means of the dynamic weight adjustment regarding the real-time quantified risk, the framework is proved that can be more sensitive and timelier to capture preliminary risk caused by the slight anomaly of UAVs. Third, we provide a systematic methodology to integrate qualitative knowledge and quantitative data, which may be referred to in similar engineering scenarios with complicated compositions and massive CM data.

There are two possible limitations for our hybrid framework in practical applications: 1) this paper mainly focuses on the hierarchical risk of UAVs themselves, where the external factors such as signal strength, atmospheric environment, etc. are not considered. 2) this paper mainly focused on the risk quantification of UAVs, how to apply these results to the risk-related decision-making is not researched yet in a systematic way. Therefore, in future research, the framework will be further developed to integrate more risk-related factors and support the decision making of risk management.

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