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Health status assessment of unmanned aerial vehicle (UAV) attitude control system based on an improved multivariate state estimation method

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Abstract

In this paper, a health status assessment scheme is studied for the attitude control system (ACS) of fixed-wing unmanned aerial vehicle (FWUAV) based on an improved multivariate state estimation technology that incorporates a dynamic memory matrix. Firstly, the parameters of the FWUAV representing the health status of the ACS are selected as feature parameters, and the historical health data of the feature parameters for the FWUAV is compared with the real-time test data. At the same time, the multivariate state estimation technology is applied to obtain the abnormal degree of components for the ACS. Based on the analytic hierarchy process and the expert experience, the weights are obtained for the different elements at the same functional level of the ACS. Secondly, the functional structure of the ACS is analyzed, and the abnormal degree is calculated for the ACS by combining the concept of reconfigurability and the weight information of each element, and the health status assessment indicators are further established. The health status result for the ACS of the FWUAV is acquired according to the efficiency value of the indicators and the abnormal degree of the ACS. Finally, the effectiveness of the developed algorithm is verified by the simulation analysis.

Keywords: Fixed-wing unmanned aerial vehicle, health status assessment, health assessment index system, state estimation

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1. INTRODUCTION

The health status of the system refers to its ability to maintain normal functions [1], and the health status of the attitude control system (ACS) of the fixed-wing unmanned aerial vehicle (FWUAV) is the ability of the ACS to maintain the stable operation of the FWUAV and achieve the attitude control effect with certain accuracy. As everyone knows that the ACS of FWUAV has a complex structure and is composed of multiple subsystems [2] and components. Once a subsystem or component fails or the status is abnormal, the efficiency or reliability of the entire ACS will decline. Therefore, for the health status management of the ACS for the FWUAV, if the key factors affecting the health status of the system can be extracted from the complex physical structure of the FWUAV, the effective abnormal status information can be quickly screened, and the reasonable decisions can be made using scientific methods, which will be helpful to improve the effectiveness and real-time of the health status management of the ACS for the FWUAV.

The concept of system health management was proposed by the National Aeronautics and Space Administration, which refers to the process, technology and method of preventing or minimizing the impact of system failures during the whole life cycle. The concept of the system health has been closely related to "reliability" since its birth [3], so the assessment of the health status of the FWUAV system is conducive to the prevention of the system failure and improves the reliability of the system. As a key subsystem for the stable operation of the FWUAV, the ACS consists of sensors, actuators and controllers, which coordinate and cooperate to maintain and adjust the attitude of the FWUAV. Its health status plays an important role in the smooth flight of the FWUAV. Due to the complex and uncertain flight environment of the FWUAV [4], the possibility for abnormal ACS of the FWUAV is increased. Its control system plays an important role in flight tasks, and once its health status is abnormal, it will lead to huge losses. Therefore, it is of great significance to evaluate the health status of the FWUAV control system.

At present, the development of health status assessment technology mainly includes three stages. The first stage is mainly the way of human observation in the environment, and the assessment is mainly based on the experience of experts. The assessment results are the product of the simple data processing based on the empirical knowledge [5]. The second stage is mainly based on the vigorous development of the sensing technology, the signal acquisition, the data analysis and the dynamic testing technology and the rise of computer technology; the health assessment technology combined with data processing has been rapidly developed. The third stage is the current development status; that is, the data processing technology [6,7] of the second stage is combined with the intelligent diagnostic technology [8–10] and the cross-integration with multi-disciplines [11]. Based on the above health status assessment technologies, the health status assessment works of the aircraft have been reported in large numbers.

For instance, a machine learning-based battery management system was constructed for the state-of-charge prediction and state-of-health estimation of the UAV [12]. The fault diagnosis method was studied for the actuator damage of the UAV based on the embedded recorded data and stacked machine learning models [13]. An adaptive two-stage unscented Kalman filter algorithm was explored for the actuator health assessment of the quadrotor UAV [14]. A health evaluation method was investigated for the multicopters based on the stochastic hybrid system [15]. The reliable flight performance assessment scheme was designed for the multirotor based on the interaction of the multiple model particle filter and the health degree [16]. The problems of the fault diagnosis and the reconstruction were analyzed for the spacecraft ACS [17]. An efficient nonlinear actuator fault detection and isolation system was designed for the UAV [18]. The flight validation was shown for an embedded structural health monitoring system of the UAV [19]. A supervised learning algorithm was proposed for the spacecraft ACS health monitoring [20]. The battery health management approach was developed for the electric UAV [21]. Although the above studies have proposed many methods for the health management of aircraft, there are few reports on the strategies for the health status assessment of the FWUAV control system using the multivariate state estimation technology (MSET) [22]. As the MSET is an advanced pattern recognition technology that can complete the status assessment by measuring the similarity between the various monitoring parameters in the normal operating range, the better assessment results can be obtained by applying this technology to the design of the ACS health assessment method[23]. Therefore, the health assessment method for the ACS of the FWUAV based on the dynamic memory matrix MSET is worthy of further research.

With the above analysis as the research motivation, a health status assessment approach is designed based on an improved MSET for the ACS of the FWUAV, and the health status assessment indicators are also built. Finally, the simulation analysis is given to illustrate the effectiveness of the studied approach. The most important contributions in this paper are shown as follows:

(i) A double-K method [the K-means & the K-nearest neighbor (KNN)] is employed to construct the dynamic memory matrix;

(ii) The abnormal degree of components for the ACS of the FWUAV is obtained based on an improved MSET;

(iii) The health assessment index system for the ACS of the FWUAV is constructed by extracting the key measurement parameters.

The rest of this paper is organized as follows. In Section 2, the analysis of the structure composition for the ACS of the FWUAV is described, the component abnormal status assessment method is presented, the health status assessment system for the ACS of the FWUAV is established, and the weights of health assessment indicators are determined. In Section 3, the simulation results are given. Finally, a conclusion is given in Section 4.

2. FWUAV ATTITUDE CONTROL SYSTEM STRUCTURE COMPOSITION AND HEALTH STATUS ASSESSMENT ALGORITHM

2.1 The structure composition of the FWUAV attitude control system

The ACS is very important for the FWUAV, and its health depends on the health of the device groups and components that make up the system. The ACS of the FWUAV mainly comprises the sensors, the onboard controllers, and the servo actuation devices, i.e., the actuators. The role of the sensor is to collect information such as the angular velocity, the attitude, the position, the altitude, the airspeed, *etc*., which is the basis of the ACS, while the role of the controller is to calculate and generate the control instructions by calculating the attitude information obtained from the sensors, outputting control signals to the actuators to maintain the attitude stability performance or to track the desired attitude signals; the role of the actuator is to execute the action according to the instructions of the controller to generate force and torque to act on the airframe, so as to satisfy the health and safety of the FWUAV. The components of a typical FWUAV attitude system and the proposed health status assessment algorithm are shown in Figure 1.

The following is an analysis of the components for the ACS of the FWUAV, and the characteristic parameters are selected based on their functions. Firstly, the sensors mainly include the angle of attack (AOA) sensor and the inertial measurement unit (IMU), which are mainly used to measure the airspeed, the attitude angle, the attitude angle rate, and other information. The output information of the sensors is very important as the feedback information for the attitude control computer to solve its own attitude and output control signals. However, under the unknown disturbances such as the complex electromagnetic environment, the sensor output is prone to noise mixing. Therefore, when the conditions are available, it is necessary to detect the output noise of the sensor to ensure the correctness and reliability of the attitude control closed-loop data. Taking IMU as an example, the current and the output noise during the normal operation should be within the required range and changed smoothly. If there is a large oscillation, even if it is within the normal range, it characterizes that the performance of the device has deteriorated, which will be the cause of FWUAV failure

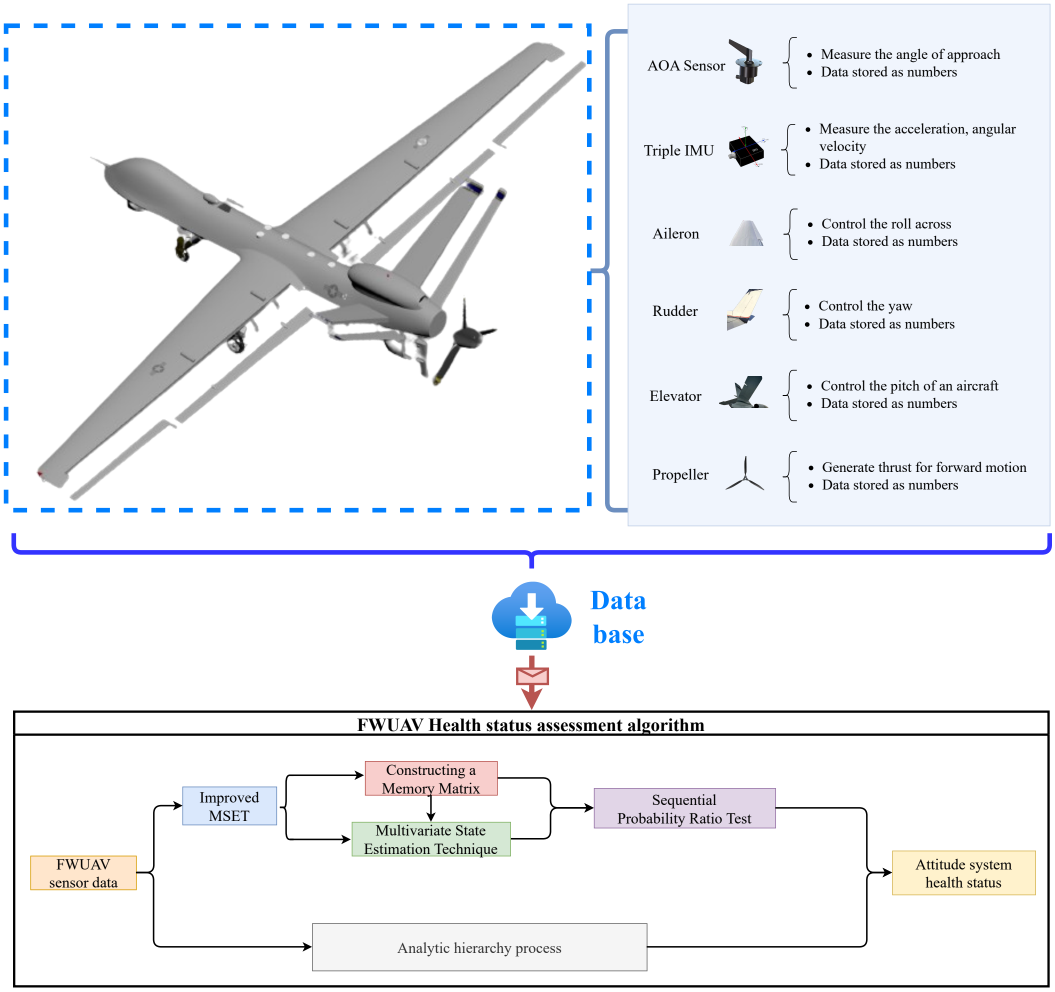

Figure 1. Composition of FWUAV attitude control system.

and should be paid enough attention. Therefore, the characteristic parameters of the IMU are selected as supply voltage and power consumption.

Secondly, the controller for the ACS of the FWUAV is the control computer, which provides the control law in different working modes and working states, and the possible failures are reset or crash, and the backup function for the important parameters such as the attitude control time, the control mode, and the dynamics parameter does not cause major abnormalities in general, but the control computer still has reset and other cases. The characteristic parameter of the controller is selected as the power supply voltage. In the case of normal power supply, the ability of the controller to calculate the control law depends on the soft design such as the control law, so the power supply voltage is selected from the returned data as the characterization parameter to assess whether the controller is working normally.

Thirdly, the actuators mainly include ailerons, elevators, rudders, and propellers, and their main functions are to output the attitude control torque according to the control commands to control the attitude. Most of the actuators are driven by servo motors, so the actuator failures can be caused by the short-circuit or the broken circuit problems, as well as the overheating and software failures due to coupling with other subsystems. Once a failure occurs, the control system will experience a health degradation, which may seriously affect the flight safety of the FWUAV, so the health status of the actuator components needs to be focused on. Therefore, the power supply voltage, the speed, the current and the temperature of the servo actuator device are selected as the characteristic parameters of the actuators.

2.2 Component abnormal condition assessment

Once the faults occur for the actuators and sensors of the FWUAV, even if the FWUAV has a certain fault tolerance ability, the status of some components will still be different from the usual situations, that is, in an abnormal status. However, the faults of the components do not mean that they are in a normal status. There are many reasons for the abnormal status of the component, such as the environmental changes, the system behavior changes, and the command input errors. To sum up, the abnormal status of components includes the failure of UAV components, but is not limited to the failure situation. Therefore, the analysis for the abnormal status of components comprehensively considers the impact of more aspects, including the failure, and that can reflect the health status of FWUAV in a more comprehensive way.

2.2.1 An improved multivariate state estimation algorithm for the ACS of the FWUAV

First of all, the status observation needs to select the data to characterize the internal characteristics, which are generally reflected directly or indirectly based on the feedback signal data by the sensor of ACS. The status data generated by the normal operation of the system is taken as the historical health data set. By analyzing the relationships between the parameters in historical health data sets, the MSET[24] applies the learned relationships between parameters to the observation of the test data, while using the learned patterns to assess the current status of the current test system data. Although there may be coupling and redundancy among the parameters, each quantity can reflect certain characteristics of the actual physical process. The results of the status estimation are obtained by comparing the patterns in the historical health data with the current test data and weighting the states of each parameter. The weights are determined by applying the learned patterns to the overlapping degree of the historical health data and the current test data of each parameter. To sum up, the MSET has certain learning ability and is a machine learning regression technology with supervision ability. In the field of machine learning, the historical health data is labeled as "normal state" and used as the training data, and the current test data is used as the observation data to be evaluated for obtaining final assessment results, which is the essential feature of supervision ability.

The basic principle of MSET is as follows: Supposing that the n-dimensional measurement data of a part up to time t_m is obtained, and the data is expressed as a matrix form, in which the observation data of characteristic parameters at any time is a column vector, then the $n \times m$ order observation matrix is obtained. For the ACS of the FWUAV, which is shown in Figure 2, where n is the number for the selected characteristic parameters of the ACS sensor ($n = 19$), and m is the number of time points observed.

Taking x_{ji} to denote the observed value of the parameter j at the moment t_i, then the observed value of each feature parameter at the moment t_i constitutes the observation vector $X(t_i) = [x_{1i}, x_{2i}, ..., x_{ni}]^{\mathrm{T}}$, where $n = 19$. In addition to the observation data, it is set that all the historical data under the normal operation of the component for the ACS can be obtained, which is denoted as T and called the training data; i.e., T covers the dynamic range of the feature parameter values during the normal operation of the ACS, but it is not required to obtain all the values of the feature parameters under the normal state of the components for the ACS. A number of typical values of the feature parameters are selected from the training data T, and the resulting matrix is called the memory matrix, denoted as $\aleph$. If the training data that are not selected into the memory matrix, which are called the remaining training data, denoted as L, then $T = \aleph \cup L$. The linear weighting of the data in the memory matrix is used as an estimation of the state of the evaluation object, denoted as X_{est}; i.e., $X_{est} = \aleph \cdot W$, W is a weight vector, and the value is obtained by minimizing the estimation error vector ϵ_X.

Defining the state estimation error as $\varepsilon_X = X_{obs} - X_{est}$, where X_{obs} is the observed value, and the minimization

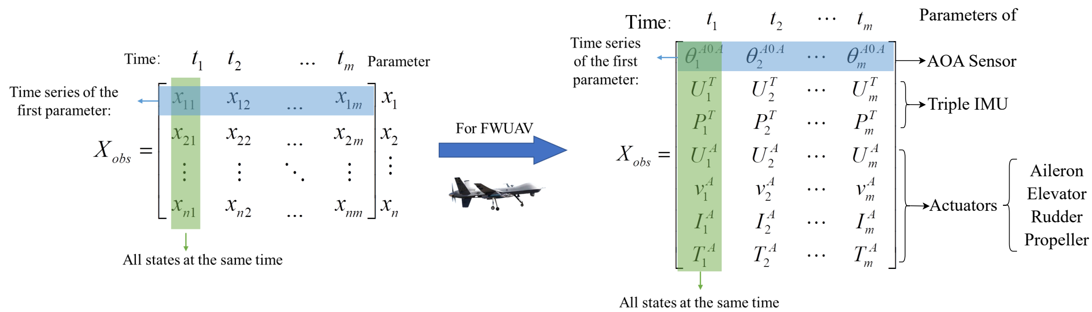

Figure 2. The observation matrix for FWUAV.

of ϵ_X implies the shortest length of the error vector, which can be written as

$$\min_W \|\epsilon_X\| = \min_W \|X_{obs} - X_{est}\| \tag{1}$$

Clearly, (1) is equivalent to [24]:

$$\min_W \{\epsilon_X^{\mathrm{T}}\epsilon_X\} = \min_W \{\{X_{obs} - X_{est}\}^{\mathrm{T}}\{X_{obs} - X_{est}\}\} \tag{2}$$

Because of $X_{est} = \aleph \cdot W$, calculating the derivative of (2) with respect to W and setting it to zero to obtain the minimum value of the squared error, one has

$$\frac{d\{\epsilon_X^{\mathrm{T}}\epsilon_X\}}{dW} = \frac{d\left\{\{X_{obs} - X_{est}\}^{\mathrm{T}}\{X_{obs} - X_{est}\}\right\}}{dW} = 2\aleph^{\mathrm{T}}(\aleph W - X_{obs}) = 0 \tag{3}$$

Then, the weight vector W is obtained by solving (3); we have

$$W = (\aleph^{\mathrm{T}} \cdot \aleph)^{-1} \cdot (\aleph^{\mathrm{T}} \cdot X_{obs}) \tag{4}$$

The state estimation X_{est} can be obtained from the weight vector obtained as follows [24]:

$$X_{est} = \aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph)^{-1} \cdot (\aleph^{\mathrm{T}} \cdot X_{obs}) \tag{5}$$

Then, the residual of the estimation can be described as

$$R_X = X_{est} - X_{obs} = (\aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph)^{-1} \cdot \aleph^{\mathrm{T}} - I) \cdot X_{obs} \tag{6}$$

where R_X is the actual residual.

Applying the above estimation procedure to the remaining training data yields the following estimations:

$$L_{est} = \aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph)^{-1} \cdot (\aleph^{\mathrm{T}} \cdot L) \tag{7}$$

Similarly, the residual of the remaining training data is obtained as

$$R_L = L_{est} - L \tag{8}$$

where R_L is the health residual.

Remark 1: In the estimation of the weight vector, $\aleph^{\mathrm{T}} \cdot \aleph$ is required to be invertible, which is generally difficult to be satisfied in practical applications. For example, when the number of states (columns of $\aleph$) in the memory matrix $\aleph$ is smaller than the number of state parameters (rows of $\aleph$), $\aleph$ is not full rank. To solve the matrix invertibility problem, it is common to use the MSET method with the nonlinear operator "⊗" instead of the vector product "·". In practice, the Euclidean distance operator[25] and the Manhattan distance operator[26] are often used as the nonlinear operators, which are defined respectively as

$$x \otimes y = \sqrt{\sum_{m=1}^{k} (x_m - y_m)^2}, x \otimes y = \sum_{m=1}^{k} |x_m - y_m| \tag{9}$$

2.2.2 Dynamic Memory Matrix Construction Algorithm Based on Double-K Algorithm

The construction of the memory matrix is the key to the performance of MSET[24]. The traditional method usually uses a fixed memory matrix, and the construction method is prone to cause information redundancy to reduce the overall computational speed on the one hand, and on the other hand, the estimation accuracy based on a fixed memory matrix may degrade over time because the operating conditions are constantly changing and may require frequent maintenance[27]. Therefore, it is necessary to improve the flexibility of memory matrix construction.

Due to the similarity among many data points in the memory matrix, which are all derived from normal operation of the device, especially with a large sample size, the redundancy within the memory matrix can be significantly reduced by representing one data point as a representative for a cluster of highly similar data. A dynamic memory matrix construction method is designed based on the K-means and KNN algorithms. As two typical clustering methods, the K-means demonstrates the high computational efficiency and the strong adaptability, enabling the partitioning of the dataset into multiple categories based on their attributes[28]. The core of the KNN algorithm is to infer the output based on the characteristics of several known samples that are nearest to the input[29].

In this paper, the K-means algorithm is selected for constructing the initial dynamic memory matrix and the KNN algorithm is utilized for constructing the dynamic memory matrix based on different observations. To construct the initial memory matrix, the m_1 clustering centers in the normalized ACS training matrix are selected as the state vectors to construct the initial memory matrix, where m_1 is not more than 50% of the state vectors of the training matrix. This method is implemented using Euclidean distance and the improved K-means algorithm as given below:

Step 1: The same method of normalization is chosen for all matrices and vectors, which can be expressed as $z_{ij} = \frac{x_{ij}-\mu_i}{\sigma_i}$ and $z_{ij} = \frac{x_{ij}-min_i}{max_i-min_i}$, where x_{ij} is the initial matrix vectors.

Step 2: The m_1 state vectors are randomly selected as clustering centers in the normalized ACS training matrix, $A = \left[A_1, A_2, \cdots, A_{m_1}\right]$.

Step 3: The distance $d\left(X_i, A_j\right)$ between the remaining samples X_i to each cluster center A_j is calculated separately using Euclidean distance and classified into the class corresponding to the cluster center with the smallest distance.

$$d\left(X_i, A_j\right) = \sqrt{\sum_{k=1}^{p} \left(x_{i,k} - A_{j,k}\right)^2} \quad , \quad (i = 1, \cdots, m; j = 1, \cdots, m_1) \tag{10}$$

$$X_i \in \arg\min_{A_j} d\left(X_i, A_j\right) \tag{11}$$

Step 4: For each category A_j, recalculating the cluster center (i.e., the mean value $\mu_j = \left(\mu_{j,1}, \mu_{j,2}, \cdots, \mu_{j,p}\right)^T$ of each feature), finding the Euclidean distance $d\left(X_i, \mu_j\right)$ of the respective state vectors to the cluster center and selecting the closest state vector to the mean value as the new cluster center A'_j. Then, we have

$$\mu_j = \left(\mu_{j,1}, \mu_{j,2}, \cdots, \mu_{j,p}\right)^T = \left(\sum_{i=1}^{k_j} x_{i,1}^j \Big/ k_j, \sum_{i=1}^{k_j} x_{i,2}^j \Big/ k_j, \cdots, \sum_{i=1}^{k_j} x_{i,p}^j \Big/ k_j\right)^T, \quad (j = 1, \cdots, m_1) \tag{12}$$

$$d\left(X_i, \mu_j\right) = \sqrt{\sum_{k=1}^{p} \left(x_{i,k} - \mu_{j,k}\right)^2}, \quad (i = 1, \cdots, m; j = 1, \cdots, m_1) \tag{13}$$

$$A'_j = \arg\min_{X_i} d\left(X_i, \mu_j\right) \tag{14}$$

where k_j denotes the number of state vectors in the j-th cluster, and $x_{i,l}^j$ indicates the l-th characteristic parameter of the i-th state vector in cluster A_j, and $l = 1, \cdots, p$.

Step 5: Repeating steps 3 and 4 until the sum of squares of the errors I_{SSE} in the cluster no longer changes, one has

$$I_{SSE} = \sum_{j=1}^{m_1} \sum_{X_i \in A_j} \left\|X_i, A_j\right\|^2 \tag{15}$$

Step 6: The initial memory matrix $\aleph$ is constructed by taking the final m_1 cluster centers of state vectors.

The initial memory matrix constructed using this method not only has better flexibility, but also helps remove redundant vectors in the matrix by clustering, and it can reduce useless calculations in the traditional MSET[27]. Moreover, to obtain the dynamic memory matrix, the steps for calculating the dynamic memory matrix of the observation process using the KNN algorithm are as follows:

Step 1: The same method of normalization is chosen for all matrices and vectors.

Step 2: For the observation input $X_{obs} = [X_1 \cdots X_m]$, the Euclidean distance $d_i\left(X_{obs_i}, Y_j\right)$ between each of the state vectors X_{obs_i} and each of the state vector Y_j in the training set T is calculated separately, which can be written as

$$d_i\left(X_{obs_i}, Y_j\right) = \sqrt{\sum_{k=1}^{p} \left(x_{obs_{i,k}} - y_{j,k}\right)^2}, \quad (i, j = 1, \cdots, m; k = 1, \cdots, p) \tag{16}$$

where $x_{obs_{i,k}}$ is the k-th characteristic parameter of the i-th state vector in the observation matrix, and $y_{j,k}$ is the k-th characteristic parameter of the j-th state vector in the training matrix.

Step 3: Upon arranging the distance vector $D_i = \left(d_{i,1}, d_{i,2}, \cdots, d_{i,m}\right)^T$, the k samples with the smallest distances are selected from the training set T, thereby identifying the k nearest neighbors denoted as $T_i = \left[Y_{i,1}, Y_{i,2}, \cdots, Y_{i,k}\right]$.

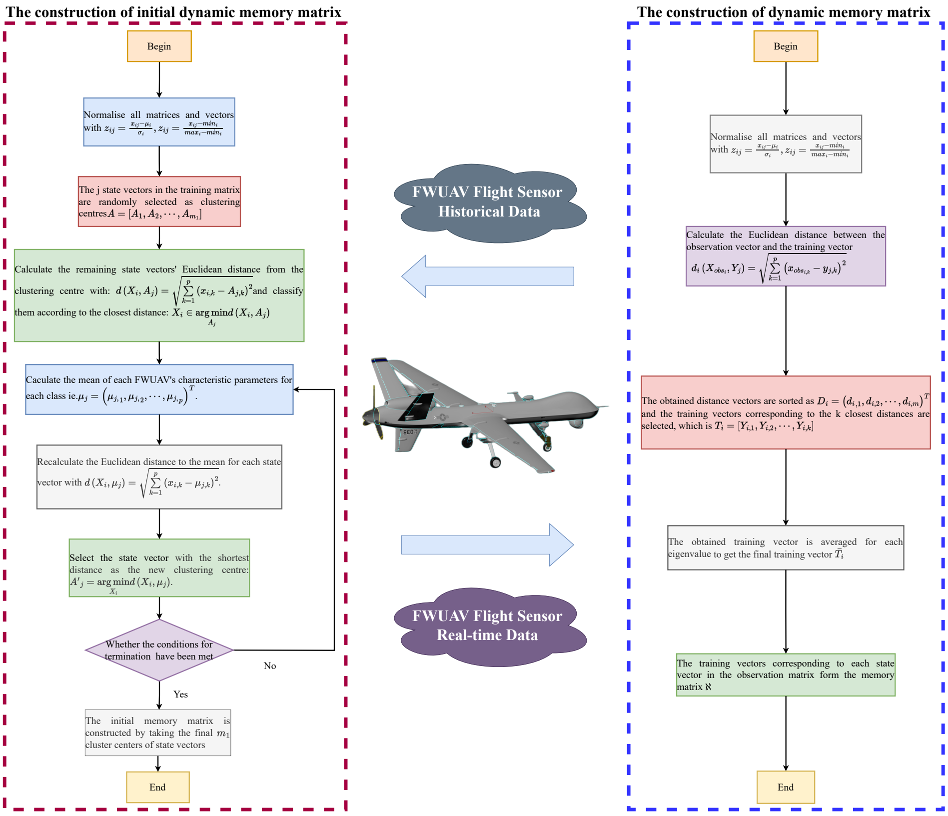

Figure 3. Dynamic memory matrix construction process.

Step 4: For the training matrix constructed to the observation vector X_{obs_i}, the mean value for each characteristic parameter is taken as the corresponding training vector element, and finally, the corresponding training vector $\bar{Y}_i$ will be obtained as follows:

$$\bar{Y}_i=\sum_{j=1}^{k}Y_{i,j}\Big/k=\left[\sum_{j=1}^{k}y_{i,j}^{1}\Big/k \quad \sum_{j=1}^{k}y_{i,j}^{2}\Big/k \quad \cdots \quad \sum_{j=1}^{k}y_{i,j}^{p}\Big/k\right]^T,\quad (i=1,\cdots,m) \tag{17}$$

Step 5: The matrix consisting of the training vectors corresponding to each observation vector is used as the memory matrix ℵ.

According to the analysis above, the double-K algorithm is used to construct the dynamic memory matrix, which plays a pivotal role in minimizing information redundancy within the matrix. This construction process is paramount for optimizing the performance of the algorithm, as it systematically identifies and retains only the most relevant and non-repetitive data points from the input dataset. The resulting dynamic memory matrix serves as a refined representation of the dataset, which can facilitate more precise and efficient computation during the algorithm's execution. The specific construction process can be represented by Figure 3.

2.2.3 MSET based on double-K dynamic memory matrix

Assuming that the object to be evaluated has p feature quantity, the implementation steps of the MSET based on the optimization of the double-K algorithm are as follows:

Step 1: Obtain the training data set and its statistical characteristics. The characteristic parameter data generated under normal working conditions is regarded as health status data, and the health status data of the

ACS is taken as training data T to obtain the statistical characteristics of each characteristic quantity, including the mean value, the standard deviation, the maximum value and the minimum value. The training data T is a matrix containing the state quantity of each characteristic parameter at each moment, and the number of columns for the matrix T is the number of moments K, the number of rows is the number of characteristic parameters p; then, the dimension of the matrix T is $p \times K$ as follows:

$$T = [Y_1 \quad \dots \quad Y_K] = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1K} \\ y_{21} & y_{22} & \cdots & y_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pK} \end{bmatrix} \tag{18}$$

where $K > 2p + 2$.

In the step of obtaining the mean value, the standard deviation and the maximum and minimum values of the typical statistical characteristics for the assessment object under the health status from the historical health data, the health status does not need to contain all the historical health data, but the selection of health data sets needs to have certain typical significance. Then, the estimation of the mean and standard deviation for the i-th characteristic quantity can be expressed as

$$min_i = \min_{k=1}^{K} (y_{ik}), max_i = \max_{k=1}^{K} (y_{ik}) \tag{19}$$

Remark 2: In practice, the entire historical data of the ACS may not necessarily contain the full dynamic range, so the selection of the training data T needs to be addressed. The selection can consider part of the observation data and the proposed observations generated using these observations as the training data, and the data updating can take a moving window approach; i.e., after each time the observation data are obtained, the last columns of the observation matrix are used as the training data T. This selection of T can help monitor the abnormal trend of the ACS.

Step 2: Obtain the current test data set of the ACS. The data set of the ACS is selected from the test data of the current state characteristics to form the $p \times m$-dimensional observation matrix $X_{obs} = (x_{ij})_{p\times m}$, where p is also the number of characteristic parameters, m denotes the number of time points in the current time period, and the matrix element $x_i j$ stands for the x_{ij} observation of the j-th observed value, and the observation matrix X_{obs} is as follows:

$$X_{obs} = [X_1 \cdots X_m] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pm} \end{bmatrix} \tag{20}$$

Step 3: Standardization of the historical health data and the test data. Since the characteristic parameters are all FWUAV system parameters, but are of different types and involve diverse aspects of physical concepts, and, thus, have varying scales and levels of quantity. Thus, the training data T and the observation matrix X_{obs} need to be standardized first if the historical health data and test data are to be used to obtain the assessment results. The standardization method can adopt the z-score or min-max standardization formula, and the results of x_{ij} standardizing the observation matrix are $z_{ij} = \frac{x_{ij}-\mu_i}{\sigma_i}$ and $z_{ij} = \frac{x_{ij}-min_i}{max_i-min_i}$, respectively. The obtained normalized observation data is denoted as $Z_{obs} = (Z_1 \cdots, Z_m)^{\mathrm{T}}$. Similarly, the normalized training data set is T', and the same normalization method needs to be used for the training data and the test data; otherwise, it may cause the problem of different data scales.

Step 4: The observation residual estimation method based on MSET is as follows: The dynamic memory matrix $\aleph$ is constructed according to the double-K algorithm, where $\aleph$ is a $p \times M$ matrix; due to the dynamic memory matrix constructed by the double-K algorithm, the number of columns m of the matrix may change during the operation, but it must be guaranteed that $M > 2p + 2$ during the operation. The data from the data matrix T' that is removed from the memory matrix $\aleph$ is called residual data and is denoted by the capital letter L, i.e., $T'_{p\times K} = \aleph_{p\times M} \cup L_{p\times N}$, where $M + N = K$.

Remark 3: The construction of the memory matrix is key to the performance of the algorithm. In order to avoid the overfitting problem, the memory matrix should not have too much data.

In addition, the observation residuals R_x and Z_{est} are calculated. The observation residual estimation R_X is obtained from the observation matrix Z_{obs} and the memory matrix $\aleph$ with:

$$\begin{aligned} Z_{est} &= \aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph + \alpha I)^{-1} \aleph^{\mathrm{T}} \cdot Z_{obs} \\ R_X &= [\aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph + \alpha I)^{-1} \aleph^{\mathrm{T}} - I] \cdot Z_{obs} \end{aligned} \tag{21}$$

where $\alpha > 0$ is the constant regularization factor to be selected.

2.2.4 Component anomaly state estimation based on MEST & SPRT

The sequential probability ratio test (SPRT)[30] is a method of measuring the degree of deviation for an observation from the normal state by comparing the probability of the observation occurring in the normal state and the abnormal state with the ratio of the probabilities. The basic principle is as follows: Assuming that $H_0 : \theta = \theta_0$, $H_1 : \theta = \lambda\theta_0 \overset{\wedge}{=} \theta_1 (\lambda > 1)$, denoting $Y_n = (Y_1, ..., Y_n)$ as the sample data, and taking the likelihood function as $L(Y_n; H_i) = \prod_{i=1}^{n} f(y_i |H_i)$, where $f(y_i |H_i)$ is the density function of the distribution for Y_i. Defining the likelihood ratio as $\Lambda(Y_n) = \frac{L(Y_n;H_1)}{L(Y_n;H_0)}$, the determination of H_0 and H_1 is obtained by comparing $\Lambda(Y_n)$ with an upper limit value $\mathcal{B}$ and a lower limit value $\mathcal{A}$. The decision-making rules are as follows: (i) If $\Lambda(Y_n) \geq \mathcal{B}$, then H_1 is accepted; (ii) If $\Lambda(Y_n) \leq \mathcal{A}$, then H_1 is accepted; (iii) If $\mathcal{A} < \Lambda(Y_n) < \mathcal{B}$, then make no decision, continue with the observation and repeat the above steps. Moreover, the upper limit value $\mathcal{B}$ and lower limit value $\mathcal{A}$ are defined as $\mathcal{A} \approx \frac{\beta}{1-\alpha}$ and $\mathcal{B} \approx \frac{1-\beta}{\alpha}$, respectively, for a given false alarm rate α and missed alarm rate β.

The input data of SPRT-based anomaly detection are health residuals R_L and actual residuals R_x, and the basic idea of the test is to examine whether they come from the same object, if so, the assessment object is in a normal state; otherwise, it is in an abnormal state. The realization process of SPRT is given below for the two cases of normal overall and non-parametric. It should be noted that the following test method is only for one-dimensional scalar; for the detection of multi-dimensional observation vectors, one way is to introduce weight vectors to turn multi-dimensional vectors into one-dimensional vectors, and the other way is to test each feature parameter separately. In the traditional MSET&SPRT method, it is assumed that the residuals follow a normal distribution. The null hypothesis describes the health status of the assessment object, i.e., the mean value is 0 and the standard deviation is σ. And the four following alternative assumptions describe the degradation state of the ACS: (i) the mean value shifts to +$\mathcal{M}$, the standard deviation is σ; (ii) the mean value shifts to -$\mathcal{M}$, the standard deviation is σ; (iii) the mean value is 0, and the standard deviation is $\mathcal{V}\sigma$; (iv) the mean value is 0, and the standard deviation is $\sigma/\mathcal{V}$, where $\mathcal{M}$ and $\mathcal{V}$ are disturbance parameters determined before testing, which need to be analyzed according to the specific system and the behavior. In addition, the mean value of the healthy residuals R_L is first obtained and the null hypothesis is acquired by subtracting the mean value from the healthy residuals R_L before implementing the SPRT; the observation residuals of the observed data are used as inputs, and the mean value of the healthy residuals needed to be subtracted before performing the SPRT test. The SPRT implementation algorithm is as follows:

Step 1: The observation residual R_X is obtained.

Step 2: The health residual R_L is calculated. The estimation matrix of the remaining training data L_{est} and the health residual R_L are obtained from the remaining data L and the memory matrix $\aleph$, the expressions for L_{est} and R_L are

$$\begin{gathered} L_{est} = \aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph + \alpha I)^{-1} \aleph^{\mathrm{T}} \cdot L \\ R_L = [\aleph \cdot (\aleph^{\mathrm{T}} \cdot \aleph + \alpha I)^{-1} \aleph^{\mathrm{T}} - I] \cdot L \end{gathered} \tag{22}$$

Step 3: Calculate the degree of anomaly Θ from the historical health status based on the SPRT. Calculating SPRT as an indicator of an abnormal state, and the $p \times m$-dimensional observation residual matrix and $p \times N$-dimensional health observation residual matrix are written in the following vector form:

$$\begin{gathered} R_X = [R_{X_1}, R_{X_2}, \cdots, R_{X_m}] \\ R_L = [R_{L_1}, R_{L_2}, \cdots, R_{L_N}] \end{gathered} \tag{23}$$

Supposing that each column vector of the observation residual matrix R_X and the health residual matrix R_L have the multivariate normal distribution, we have

$$\begin{gathered} R_{x_j} = [R_{X_{1j}}, R_{X_{2j}}, \cdots, R_{X_{pj}}]^{\mathrm{T}} \sim N_p(\mu, \sum R_{X_j})(j = 1, 2, \cdots, m) \\ R_{L_n} = [R_{L_{1n}}, R_{L_{2n}}, \cdots, R_{L_{pn}}]^{\mathrm{T}} \sim N_p(\mu, \sum R_{L_n})(n = 1, 2, \cdots, N) \end{gathered} \tag{24}$$

The probability ratio of the R_X to the R_L is taken as the anomaly degree as follows:

$$\Theta = SPR = \frac{\prod_{j=1}^{m} f(R_{X_j}; \mu, \sum R_{x_j})}{\prod_{n=1}^{N} f(R_{L_n}; \mu, \sum R_{L_n})} \tag{25}$$

where $f(\cdot)$ is the p-dimensional multivariate normal distribution function, representing the probability density of the p-dimensional vector ξ, and its expression can be written as

$$f(\xi) = (2\pi)^{-p/2} \left| \sum \xi \right|^{-1/2} \exp((-\frac{1}{2}(\xi - \mu)^T \sum\nolimits_{\xi}^{-1} (\xi - \mu)) \tag{26}$$

where μ and $\sum_{\xi}$ are the mean value and the covariance of the distribution for ξ subject to the multivariate normal distribution, respectively.

Step 4: Calculate the component abnormal state index H. The logistic function of the degree of deviation Θ from the normal state of the component is used as the component abnormal state indicator, i.e., $H = \frac{2}{1+e^{\Theta}}$.

2.3 Establishment of a health status assessment system for ACS

2.3.1 Establishment of a set of indicators for assessing the ACS health status

The health status assessment indexes are both the direct parameters for assessing the health status of components and the basic parameters for assessing the overall health status of the ACS. The ACS enables the FWUAV to follow the attitude desired signal, and the dynamic performance, the steady-state performance, and the cumulative effect of time involved in the tracking process, as well as the key measurement parameters of each component for the control system, collectively constitute the set of health assessment indexes for the ACS of the FWUAV. Therefore, the index parameters are chosen in the health status assessment index system as the steady-state tracking error, the overshooting amount, the regulation time and the time error integral related to the attitude angle. Next, the above indicators are explained as follows:

(i) The steady-state error is an important dynamic measure of the accuracy for a system and is usually expected to be zero or not to exceed a certain range. It refers to the deviation from the commanded attitude signal and the actual attitude after the FWUAV has returned to a steady state after perturbations.

(ii) The overshoot is an indicator describing the maximum degree of the deviation for the controlled variable from the steady state, and it is a dynamic indicator reacting to the stability of the transient process. The overshoot is one of the important dynamic indicators of the attitude maneuvering, and the overshooting too much may result in the attitude angle being too large and exceeding the flight envelope, which will affect the flight safety.

(iii) The regulation time mainly measures whether the system can quickly return to a stable state when it is subjected to frequent perturbations, reflecting the rapidity of the system's response. After the system encounters perturbations, a shorter regulation time implies a stronger attitude maneuvering performance, while a longer regulation time implies a poor attitude maneuvering performance.

(iv) The time integral index is the integral of the controlled quantity deviation from the static value along the time axis in the transient process, and the absolute value error e integral is chosen here, and the integral model is $f(e,t) = |e|, J = \int_0^\infty |e|dt$, which is increased by the increase of the error amplitude and the growth of time. The larger the integral value, the control effect will be worse, and the control effectiveness will gradually become weaker with time.

Once the assessment hierarchy of the system has been determined, the data for the indicators to be assessed can be normalized and the weights assigned to the indicators can be determined.

2.3.2 Determination of the weights for the health assessment indicators based on the analytic hierarchy process

Health assessment indicators are juxtaposed, but the importance of each indicator to the ACS of the FWUAV is different, so the establishment of the health assessment indicator methodology actually needs to analyze the importance of each indicator parameter in the indicator set. The determination of indicator weights can enable the health assessment algorithm to effectively capture the important aspects of FWUAV system health. The determination of the weights for the health assessment indicators in this paper will be based on the analytic hierarchy process (AHP) method[31]. The steps of the AHP methodology applied to health status assessment are as follows:

Step 1: Establish a hierarchical model based on the functional structure. A hierarchical structure model is constructed based on the functional components of the assessment system. Taking the ACS of the FWUAV as the top level, and the systematically expanding downward layer by layer according to the functional structure. Then, the complete system hierarchy is obtained and the appropriate assessment indicators are defined for each level.

Step 2: Normalize the indicators based on utility functions. A suitable utility function is selected based on the physical meaning of each indicator to normalize the indicator data. The choice of utility functions should comprehensively consider the impact of the indicator on the system. Additionally, the threshold values for the indicator attributes should be determined in accordance with practical considerations.

Step 3: Construct all judgment matrices for each level. The process of constructing judgment matrices involves applying pairwise comparison methods. The constructed judgment matrices are positive reciprocal matrices. The definition of a judgment matrix B is as follows:

$$B = (c_{ij})_{n\times n} = \begin{bmatrix} C_{11} & C_{12} & \dots & C_{1n} \\ C_{21} & C_{22} & \dots & C_{2n} \\ \dots & \dots & \dots & \dots \\ C_{n1} & C_{n2} & \dots & C_{nn} \end{bmatrix} \tag{27}$$

where $n = 19$ represents the number of indicators; $C_{ij} = f(x_i, x_j)$ denotes the scale of importance for com-

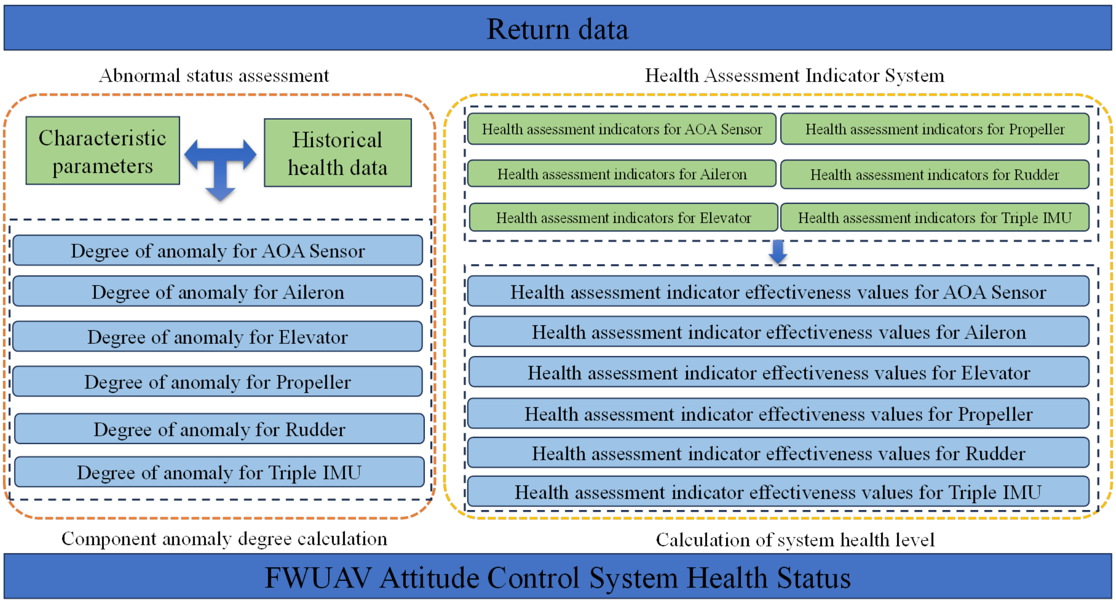

Figure 4. Schematic diagram of attitude control system health assessment for FWUAV.

paring indicators x_i and x_j, when $i = j$, $C_{ij} = 1$; and when $i \neq j$, $C_{ij} = 1/C_{ji}$. The selection of $f(x_i, x_j)$ is determined by the importance level between indicators x_i and x_j.

Step 4: Consistency Check. After constructing judgment matrix B, a consistency check is required to ensure the logical validity of the weight selection. The consistency index (CI) is calculated based on the maximum eigenvalue $\lambda_{\max}$ of the judgment matrix B using $CI = \frac{\lambda_{\max}-n}{n-1}$. Then, the consistency ratio (CR) is calculated using $CR = \frac{CI}{RI}$, where RI is the random index corresponding to the order of the matrix. If $CR < 0.1$, the judgment matrix is considered consistent[32]. If it does not meet this criterion, the matrix needs to be updated to achieve consistency.

Step 5: Perform the assessment based on the weights. The weight vector is calculated for a single layer using the following formula, known as the eigenvector method:

$$\omega_i = \frac{1}{n} \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{28}$$

where ω_i is the weight parameter and the a_{ij} is element of the eigenvector.

3. SIMULATION ANALYSIS

3.1 The overall flow of the algorithm

The FWUAV health assessment algorithm in this paper is designed in terms of the abnormal degree of deviation for the returned data from the historical health data and the effectiveness of the ACS in accomplishing the FWUAV attitude angle maneuvering task, which not only describes whether the system is functioning properly by combining the actual data of the system components in operation at the detailed level, but also describes the health status of the ACS from the macroscopic perspective for the effectiveness of the ACS. The overall structure of the FWUAV health assessment algorithm that combines the returned data and health assessment indicators is schematically shown in Figure 4.

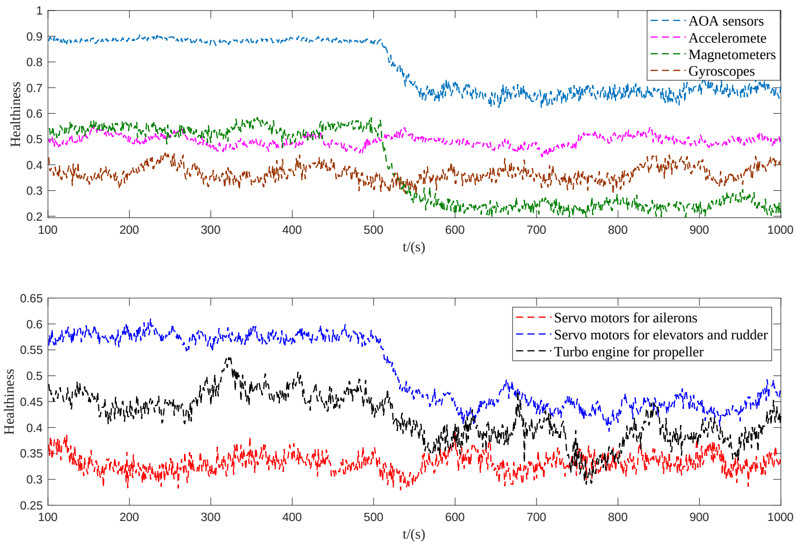

Figure 5. Healthiness of sensor components and actuator components.

3.2 Simulation results

The configuration of the ACS includes an attitude control computer, three magnetometers, three gyroscopes, three accelerometers, two AOA sensors, and actuators including two servo motors for the ailerons, one servo motor for the elevator and rudder, one servo motor for the rudder, and a set of turboprop engines. The experimental data are 1000 sets of return data and 1000 sets of historical health data, mainly including FWUAV attitude system steady-state error, overshoot, integrated time and absolute error (ITAE) and regulation time.

Setting the K value of the KNN algorithm as 6 and the cluster of K-means as $m-3$, and setting the constant regularization factor of the MSET algorithm as 1, and the weights for the characteristic parameters of the attitude system are set based on the AHP method. Firstly, the weights of the controller, the actuator group and the sensor group are computed as $W_C = 0.1858$, $W_A = 0.6568$ and $W_S = 0.1575$, respectively. The weights of each component of sensors are calculated as $S_1 = 0.6231$, $S_2 = 0.1963$, $S_3 = 0.1638$, and $S_4 = 0.01689$, respectively. The weights of each component of actuators are $A_1 = 0.7903$, $A_2 = 0.1327$, and $A_3 = 0.07692$. The weights of the health assessment indicators are calculated separately as $I_1 = 0.6089$, $I_2 = 0.2274$, $I_3 = 0.1419$, and $I_4 = 0.02178$.

The data deviation from the healthy state is set at 500s and 900s in the test data, where the lowest data health is injected at 500s. Based on the health assessment algorithm proposed in this paper to calculate the health degree, the final results obtained for the health status of the ACS are shown in Figure 4-Figure 8

As shown in Figure 5, the healthiness of the AOA sensors and magnetometers in the sensor components plummeted at the 500th second, corresponding to the unhealthy data injected at that time. Similarly, the healthiness of all components in the actuator dropped significantly at 500 s. In Figure 6, the overall healthiness of both the sensor and actuator groups declined at 500 and 900 s, with the most significant drop occurring at 500 s. This indicates that the injected faults are effectively detected by the algorithm. According to the results in Figure 7, the individual health assessment indicators for various components also showed varying degrees of decline at these times, further validating the sensitivity of the method to detect faults. Figure 8 shows the overall healthiness of the ACS of the FWUAV. The healthiness decreases at the corresponding moments (500 and 900 s), which demonstrates that the assessment algorithm can effectively reflect the health status of the

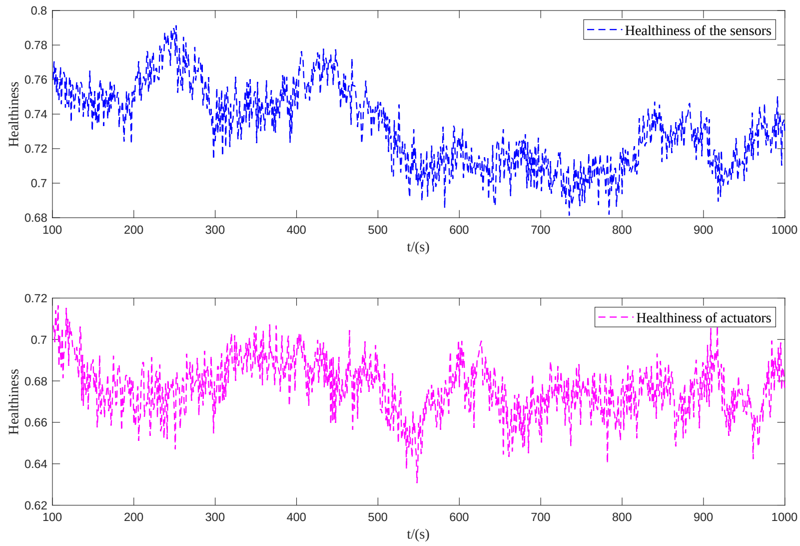

Figure 6. Healthiness of the sensor group and actuator group.

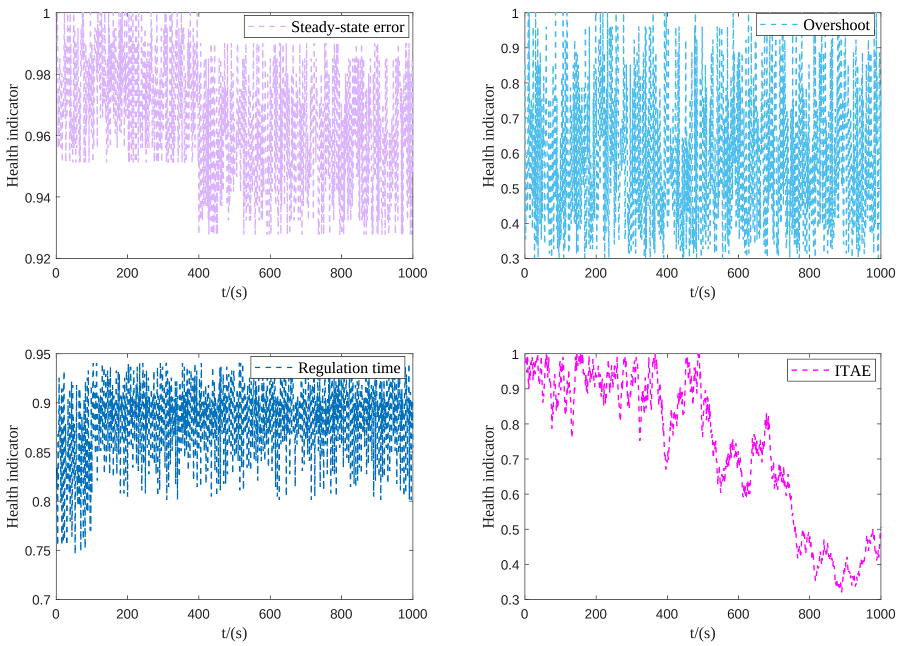

Figure 7. Effectiveness values of health assessment indicators.

ACS. These results illustrate the superiority of the proposed estimation algorithm for detecting and reflecting health status changes in real time, compared to existing methods. The significant drops in healthiness at the times of injected faults demonstrate accuracy and reliability of the algorithm in health assessment.

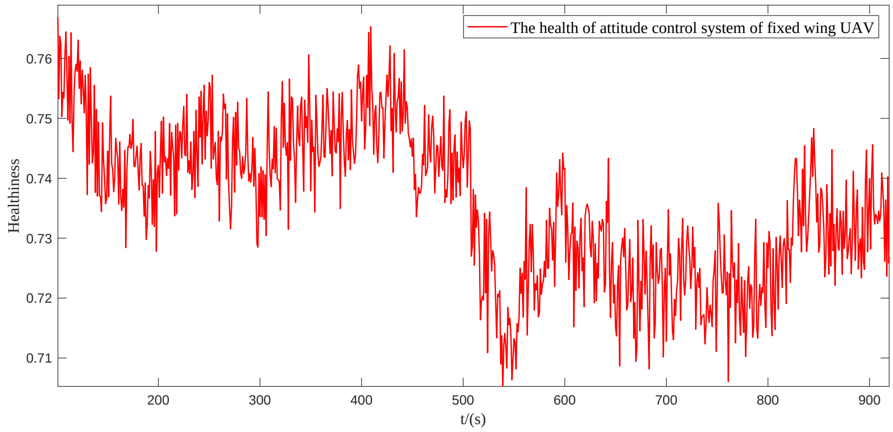

Figure 8. Healthiness of attitude control systems for FWUAVs.

4. CONCLUSIONS

In this paper, an algorithm has been designed for evaluating the health status of the ACS. The parameters that can characterize the health status for the ACS of the FWUAV have been selected as feature parameters, and the state fluctuation characteristics have been obtained. The abnormal degree of the ACS components has been obtained by applying the dynamic memory matrix MSET to calculate the feature parameters. Further, based on the functional structure of the ACS, the abnormal state of the component group and the system can be calculated based on the abnormal state of the component, and the health state indication system of the ACS can be established based on the AHP and SPRT methods, so as to confirm whether the ACS is in a healthy state. Finally, the health status assessment process of the ACS is demonstrated by the simulation analysis to verify the effectiveness of the algorithm.

DECLARATIONS

Authors' contributions

Made significant contributions to the conception, writing and simulation: Yuan R
Made significant contributions to the writing: Shao S
Made substantial contributions to the revision: Chen M

Availability of data and materials

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication
Not applicable.

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CITATIONS

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