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A Novel Application of Intelligent Algorithms in Fault Detection of Rudder System

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ABSTRACT The rudder system is extensively used in aerospace, ships, missiles and other safety demanding areas. Therefore, it is paramount to ensure that the performance of the system is optimal. Rudder system testing equipment is a special tool used to diagnose its failure. Traditional ones can only artificially analyze the massive and complex tested data. Due to the low-test degree of automation, the performance of such testing tools is limited. Aiming to address this shortcoming, we developed a new rudder system testing equipment with four independent loading platforms and intelligent data analysis systems. It sufficiently shortens the installation and commission time of pneumatic actuators and the processing time of the testing data which largely improves its performance and accuracy. Given the imbalanced nature of the data an adaptive sampling algorithm considering informative instances (ASCIN) leveraging the Support Vector Machine (SVM) is proposed to process the originally collected data. The optimal parameters in SVM and ASCIN are searched by Whale Optimization Algorithm (WOA). Experiments are designed to assess the performance of ASCIN in comparison with existing approaches in the area of imbalanced data learning. The results show that the algorithm developed in this study has higher performance relative to traditional approaches. The application of these intelligent algorithms in fault detection and location of rudder system overcomes the limitation of traditional testing equipment and provides a new concept for future research into more intelligent one.

INDEX TERMS Rudder system, fault diagnosis, intelligent algorithm, data analysis.

I. INTRODUCTION

The rudder system is widely used in aerospace and navigation fields, like in civil aircraft, ship and missile. The directional stability is strongly crosslinked with the performance of a rudder system. Failure of rudder system in missile application may cause catastrophic accidents. Therefore, selecting a qualified rudder system for precise control of the course is critical. The rudder system consists of four pneumatic servos and one steering engine control amplifier circuit board. In addition, the system contains a guidance for the production of pneumatic servo and the circuit board for identified faults.

Initially, in missile rudder system testing was performed using manual measuring method. This method was later found to be inefficient with substantial manual errors caused by heavy testing workload. With the development of the technology, the emergence of high performing automated testing system has rendered traditional manual testing methods obsolete. Automatic testing system allows rapid calculation of results and higher testing accuracy [1]. However, the signals acquired by this testing tool still require artificial observations, analysis and decision making [2], [3]. The operator processes the collected data manually and then analyzes the system condition based their experiences. This detection process is implemented half automatically. The rapid development of machine learning provides new opportunities for diagnosing defects in the rudder system. However, this field requires advanced intelligent reforms [4].

It is therefore important to develop effective data analysis tools and learning methods for processing the features collected from the rudder system testing facility for better performance. In practical application, the production of

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rudders and corresponding private circuit boards is highly controlled, thus the number of unqualified products is relatively small. For this reason, the raw data collected from such testing facilities is imbalanced, with the number of normal features outnumbering that of fault features. Considering the imbalance within the dataset, several approaches have been used to adjust the typical classifiers or features. Classical classification algorithms have been designed to offset the imbalanced dataset. Although the algorithm is effective for balanced datasets, when applied to skewed data, its performance rapidly reduces thereby decreasing the precision of the classifier. Common methods used for the skewed data learning mainly focus on resampling and balancing the original dataset [5]–[13]. Over-sampling the minority class samples and applying the informative examples is one of the most promising and effective approaches for imbalanced data learning [5], [14], [15]. Notably, no extra information is needed in oversampling method except the dataset itself. In addition, more valuable minority samples are generated through over-sampling by emphasizing the informative samples to obtain balanced dataset.

Research has indicated that the data points near the decision boundary are more important [16]. Some of these points lie on the margins at both sides of the decision boundary and are called support vectors (SVs) [5]. They are important for the training model since it determines the hyper-plane setting [17]. Therefore, the SVM algorithm is employed to diagnose failures of the rudder system. SVM is used because of the following reasons. First, the basic theory and the classification mechanism of SVM are simple. Second, SVM utilizes the kernel function to transform the input to higher dimensional space which allows separation of the nonlinear separable data by a hyper plane. Then, the hyper plane (decision boundary) is used to calculate the informative data points. Radial basis function is used as the kernel function in this study. The penalty factor c and kernel parameter g play important roles in SVM classification. For this reason, the WOA is applied for parameters optimization (The optimized SVM called: WOA-SVM). In recent years, SVM has been widely applied in small samples data analysis and fault diagnosis with good results [18]–[22].

Some scholars have demonstrated the efficiency of over sampling method while considering the informative samples. Zhang et al. developed a framework which combined both the majority and minority features in a nearly optimal fashion to construct the feature selection metrics [23]. Treating all data as equally important introduces redundancy to the information. The ensemble SVM strategy proposed in a previous study [7] mainly considers the distribution of the SVs and this method was found to be effective. In this method, only the SVs are considered and the base classifiers are not completely independent. Recently, Wang et al. developed an ensemble method which accounts for the samples near the decision boundary of SVM and achieved good results [24]. However, the importance of the datasets near the decision boundary is compatible, which undoubtedly generates less significant or even bad data points.

In our study, to generate more sensitive data and rectify the skewness of decision boundary, we weighted the data points according to their distance from the decision boundary. This formed the main principle of ASCIN algorithm. The intelligent algorithms ASCIN, SVM and WOA are employed to the rudder system testing equipment which significantly improve its accuracy and efficiency. The parameters in ASCIN and SVM are optimized by WOA. SVM is mainly used to determine the informative samples and to facilitate data classification. The application of intelligent data analysis in rudder system testing equipment not only improves the degree of automation but also the accuracy of diagnosing different types of faults. It also guides the production of steering gears and corresponding circuit boards.

In summary, it has broken the traditional model. Under the traditional method, the collected massive data which imply the system fault condition are compared to the standard indicators by manual operation to diagnose the faults, and then according to the experience of the operators and the comparison results, the failures can be located. The whole process is semi-automatic. However, the data analysis, fault model establishment and fault location of proposed system are accomplished by computer independently and automatically. This function depends on the application of machine learning, and the detail are described as follows.

II. RUDDER SYSTEM FAULT DETECTION PROCESS

In this study, fault diagnosis in the rudder system is divided into two steps; testing and data learning. The main modules are shown in Figure 1. In the first stage, the parameters reflecting the performance of rudder systems are measured and acquired. Thereafter, the main features are collected according to the signal conditioning. In the learning stage, intelligent machine learning algorithms are applied to analyze and create a detection model which can diagnose the rudder system. The features collected after the testing are shown in 'Features' in Figure 1. (The detail description parameters are shown in Appendix 2)

A. RUDDER SYSTEM TESTING EQUIPMENT

The automatic rudder system testing equipment is developed as shown in Figure 1. In the testing system, the power supply unit consists of an electronic source and the pneumatic power. The electronic source generates the required working voltage for each functional circuit, sensor and machine. The testing device needs 220V AC, however, some parts inside the chassis need 5V DC or 24V DC. Changes in voltage are accomplished by AC/DC and DC/DC modules. The pneumatic power supplies compressed air at a given pressure and flow rate to the pneumatic steering gear.

The measurement unit consists of torque transducer, photoelectric coder, data acquisition card and signal

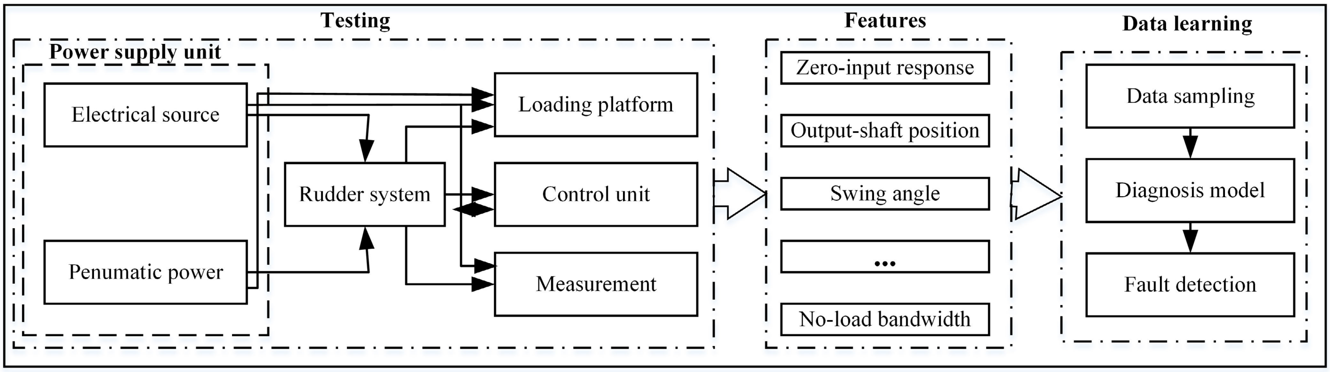


FIGURE 1. Process of the rudder system fault detection.

condition circuit. Torque is measured with the torque transducer and torsional angle is measured with the photoelectric coder. The signal conditioning circuit ensures that the control and feedback signals of the rudder system and output signal of sensors can be adjusted and filtered. The signal produced after conditioning is more sensitive and easier to collect. These signals are collected and stored in the data acquisition card.

The control unit consists of a switch control circuit, industry personal computer (IPC) and the master control computer.

The switch control circuit controls the power supply junction or cut off. The IPC forms the core of the test equipment, which regulates the signal transmission, processing and display. The master control computer is used for data analysis and to control the entire testing procedures.

The loading platform consists of a mounting table and four independent loading channels. The testing equipment can load four sets of rudder systems and tests at least one rudder system at a time. This design greatly improves the efficiency of the testing system. However, it compromises data processing. Consequently, using machine learning methods to analyze these massive complex data collected from the testing facility can effectively solve the problem. The computer-assisted diagnosis not only saves manpower and time but also improves the efficiency, accuracy and the degree of automation.

B. DATA LEARNING PROCESS

The original imbalanced data collected from the testing equipment is automatically transmitted to the computer for machine learning processing instead of manual intervention. The data process consists of three aspects: data sampling, diagnosis model establishment and fault detection. In the first two stages, an adaptive sampling method ASCIN leveraging the SVM is proposed to balance the data and achieve optimal learning results. This machine learning method can directly detect faults. In the process of learning, the optimal parameters in SVM and ASCIN are searched by WOA. During the last stage, the newly processed data set is fed into the optimized classifier SVM to determine the fault location.

III. ALGORITHMS FOR FAULT DIAGNOSIS

A. THE WHALE OPTIMIZATION ALGORITHM

An alternative metaheuristic swarm algorithm was developed for the first time in reference [25], which was named WOA since it simulates the feeding style of humpback whales. Similar to the PSO [26], a population of the solution is initialized randomly and then used to determine the best solution P* by calculating the fitness function for each solution P. The performance of WOA was found to be superior to that of the optimization algorithm PSO [20], [25], owing to its higher exploration ability. The population updating is achieved by employing the following two methods ① encircling, and ② bubble-net [27].

In the encircling phase, the updating procedure is shown in Eq. (1)

$$\begin{cases} P(t+1) = P^*(t) - A \cdot D \\ D = |CP^* - X(t)| \end{cases} \tag{1}$$

where D represents the distance between the best solution P* and P at the iteration t. t indicates the current iteration, A and C are coefficient vectors, which are calculated as follows.

$$\begin{cases} A = 2a \times r_1 - a \\ C = 2 \times r_2 \end{cases} \tag{2}$$

where a is linearly decreased from 2 to 0 over the course of iterations and r_1 and r_2 is a random vector in [0,1]. In the bubble-net method the solution can be updated using ① shrinking encircling or ② spiral updating. Supposing the search space is two-dimensional, the candidate position Pi located at (X, Y) is updated based on the best position P* (located in (X*, Y*)) as shown in Figure 2. Any position can be reached with respect to the current position by adjusting A and C. Similar concepts are applicable to the n-dimensional search space.

The shrinking encircling mechanism is accomplished by decreasing the value of a shown in Eq. (4), and the position is undated according to Eq. (1) and Eq. (2). Figure 2 shows the convergence mechanism of position Pi with iteration.

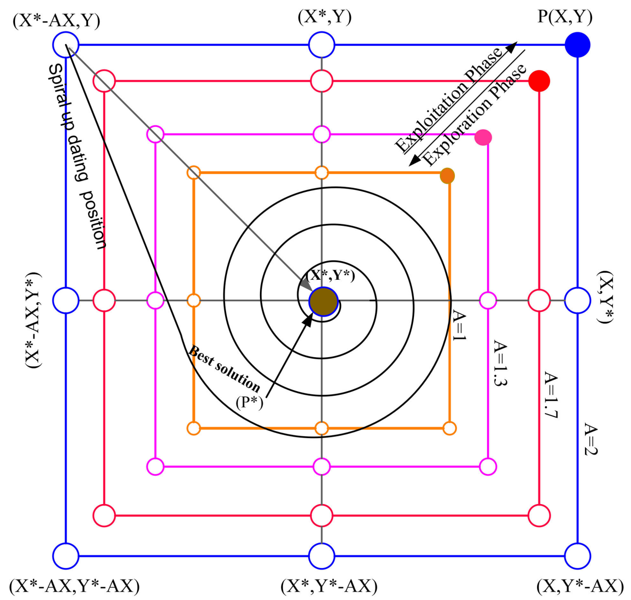


FIGURE 2. Bubble-net search mechanism implemented in WOA.

If the spiral updating strategy is used, the following spiral equation simulates the helix-shaped movement of the whales.

$$P(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + P^*(t) \tag{3}$$

where $D' = |P^*(t) - P(t)|$ depicts the distance between the position of current and the best at the ith iteration. Parameter $l \in [-1, 1]$ is a random number and the constant b is used to define the shape of the logarithmic spiral [25]. In WOA algorithm, the solutions updating mechanism involves switching between the shrinking encircling and spiral-shaped path as in Eq. (4).

$$P_i(t+1) = \begin{cases} P^*(t) - A \cdot D & if\ r \geq 0.5 \\ D \cdot e^{bl} \cos(2\pi l) + P^*(t) & if\ r < 0.5 \end{cases} \tag{4}$$

where r is a random number in [0,1] denoting the probability of swathing between the above two techniques (see in Eq. (1)-(3)) [27].

In nature, there exists a random search mechanism where the best position P^* is replaced by a random position P_r.

$$\begin{cases} P(t+1) = P_r(t) - A \cdot D \\ D = |B \cdot P_r - P| \end{cases} \tag{5}$$

B. SUPPORT VECTOR MACHINE

SVM is a pattern recognition algorithm that utilizes an optimized hyperplane to separate the space expressed by a normal vector w and a hyperplane offset b [28]. The hyperplane is obtained from the following function.

$$\begin{cases} \alpha_i \geq 0 i = 1, 2 \ldots m \\ y_i(w^T x_i + b) - 1 \geq 0 \\ \alpha_i(y_i(w^T x_i + b) - 1) = 0 \end{cases} \tag{6}$$

The x_i and y_i are the input and output vector, respectively, and $y_i \in \{-1, +1\}$ determine the label of ith instance. Where α is a vector which signs the Lagrange multiplier. In the above function, when $\alpha_i > 0$, the solution x_i stands for SV, and not support vector (NSV). SVs lies in the planes $w^T x + b = \pm 1$, which determines the position of classification of hyperplane H (satisfying the function $w^T x + b = 0$). In conclusion, the hyper-plane settings are adjusted based on the SVs, and not NSVs in the majority.

The kernel function $\Phi(x)$ is applied to the non-linear separable problems and the data is mapped to a new feature space. Next, the decision boundary is described using the following formula: $w^T \phi(x) + b$, in which w is obtained from the following expression: $w = \sum_{i=1}^{N} \alpha_i y_i \phi(x_i)$.

1) SVM ON IMBALANCED DATASET

The performance of SVM decreases when applied to imbalanced dataset, especially to minority class examples. The minority class samples are misclassified as majority class because the decision boundary in SVM is biased towards the minority class. Wu and Chang [29] stated that the skewness of the decision boundary is due to the imbalanced SVs ratio and imbalanced training data ratio. The number of majority class data points and the majority class SVs is larger than the minority. However, the concept was challenged by Akbani et al. [30]. The principle of SVM is a trade-off between margin maximization and classification error minimization. The cumulative misclassification cost of minority class data is relatively small for its small number, therefore, SVM tends to maximize the margin by regarding the minority class cases as the majority.

Nevertheless, the skewed decision boundary of SVM is due to the smaller number of the minority class instances compared to the majority. In the following section, we describe the solution to this problem.

C. THE PROPOSED SAMPLING ALGORITHM ASCIN

In this paper, we propose a new over-sampling algorithm which integrates the SVM for imbalanced data learning. As described above, the skewness of the decision boundary is directly related to the imbalance in the dataset. In ASCIN, the sensitive generate minority class data points are generated and balanced in the dataset. The procedures used to perform ASCIN are as follows.

Step 1: Partition of the original dataset into training dataset (account for 70%) and testing dataset (account for 30%). The imbalance ratio in both datasets is similar to that of the original dataset. Next, the imbalanced gap in the training data is calculated and set as the upper bound for generating the synthetic minority class data points.

Step 2: SVM is developed on the original training dataset and the G-mean (detailed in Section 4.1) is recorded to evaluate the performance of the model. This is followed by calculation of the decision boundary.

Step 3: The Euclidean Distance of the minority class data points in training dataset from the decision boundary is calculated. The $p\%$ of them with short distance are considered to be informative samples and weighted according to the distance from decision boundary. The smaller the distance, the larger the weight. Subsequently, the Clustering-based Synthetic Minority Oversampling Method (CSMOTE) is employed to generate new synthetic samples in the space of the above weighted dataset. The oversampling degree for the minority class data points is $d\%$. Finally, new training dataset that contains some new generated minority class points is obtained.

Step 4: The newly generated SVM is then tested on the new training dataset and new decision boundary to obtain informative samples. These steps are repeated and the relative indices and the number of newly generated data points are recorded.

Step 5: In this step, the data set corresponding to the best classifier performance is obtained. The model is then trained on the above dataset.

During the iterations, the algorithm WOA is used to obtain the best value of the SVM parameter c, g and the ASCIN parameter $p\%$ as well as $d\%$ according to the value of evaluation matrix G-mean. The pseudo-code of ASCIN is described in Table 1. (The notification of Algorithm ASCIN is shown in Appendix 1)

TABLE 1. The algorithm ASCIN.

GIVEN D, R, P, D	
1.	Partition D into Training S' and Testing T dataset according to r.
2.	Calculate the imbalance gap i_gap in S'. $i\_gap = Maj\_num - Min\_num$
3.	Develop the i_SVM model on S' to obtain the decision boundary. $D\_B' = w^T x + b,\ w = \sum_{j=1}^{Ns} \alpha_i y_i \phi(x_i)$
4.	Calculate G-mean for i_SVM on S' : $I\_G\text{-}mean,\ S\_G\_D=0$.
5.	$S = S'$, $SVM = i\_SVM$, $D\_B = D\_B'$, $G-mean = I\_G-mean$
	While $S\_G\_D < i\_gap$
6.	Calculate the Euclidean Distance of minority data points from D_B. $E\_D(x^t) = \frac{\lvert \sum_{k=1}^{m} w_k^t + b \rvert}{\sqrt{\sum_{k=1}^{m} w_k^2}}$
7.	Identify the informative data points $S_{\inf}$ (Top of p% of data points close to D_B according to E_D).
8.	Weigh the dataset $S_{\inf}$ according to E_D and eliminate the noise among them. Name the new dataset $W\_S_{\inf}$. The weight value is calculated as follows, and then normalize the weights. $w^t = \sum E\_D(x^t) \big/ E\_D(x^t)$
9.	Over-sample data points in $W\_S_{\inf}$ by $d\%$ using CSMOTE. The new generated dataset is recorded as $New\_S_{\inf}$.
10.	$S = S \cup New\_S_{\inf}$
11.	Calculate S_G_D, $S\_G\_D = S\_count - S'\_count$
12.	Develop an SVM on S and compute *G-mean* for SVM on T, then record the value of G-mean. $G\_m = [G\_m, G-mean]$
	End
13.	Find the maximum value in G_m and record its index.
14.	Select the sampled dataset with the maximum *G-mean*.
15.	Train the model on the above dataset
16.	Evaluate the model on the testing dataset by several evaluation matrices

1) THE ALGORITHM CSMOTE

In the basic generation algorithm SMOTE, the new synthetic data points are created by interpolation between one datapoint and its K nearest neighbors (the neighbors belong to the informative minority class samples). This mechanism may lead to the new generated data falling in the cluster of majority class samples [11]. Therefore, CSMOTE is used to generate samples as follows: 1) K-means Clustering is used to categorize data samples into k clusters which are $L_1, L_2, \ldots, L_k$ so that each sample belongs to a cluster. 2) A data point x is randomly selected from cluster L_t. Another data point y is randomly selected from the members of k-Nearest Neighbors of point x. It should be noted that the point y is from cluster L_t, otherwise, the above steps have to be repeated. 3) One synthetic data, w, is generated according to $w = x + \beta \times (y - x)$, where β is a random number in the range [0,1].

2) PARAMETERS OPTIMIZATION

For improved classification performance, it is important to find the most optimal value of the related SVM and ASCIN parameters. A previous study applied the WOA for SVM parameter optimization [20]. It has been proven to be superior to PSO optimization algorithm in terms of performance. The details of the overall processes are described below:

Step 1: The parameters whales' numbers, expressed as *Search_Agents*; the variables' number (expressed as *dim*); the maximum iteration number (expressed as *Max_itr*): the value of lower and upper boundary are defined as $lb = [lb_1, lb_2, \ldots lb_n]$ and $ub = [ub_1, ub_2, \ldots ub_n]$ respectively. In this study, the parameters are set as follows: *Search_Agents* = 50, *dim* = 4, *Max_itr* = 50, $lb = [0.001, 0.001, 0, 0]$, and $ub = [1000, 1000, 1, 1]$. Thereafter, the first random population of whales is calculated. The iteration value is set as 1 in the first period.

Step 2: Four parameters$c$, g $p\%$ and d are optimized. The fitness function is defined as the G-mean of the classifier.

Step 3: In this step, the fitness value of each whale is calculated, $fit_t^k = -(G - mean), t = 1, 2, \ldots M$, and the value is then used to rank the first batch of whales and the one with best fitness value is selected. Subsequently, the location of whales is updated in reference to the best one.

Step 4: The population is then updated according to the formula (1)-(5). The iteration is performed until the largest iteration is obtained.

IV. EXPERIMENTS

In this study, 850 sample datasets with 18×4 features are collected and used to create the detection model. The 4 indicates the number of pneumatic-servo-actuators (detailed description of different features is shown in Appendix 2). The number of minority class samples is 200 and the imbalance ratio is 17.64%. A rudder system fault diagnosis experiment is then developed to verify the performance of the proposed intelligent algorithms in dealing with imbalanced data classification problem and fault diagnosis of rudder system. The effectiveness of the algorithm ASCIN is validated by learning the dataset collected from the testing facility. To determine the performance of ASCIN, it is compared to different sampling methods. Then WOA-SVM is applied to fault location.

A. THE EVALUATION METRICS

In this study, majority of the samples are considered positive, whereas few are negative. By convention, the classification accuracy of overall data is applied to evaluate the performance. However, for classification tasks of imbalanced dataset, other assessment methods should be adopted to evaluate the performance. In this study, the confusion matrix F-measure, G-mean and TNR are also selected to evaluate the learner [31]. They are calculated as follows:

$$Accuracy = Acu = \frac{TP + TN}{TP + FN + FP + FN} \tag{7}$$

$$F\text{-}measure = \frac{2^{*}Precision^{*}Recall}{Precision + Recall} \tag{8}$$

$$G\text{-}mean = \sqrt{TPR^{*}TNR} \tag{9}$$

where Precision, Recall, TPR and TNR are further defined as:

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = TPR = \frac{TP}{TP + FN} \tag{11}$$

$$TNR = \frac{TN}{TN + FP} \tag{12}$$

where TP is the number of true positive examples; FP is the number of the false positive examples; FN is the number of false negative examples and TN is the number of true negative examples. The indicator G-mean matrix is a coordinate between the TPR (classification accuracy of positive) and the TNR (classification accuracy of the negative).

B. THE EXPERIMENTAL PROCESS

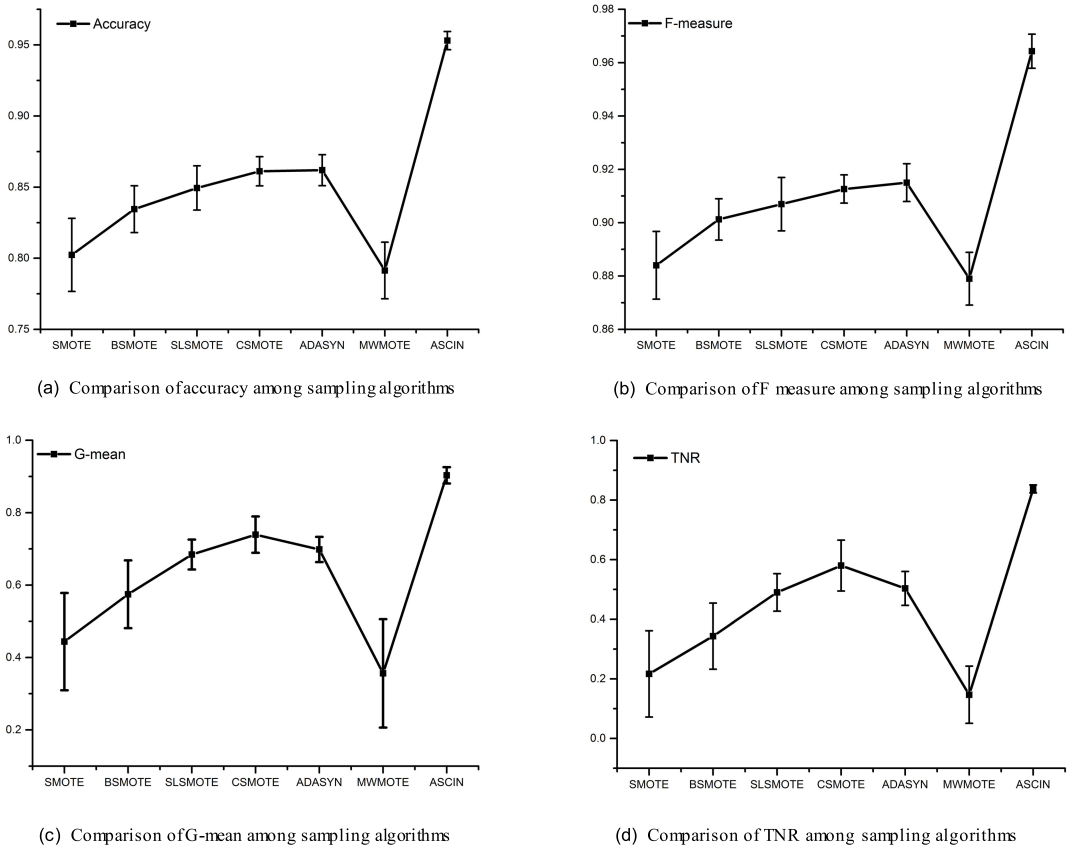
The experimental process consists of two stages: data collection and data learning. The data learning process is briefly discussed in Section 2.2. The data collection process is similar to the traditional automatic testing equipment. We record the corresponding output responses at different input excitation input stimulus (given by the programs). For instance, when the system is given a step signal, the parameter ''transition time'' can collected according to the shortest time the system changed from the original stable state to the new equilibrium state. Detailed correlations between the input and the collected parameters are shown in Appendix 2.

C. THE EXPERIMENTAL RESULTS AND ANALYSIS

In this study, we compared the performance of ASCIN to six common imbalanced data learning algorithms: Synthetic Minority Oversampling Technique (SMOTE) [13], Borderline Synthetic Minority Oversampling Technique (BSMOTE) [12], Safe-Level Synthetic Minority Oversampling Technique (SLSMOTE) [8], Cluster-Based Synthetic Minority Oversampling Technique (CSMOTE) [9], Adaptive Synthetic Sampling (ADASYN) [10] and Majority Weighted Minority Oversampling

Technique (MWMOT) [11]. The classification results based on the original imbalanced dataset are provided for reference. The parameters used in the above methods are defined as default or the recommended value. To avoid overfitting, 5-fold cross validation is applied in these experiments. The dataset is then partitioned into five subsets with equal size. In cases where the five subsets do not have the same size, the former four subsets should be the same at least. The model is repeated five times, each time the model is trained on four of the subsets and the rest are used to test the model. In each iteration, the test dataset is different. The final model performance is the average of the five models. To further reduce the effect of randomness, eight trials are repeated under the same conditions. The parameters used in our method are optimized by WOA, therefore, the classification algorithm WOA-SVM is applied to analyze the data after other sampling approaches. Different sampling methods are assessed and compared by measuring the evaluation matrix accuracy, F-measure, G-mean and TNR. The average and deviation of metrics are shown in Table 2. In addition, Figure.3 shows the classification results in terms of evaluation metrics with several sampling algorithms and our adaptive sampling method ASCIN.

Table 2 and Figure.3 show that the proposed sampling method is more effective in processing imbalanced data collected from the testing equipment. The algorithm ASCIN achieves the highest matrix accuracy of 0.953, F-measure of 0.964, G-mean of 0.903 and TNR of 0.8375. In addition, the proposed sampling algorithm ASCIN, correctly classified nearly 84% of the minority class examples. This reflects an improvement of 133% compare to 36% in the original data. Our proposed sampling algorithm ASCIN achieves the G-mean of 0.903, reflecting an improvement of 10.34% (0.903–0.444), 57.04% (0.903–0.575), 31.82% (0.903–0.685), 22.19% (0.903–0.739), 29.37% (0.903–0.698) and 15.37% (0.903–0.356) in terms of the average G-mean compared to the ones obtained with SMOTE, BSMOTE, LSMOTE, CSMOTE, ADASYN and



(a) Comparison of accuracy among sampling algorithms

(b) Comparison of F measure among sampling algorithms

(c) Comparison of G-mean among sampling algorithms

(d) Comparison of TNR among sampling algorithms

FIGURE 3. (a). Comparison of accuracy among sampling algorithms, (b). Comparison of F-measure among sampling algorithms, (c). Comparison of G-mean among sampling algorithms, (d). Comparison of TNR among sampling algorithms.

TABLE 2. Comparison of several sampling methods (the bolded indicates the best in this column).

Approach	ACCURACY	F-MEASURE	G-mean	TNR
Original data	0.883±0.017	0.929±0.011	0.437±0.035	0.357±0.048
SMOTE	0.8024±0.0257	0.884±0.0127	0.4439±0.1345	0.2167±0.1488
BSMOTE	0.8345±0.0167	0.9012±0.0078	0.5747±0.0935	0.3433±0.1109
SLSMOTE	0.8494±0.0156	0.9069±0.01	0.6845±0.0413	0.49±0.063
CSMOTE	0.8612±0.0102	0.9126±0.0053	0.7393±0.0502	0.58±0.0853
ADASYN	0.8620±0.0109	0.915±0.0071	0.6984±0.0349	0.5033±0.057
MWMOTE	0.7914±0.0199	0.879±0.0099	0.3562±0.1499	0.1467±0.096
ASCIN	**0.953±0.0064**	**0.9643±0.0027**	**0.9032±0.0225**	**0.8375±0.0134**

TABLE 3. The confusion matrix of the classification in the testing data.

	F1	F2	F3	F4	F5	F6	F7	F8	MF	Q
F1	4					1				
F2		6							1	
F3			7						2	
F4				7						
F5					6					
F6			1			8				
F7				1			7			
F8								5	1	
MF									10	
Q										**195**

MWMOTE respectively. The algorithm ASCIN achieves the TNR of 0.838, reflecting an improvement of 286.1% (0.838–0.217), 144.3% (0.838–0.343), 71.02% (0.838–0.49), 44.5% (0.838–0.58), 66.6% (0.838–0.503) and 470.1% (0.838–0.147) in terms of the average TNR compared to the ones obtained using SMOTE, BSMOTE, SLSMOTE, CSMOTE, ADASYN and MWMOTE respectively. The algorithm ASCIN achieves the F-measure of 0.964, reflecting an

TABLE 4. The classification results of fault location.

Training data	ACCURACY	TNR
Original	84.3% (215/255)	66.7% (40/60)
Trial 1	95.3% (243/255)	80% (48/60)
Trial 2	96.5% (246/255)	85% (51/60)
Trial 3	96.1% (245/255)	83.3% (50/60)
Trial 4	**97.3% (248/255)**	**88.3% (53/60)**
Trial 5	96.5% (246/255)	85% (51/60)

improvement of 9% (0.964–0.884), 7% (0.964–0.901), 6.3% (0.964–0.907), 5.6% (0.964–0.913), 5.4% (0.964–0.915) and 9.7% (0.964–0.879) in terms of the average F-measure compared to the ones obtained using SMOTE, BSMOTE, SLSMOTE, CSMOTE, ADASYN and MWMOTE, respectively. Apart from MWMOTE, all the other sampling methods produce a higher accuracy, G-mean, F-measure, and TNR than the most basic sampling method SMOTE.

1) FAULT LOCATION

In machine learning the location of failures is a multi-classification problem. In our experiment, there are 11 systems sates in the data-set, including 9 single fault states, a multiple fault state and a qualified state. In this process, the classifier WOA-SVM is used for fault location. The best new training dataset in the above experiments which contains the new synthetic minority class samples is selected to train the new model. The noise that does not conform to the actual physical meaning should be removed and labels are assigned to the new samples.

In the first experiment involving five repeated trials, during the iteration of ASCIN, we choose the best value of G-mean to record the index of iteration and the corresponding parameters. At the beginning, the number of original training data is 595 comparing 455 majority class data and 140 minority class data. In the $5th$ iteration (the new training dataset is $455 + 351$), the best G-mean of 0.988 is obtained (only 8 negative samples are misclassified). The best parameters c, g, p% and d% are 12.33, 4.11, 27.39% and 20.3%, respectively. The new training dataset after noise removal and labeling is used for training the fault location WOA-SVM model. Similarly, 5-fold cross validation is employed to avoid over-fitting. The testing results of the testing dataset are provided in Table 3. The F1, MF and Q reflect the first type of faults, multiple fault state and qualified state, respectively.

From Table 3, the calculated classification accuracy is 97.3% (248/255), the entire qualified states are classified correctly, and the classification accuracy of the unqualified is 88.3% (53/60). It is anticipated that, if the multi-classification data imbalance problem is solved, the accuracy of unqualified will be increased.

To illustrate the stability and high performance of this method, the new training dataset obtained from the above five trials is used to train the model, and the testing results are shown in Table 4. The classification results on the original imbalanced dataset are provided for reference.

From Table 4, the classification accuracy and TNR of the original model is 84.3% and 66.7% respectively. Using the new generated training dataset, the classification accuracy of the minority samples is significantly improved.

V. CONCLUSION

In this study, we provide a data learning mechanism for automatic rudder system testing equipment that achieves excellent data acquisition and analysis. The model improves the accuracy and efficiency, as well as reduce wastage of labor resource and other costs., compared to traditional testing equipment. In addition, the four individual loading platforms shortened the installation and testing time and reduced the manpower cost to some extent, indicating the practicability of the rudder system testing equipment.

In terms of the intelligent algorithm, novel sampling algorithm ASCIN, SVM and parameters optimization algorithm WOA are used for data analysis and fault diagnosis. The ASCIN which provides a comprehensive consideration of the informative data points integrates the Clustering, SVM and WOA, hence, addresses the lower classification rate of the minority class examples and improves the performance of the classifier. This technique not only avoids the problem of adding trivial information during classification but also prevents loss of important information from the dataset. Based on the experimental results, the classification accuracy of the minority class instances (TNR) is only 0.36 under the original dataset which is far from meeting the testing requirements. The ASCIN processing produces a satisfactory classification accuracy and TNR value. Its diagnosis performance under the processed dataset is markedly superior to the original dataset. Table 2 shows that the performance under sampling method ASCIN is highly comparable to the other sampling methods. The comparison results show that it is effective and applicable to the dataset of rudder system testing equipment. The high accuracy of the proposed model to diagnose fault location promotes pneumatic steering gear production.

In summary, the experiments performed in this study reveal the high performance of the intelligent algorithms for fault detection when applied to the automatic rudder system testing equipment. This is a new paradigm in the field of rudder system testing, as it not only improves the efficiency and the accuracy of the testing equipment, incorporates the fault location function, but also provides more avenues for improving the performance of traditional rudder system testing equipment.

All the following nine parameters are measured respectively under input signals with the same amplitude and positive phase and negative phase.

APPENDIXES

APPENDIX 1

See Table 5.

APPENDIX 2

See Table 6.

TABLE 5. Notations of algorithm ASCIN.

Approach	
D	The original imbalanced dataset
r	imbalance ratio in original dataset
ingas	Imbalance gap in training data
S'	Initial training dataset
T	Imbalanced test dataset
p	Top p% of minority data points close to decision boundary
d	Oversampling degree for minority class data points for each iteration
S_G_D	Synthetic generated data points count
E_D	Euclidean Distance of the minority class data points in training dataset from the decision boundary
S_{inf}	The set of informative data points
G_m	G-mean variation log in each iteration

TABLE 6. The description of dataset.

Parameters	Unit of measure	Detailed
Zero-input response	mV	Response of the system without external input signal
Output-shaft position	cm	Given the control signal of the steering gear, the distance of the steering gear offset
Swing angle	°	Given the control signal of the steering gear, the angle of the steering gear offset
Transition time	ms	The shortest time the system experienced from the original stable state to the new equilibrium state when input step signal,
Overshoot	%	Percentage of ratio deviation of maximum output response over steady-state value to steady-state value with no-load
Steady-state error	°	The deviations in the transition from a steady state to a new steady state system when input step signal
Hysteresis characteristic	°	System inconsistency in a period when triangular waves are input
Load bandwidth	Hz	Frequency bandwidth of the loading system when input sinusoidal signal
No-Load bandwidth	Hz	Frequency bandwidth of No-load System when sine signal is input

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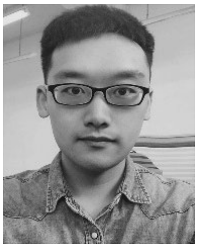

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