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Research Article

Decision Fusion System for Bolted Joint Monitoring

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Bolted joint is widely used in mechanical and architectural structures, such as machine tools, industrial robots, transport machines, power plants, aviation stiffened plate, bridges, and steel towers. The bolt loosening induced by flight load and environment factor can cause joint failure leading to a disastrous accident. Hence, structural health monitoring is critical for the bolted joint detection. In order to realize a real-time and convenient monitoring and satisfy the requirement of advanced maintenance of the structure, this paper proposes an intelligent bolted joint failure monitoring approach using a developed decision fusion system integrated with Lamb wave propagation based actuator-sensor monitoring method. Firstly, the basic knowledge of decision fusion and classifier selection techniques is briefly introduced. Then, a developed decision fusion system is presented. Finally, three fusion algorithms, which consist of majority voting, Bayesian belief, and multiagent method, are adopted for comparison in a real-world monitoring experiment for the large aviation aluminum plate. Based on the results shown in the experiment, a big potential in real-time application is presented that the method can accurately and rapidly identify the bolt loosening by analyzing the acquired strain signal using proposed decision fusion system.

1. Introduction

Bolted joint is widely used in mechanical and architectural structures, such as machine tools, industrial robots, transport machines, power plants, aviation stiffened plate, bridges, and steel towers. The bolt loosening induced by flight load and environment factor can cause joint failure leading to a disastrous accident for the aircraft. In order to keep up the integrity and operation safety of these structures, detecting bolted joint in real time is an important concern in structural health monitoring.

Till now, for the bolt loosening detection, there are some conventional nondestructive inspection techniques, which use the ultrasonic waves and electromagnetic resonance [1, 2]. However, these methods are costly, labor intensive, and time consuming to perform for a large structure and can only be performed when the aircraft is out of service, being intermittent condition monitoring. Accordingly, structural health monitoring (SHM) has been being recently focused on by many researchers since the new inspection approach utilizes advanced sensor and actuator devices being integrated in the structural material with aim to achieve a wide range of real-time online monitoring. There are a number of significant works in the SHM area concerning bolt loosening monitoring.

The problem of detecting bolt loosening has been studied by different researchers. The principle in these techniques is to seek out the changes in the dynamic properties as indicators of damage in the structure. Pai and Hess study the loosening of threaded fasteners due to shear loads, as well as the effect of fastener placement on a structure as a variable promoting self-loosening [3, 4]. Caccese et al. exhibit the promise of the transmittance function for bolt load loss detection in hybrid composite/metal bolted connections [5]. Brown and Adams examine the equilibrium point damage prognosis method across the joint [6]. Todd et al. assess the effectiveness of structural frequencies and mode shapes for bolt loosening monitoring [7]. Nichols et al. use state space models to detect joint preload loss in a framestructure

and utilize data-driven phase space models to assess the conditions of a bolted joint in a composite beam [8, 9]. Moniz et al. use a multivariate, attractor-based approach to detect the bolt loosening with FBG sensor [10]. Rutherford et al. utilize nonlinear feature identifications based on self-sensing impedance measurements for jointed portal frame structure structural health assessment [11]. Ritdumrongkul and Park present the use of a PZT actuator-sensor and the impedance-based monitoring techniques in conjunction with numerical model-based methodology in structural health monitoring to quantitatively detect damage of bolted joint of two aluminum beams [12–15]. Yang et al. use the Lamb wave propagation to monitor the loosening of bolts in a space thermal protection panel [16]. Okugawa employs the subspace state space identification algorithm (4SID) to identify the natural frequency of the smart washer for bolt loosening detection [17]. Milanese et al. research modeling and detection of joint loosening using output-only broadband vibration data [18]. Doyle et al. use the acoustoelastic and magnetomechanical impedance to detect bolt loosening in satellite bolted joints [19].

Recently, the development of artificial intelligence techniques has led to their application in the structure health monitoring. Some methods, such as artificial neural networks and support vector machines, have been employed to estimate the structure damage [20–23]. They are capable of modeling extremely complex nonlinear relationships between known structure damage and structure output response. However, for practical applications, a single decision method can only acquire a limited recognition capability for special data. Therefore, a decision fusion method is introduced to combine the advantages of different recognition algorithms and give more reliable result for the complex task.

This paper proposes an intelligent bolted joint failure monitoring approach using a developed decision fusion system integrated with Lamb wave propagation-based actuator-sensor monitoring method. Firstly, the basic knowledge of decision fusion and classifier selection techniques is briefly introduced. Then, a developed decision fusion system is presented. Finally, three fusion algorithms, which consist of majority voting, Bayesian belief, and multiagent method, are adopted for comparison in a real-world monitoring experiment for the large aviation aluminum plate. Based on the results shown in the experiment, a big potential in real-time application is presented that the method can accurately and rapidly identify the bolt loosening by analyzing the acquired strain signal using the proposed decision fusion system.

The rest of this paper is structured in the following manner. Section 2 introduces the background knowledge of decision fusion. In Section 3, decision fusion system for bonded joint monitoring is presented. Section 4 gives experimental results and discussion for large aviation aluminum plate structure. Finally, Section 5 concludes the paper.

2. Decision Fusion Method

This section covers a brief introduction of decision fusion method, which consists of the classifier selection based on entropy and multiagent fusion algorithm.

2.1. Classifier Selection Based on Entropy. Studies [24] have shown that classifer selection can affect the performance of the subsequent multiclassifier fusion. A proper combination of classifiers can generate the best recognization performance and reduce the calculated time. However, there still exit many problems to select the proper classifier team from a large pool of different classifiers. Accordingly, classifier selection technology has been being recently focused on by many researchers. The optimal combinations of classifiers should have good individual performances and sufficient level of diversity. The diversity quality of classifier selection relies mostly on the goodness of the selection criterion, which includes correlation coefficent, procuct-moment correlation measure, Q statistics, and entropy measure [25]. In these methods, entropy-based diversity measure is a new and effective method for classifier selection based on [26]

$$\mathrm{ED} = -\frac{N^{11}}{N\log_2\left(N^{11}/N\right)} - \frac{N^{00}}{N\log_2\left(N^{00}/N\right)} - \frac{N^{10}}{N\log_2\left(N^{10}/N\right)} - \frac{N^{01}}{N\log_2\left(N^{01}/N\right)}, \tag{1}$$

where N^{11} means the number of samples which are classified correctly by two classifiers e_1 and e_2, N^{00} means those samples which are misclassified by the two classifiers, N^{10} denotes those samples which are classified correctly by classifier e_1 and misclassified by classifier e_2, N^{01} denotes the number of samples which are misclassified by classifier e_1 and classified correctly by classifier e_2, and N is the total number of experiment samples.

Generally, the diversity of classifiers can give more effective information, so smaller correlation degree among the classifiers can lead to better fusion performance. According to the diversity measurement principle, it is neccesacy to select a team of classifiers and the flowchart of classifier selection can be shown in Procedure 1.

2.2. Multiagent Decision Fusion. Generally, the classifiers' output information can be divided into three levels [27]:

(1) the abstract level: a classifier e only outputs a single class label for an input x;

(2) the rank level: a classifier e ranks all classes' labels in a queue with the one at the top being the first choice;

(3) the measurement level: a classifier e evaluates the degree that x has for each class using a measurement value.

Among the levels mentioned above, from the abstract level to the measurement level, the amount of information of the classifiers' output increases in sequence. Accordingly, the classification algorithms of the measurement information can produce the best results. However, the classifiers that can supply the abstract information are more available in the real application.

According to the three levels in the classifiers' output information, decision fusion methods can be divided into

Define:

$E = \{e_1, e_2, \ldots, e_K\}$ is the set of the classifier needed to be selected

$E' = \{e'_1, e'_2, \ldots, e'_K\}$ is the set of the classifier selected

$i, j = 1, 2, \ldots, K$ to index the classifier in set E

e_j is the jth classifier in set E

e'_j is the jth classifier in set E'

$\alpha(e_i)$ is the accuracy rate of the ith classifier in set E, which is the ratio of number of samples classified correctly to the total samples.

$\mathrm{ED}(e, e_i)$ is the Entropy-base diversity measure between classifier e and e_i

Begin:

Step 1. Select the initial evaluation criterion, such as $\alpha(e_i)$.

Step 2.

$$e \leftarrow \max_{e_i \in E}\{\alpha(e_i)\}, E \leftarrow E - \{e\}, j \leftarrow 1, e'_j \leftarrow e.$$

Step 3.

$$e \leftarrow \max_{e_i \in E}\{\mathrm{ED}(e, e_i)\}, E \leftarrow E - \{e\}, j \leftarrow j + 1, e'_j \leftarrow e.$$

Note, when a similar low correlation degree appears for more than one classifier, the classifier that has the highest accuracy rate is chosen.

Step 4. If $E = \Phi$, then, go to Step 5; otherwise, go to Step 3; end.

Step 5. Find the optimal classifier sequence $E' = \{e'_1, e'_2, \ldots, e'_K\}$.

Procedure 1: Proposed procedure for classifier selection.

three types. Multiple classifiers' fusion integrates different decisions from multiple classifiers to boost the accuracy of recognition. The decision fusion methods of the used abstract information are widely adopted, which include majority voting [28], Bayesian belief [27], and multiagent method [29, 30].

In the section, the multiagent fusion algorithm is introduced in detail. In recent years, multiagent system (MAS) of artificial intelligence (AI) has been a natural model for developing a large-scale, complex, distributed system, which is loosely coupled and heterogeneous [31]. In this way, a complex system is decomposed into some small autonomous systems which can interact and cooperate with each other. They can finish the complex mission via communication and negotiation.

In the multiagent fusion method, each classifier is deemed as a single agent. The confusion matrix of the classifier denotes the recognition ability of the agent. For a test sample, Bayesian belief decision can be given by each classifier agent. A two-order correlation degree for information exchange between any two classifiers is introduced to dynamically modify each agent's belief decision. Once there are no more different decisions for these agents, a final combination decision is made. Hence, Bayesian belief method and majority voting are integrated creatively in the method. It considers a behaviour of population decision. The flowchart of multiagent method is shown in Figure 1.

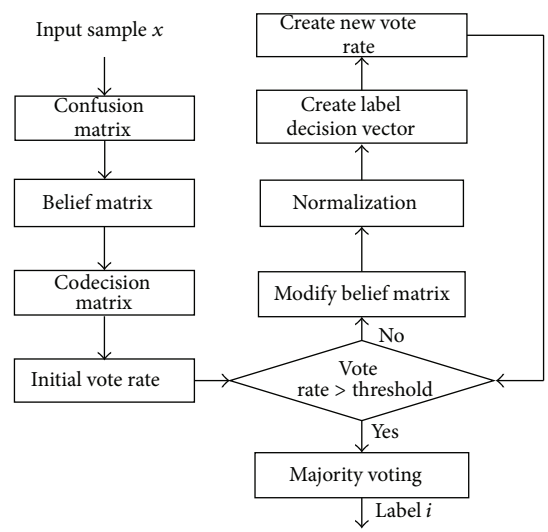


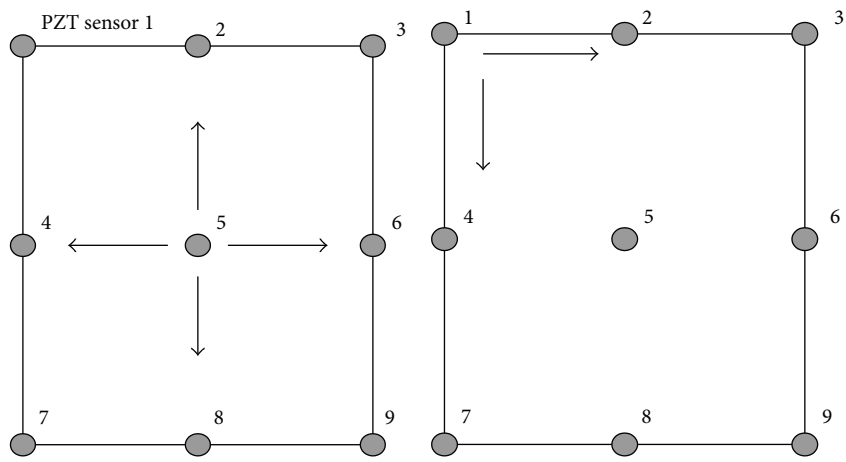
Figure 1: Flowchart of multiagent decision fusion algorithm.

Firstly, a sample set $\mathbf{U}$ consists of $\mathbf{U}_1$, $\mathbf{U}_2$, and $\mathbf{U}_3$. $\mathbf{U}_1$ is the training set of each classifier for obtaining the parameter of the classifier. $\mathbf{U}_2$ is the test set of each classifier and is also the training set of the fusion method for acquiring the parameter of the fusion method. $\mathbf{U}_3$ is the test set of the fusion method.

Confusion matrix $\mathbf{N}^{(k)}$ is firstly created on the basis of Bayesian belief method. $\mathbf{N}^{(k)}$ is regarded as the prior knowledge of each classifier agent. It can be calculated easily for test samples of $\mathbf{U}_1$ based on the trained classifier agent for $\mathbf{U}_2$.

Secondly, a five-dimensional codecision matrix $\mathbf{D} = [d_{j_1,j_2,i,k_1,k_2}]_{M\times M\times M\times K\times K}$ is required as the training parameter. It stands for decision correlation between any two classifier agents, and its element is calculated by

$$\begin{aligned} d_{j_1,j_2,i,k_1,k_2} &= P\left(x \in i \mid e_{k_1}(x) = j_1, e_{k_2}(x) = j_2\right) \\ &= \frac{|\mathbf{A}|}{\sqrt{|\mathbf{B}|} \cdot \sqrt{|\mathbf{C}|}}, \end{aligned} \tag{2}$$



(a) Single-actuator multisensor (b) Cycle-actuator multisensor

Figure 2: The active monitoring method for bolt loosening.

where i is the expected class of input sample x; j_1 and j_2 are, respectively, the decisions of classifiers e_{k_1} and e_{k_2}, where $k_1 \neq k_2$; set $\mathbf{A}, \mathbf{B}, \mathbf{C}$ to be defined as

$$\begin{aligned} \mathbf{A} &= \left\{x \mid x \in i, e_{k_1}(x) = j_1, e_{k_2}(x) = j_2, \forall x \in \mathbf{U}_2\right\}, \\ \mathbf{B} &= \left\{x \mid x \in i, e_{k_1}(x) = j_1, \forall x \in \mathbf{U}_2\right\}, \\ \mathbf{C} &= \left\{x \mid x \in i, e_{k_2}(x) = j_2, \forall x \in \mathbf{U}_2\right\}. \end{aligned} \tag{3}$$

The element d_{j_1,j_2,i,k_1,k_2} in the matrix shows the probability of the sample x of the class i assigned as j_1 class by classifier e_{k_1} and classified as j_2 by classifier e_{k_2}. $|\cdot|$ denotes the cardinal number of sets.

After obtaining the confusion matrix and codecision matrix, the initial belief matrix $\mathbf{B}(x)$ for input sample x can be calculated. $\mathbf{B}(x)$ is regarded as the initial belief probability of each classifier agent for test samples of $\mathbf{U}_3$. Each row in the belief matrix is corresponding to each classifier agent's belief probability of different column classes for the input sample x. If the class of the maximum probability in the kth row is regarded as the kth classifier agent's decision, a decision label vector can be directly obtained from the belief matrix. According to the majority voting strategy, the initial vote rate of each class can be calculated for input x.

Next, if the initial maximum vote rate is less than an accordance threshold, there are more different decisions for the classifier agents. Then, the agents can interact with each other and modify the original belief degrees themselves using the codecision matrix. The repeated modification scheme is represented as

$$b_{ki}(x) = b_{ki}(x) + \left(\frac{1}{K}\right) \sum_{k_n=1, k_n \neq k}^{K} d_{j,j_n,i,k,k_n} \cdot \sqrt{b_{ki}(x) \cdot b_{k_n i}(x)}, \tag{4}$$

where $b_{ki}(x)$ is the element of Bayesian belief matrix $\mathbf{B}(x)$ and represents belief probability of classifier k for the sample x belonging to class i; K is the number of total fusion classifiers; and d_{j,j_n,i,k,k_n} is the weight of information exchange between kth classifier and k_nth classifier. The correction term of the right formula means the information summation of classifier k interacting with other classifiers for the sample x belonging to class i.

Whenever the belief matrix is modified, a normalization process is required to ensure the row element of new belief matrix being the significant probability value. On the basis of the new belief matrix, a decision vector of the classifier agents is acquired to generate a new vote rates. If the maximum vote rate is still less than the predetermined threshold, the classifier agents have less accordance for the input sample. Hence, the interaction between the agents will continue and their belief matrix will be modified repeatedly until their decision reaches the accordance criterion. Finally, the multiagent classifiers use a majority voting method to give out the output of fusion decision.

3. Decision Fusion System for Bolted Joint Monitoring

The active SHM method is generally adopted to monitor the joint failure induced by bolt loosening [32]. The method is based on the structural vibration response and uses the piezoelectric ceramic material (PZT) element as the actuator or the sensor. Its actuator-sensor scheme includes the single-actuator multisensor and cycle-actuator multisensor as shown in Figure 2 [33]. In the first scheme, the fixed driver PZT element is arranged on the structure to stimulate the sensors surrounding the structure simultaneously. The power of the actuator is finite, and accordingly the second scheme is presented for the large structure. The PZT element around the boundary acts as actuator in turn. Each time the signals of two adjacent PZT sensors (left and right or upper and lower) are sampled. For instance, in Figure 2, when PZT element 1 acts as the actuator, the signals of PZT elements 2 and 5 as the sensors are sampled.

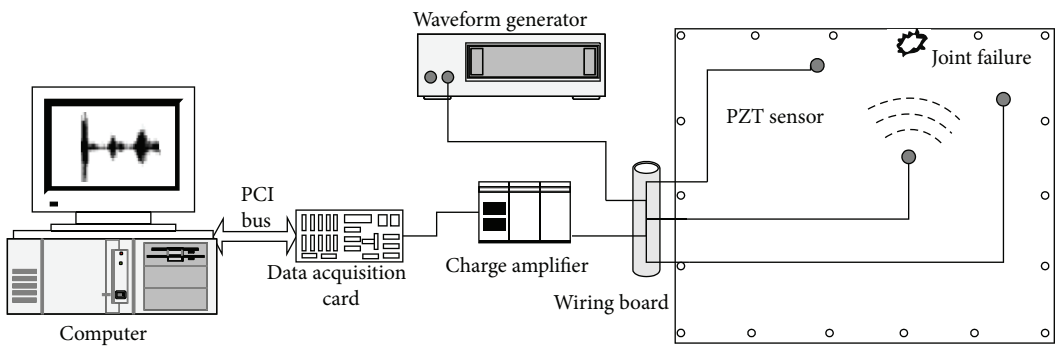


Figure 3: Sensor layout and joint failure position on the specimen.

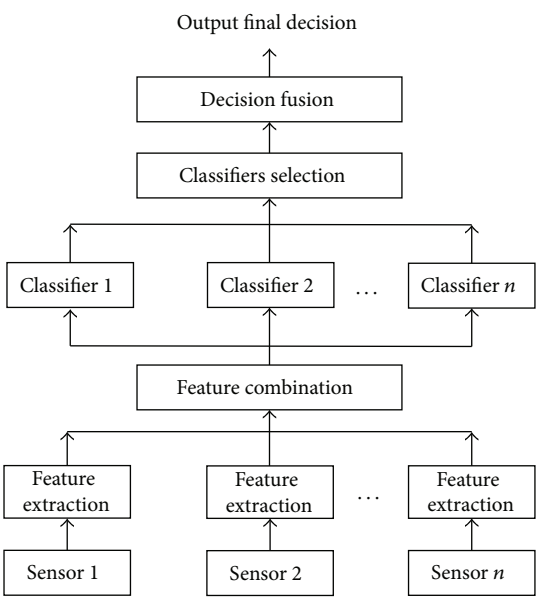


Figure 4: Framework of the proposed fusion decision system.

Generally, a sine wave can be excited by the PZT actuator to the structure at a frequency, under which the vibration response of the structure is sensitive to the bolt loosening. The experiment shows that the sensor signal varies before and after the bolt loosening [32]. An active monitoring system for bolt loosening is shown in Figure 3, which includes waveform generator, charge amplifier, and data acquisition card.

In this paper, a decision fusion system is presented for bolted joint monitoring. It is based on a self-designed fusion diagnosis toolbox by MATLAB language R2006a. This system consists of six levels: sensor, feature extraction, feature combination, multiclassifier decision, classifier selection, and decision fusion. The framework of the proposed system is shown in Figure 4. Firstly, the input signal is acquired from the sensor when the actuator stimulates the structure periodically. Secondly, the signal feature is extracted, and the features of different sensors are combined to be a feature vector. Then, a decision vector is the output of a team of classifiers, and the algorithm of classifier selection is employed to obtain the optimization classifier combination. Finally, the decision fusion method combines the selected classifiers' decisions to give out the final evaluation. This paper adopts three fusion algorithms: majority voting, Bayesian belief, and multiagent method to assess decision fusion's performance.

3.1. Experiment Setup. In order to verify the effectiveness of the presented decision fusion system integrated with Lamb wave propagation based actuator-sensor monitoring method, in this paper, the large aviation aluminum plate structure is studied as the experimental object. Figure 5 depicts a flat structure and the sensor distribution diagram. The plate structural material is the aviation hard aluminum LY12, whose basic dimensions and thickness are 120 cm × 200 cm × 0.25 cm. Around the structure there are 64 M6-bolts which are used to fix the plate with bracket, and the bolt space is 10 cm. The structure is divided into eight subregions, each of which is 49 cm × 45 cm except its edge. The PZT sensors are laid on the vertices of each subregion.

In this study, tests are conducted with healthy and unhealthy configuration which includes the full loose state of 20 bolts in different locations around the structure. Hence, twenty joint failure patterns and one health pattern are considered. In the experiment, tests are conducted with healthy and damage configuration which includes the completely loose state of 20 bolts in different locations around the structure, and each time only one bolt is loosening. In order to quantitatively measure the loosening degrees of bolt, the tightening condition S is introduced and defined as

$$S = \frac{T_s}{T_0} \times 100\,[\%]\,, \tag{5}$$

where T_s is axial tension of a tightening condition and T_0 is axial tension equivalent to 100% of tightening condition. 100% tightening condition is defined as the condition of that bolted joint being tightened to standard tightening axial tension. In our study, for uneasy calibration of partially loosening bolt and pattern overlapping obvious existence in our large structure since numerous structure joint bolts distribute densely, only the tight $S = 100\%$ and completely loose state $S = 0\%$ of bolts are considered.

Hence, the various cases tested are (i) healthy case: the structure is tested without any bolt loosening from the joint. (ii) unhealthy: the cases tested are the complete loosening of

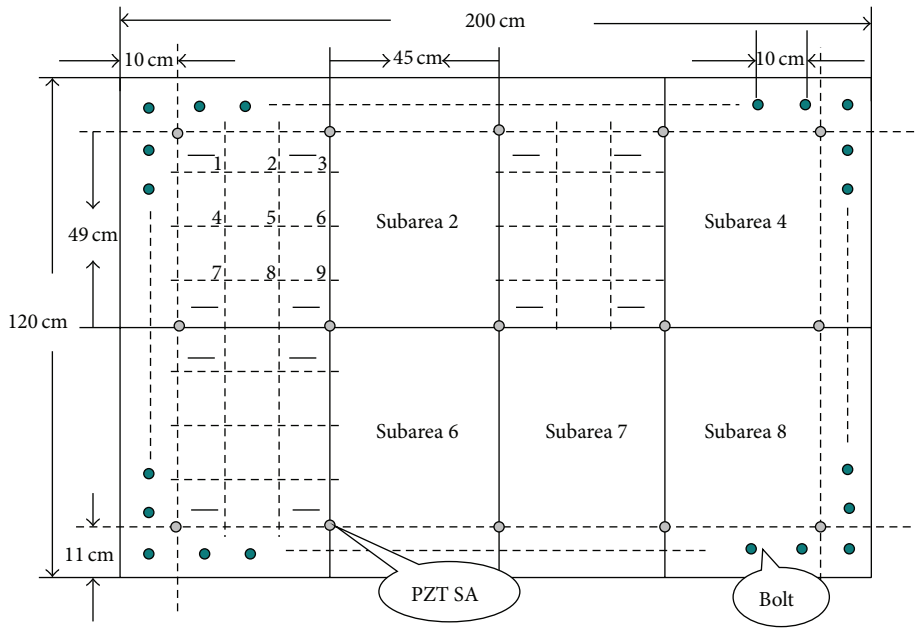


Figure 5: System setup.

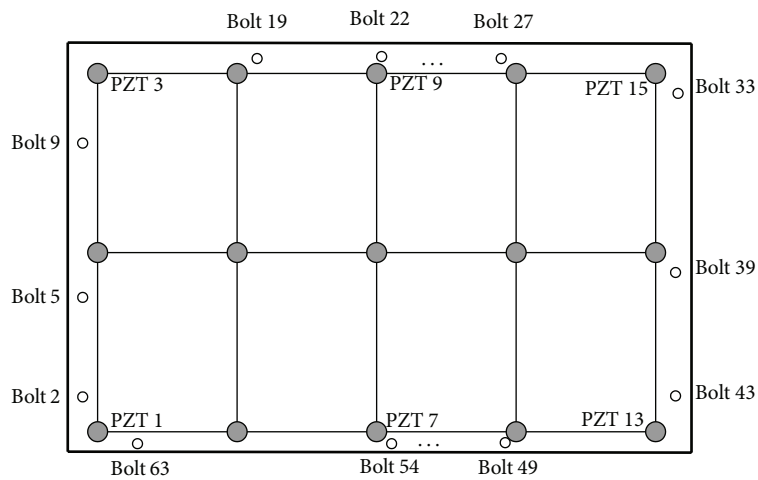


Figure 6: The loosening bolts monitored location.

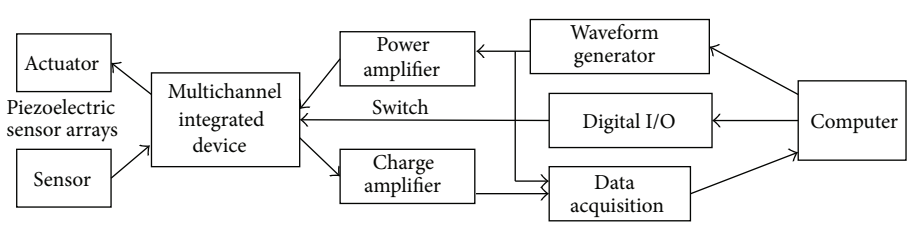
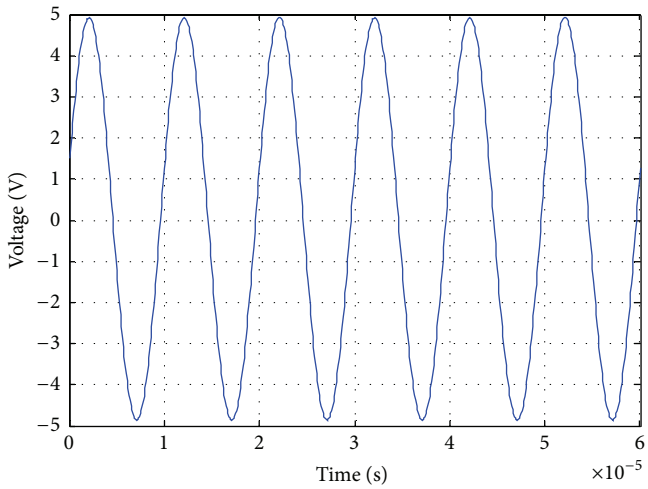


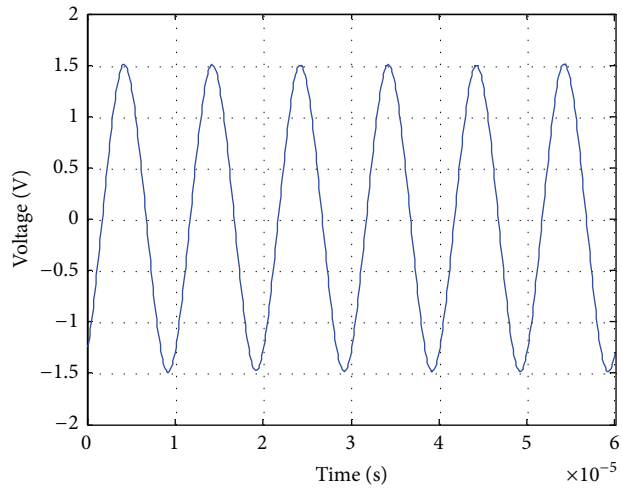
Figure 7: The principle structure of the active monitoring system.

Bolts 2, 5, 9, 19, 22, 23, 24, 25, 26, 27, 33, 39, 43, 49, 50, 51, 52, 53, 54, or 63 as shown in Figure 6.

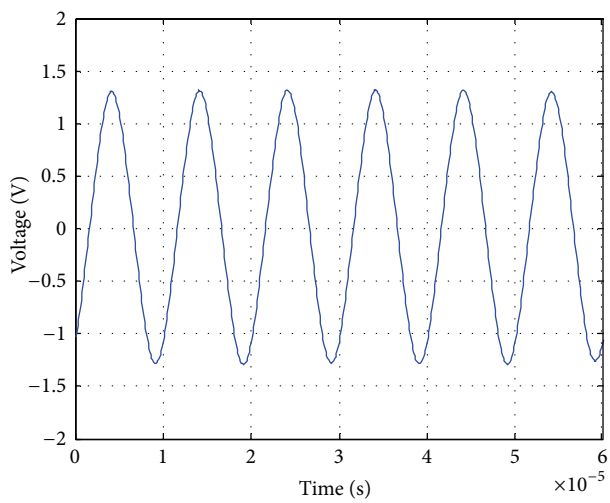
In the experiment, twelve PZT sensors around the boundary are employed to detect the bolt loosening with the cycle-actuator multisensor method. For the measurement hardware, the self-design integrate and program control multichannel piezoelectric scanning system is used in the active monitoring for bolt loosening [34]. As shown in Figure 7, the system integrates the waveform generator module, data acquisition module, charge amplifier module, digital I/O



(a) The excited sine signal



(b) The signal before bolt loosening



(c) The sensor signal after bolt loosening

Figure 8: The sensor signal change before and after Bolt 9 loosening.

module, multichannel scanning switch board, and power amplifier. It can interrogate the large numbers of actuator-sensor channel automatically and efficiently. The software is programmed with LabVIEW 8.5 and MATLAB R2006a in the industry control computer.

3.2. Data and Feature. The computer controls twelve PZT sensors circularly and periodically to excite and sense the structure strain signal. The excitation signal is the sine wave with 100 KHz. Lots of experiments [33] have shown that the vibration response of the structure under this excitation frequency is sensitive to the bolt loosening. The number of sampled data is 6000, and the measured time is 0.0006 s. The sample frequency is 10 MHz. Figure 8 gives the signal of PZT sensor 1 as actuator and PZT sensor 4 as sensor before and after bolt loosening (Bolt 9). There are two reasons for the acquired strain signal changes. Firstly, bolt loosening could cause the change of the prestress distribution in the structure, which makes the structure thickness change. Hence, Lamb wave with different modes generated by the PZT actuator propagates in the plate structure with a different velocity. Hence, PZT sensor acquires different Lamb wave signals before and after bolt loosening. Secondly, the bolt is deemed to be a scattering source on the Lamb wave propagation path between the actuator and the sensor. When bolt loosening can partly affect the scattering Lamb wave coupled with bolt, its previous propagation path changes, so the acquired Lamb wave signal changes. For sine wave excitation signal, the experiment [33] shows that the peak change is obvious before and after the bolt loosening. So, twenty-four acquired signal peaks of the twelve sensors on the plate border are combined to be a feature vector. For the chosen bolts, twenty-one modes' conditions are measured twenty-five times, and ten samples are measured to train parameters of the classifiers, and ten ones are used to train the fusion method. So finally we obtain a total of 525 samples, which consist of 210 samples for training classifiers, 210 samples for training fusion algorithms, and the remaining 105 samples for test.

Table 1: Parameters of individual classifier.

Classifier	SVM	C4.5	k-NN	IIS	LVQ
Parameters setup	Kernel function: $k(\mathbf{x}, \mathbf{y}) = (0.7\mathbf{x}^{\mathrm{T}}\mathbf{y} + 1)^2$ Euclidean distance type, penalty coefficient = 10	Percentage of incorrectly assigned samples at a node = 5	$k = 3$	Number of iterations = 50	Number of neurons = 50, epochs = 50

3.3. Classifier Description. Six pattern classification methods are utilized to identify the loosening bolt. The utilized classifiers are described as follows.

(1) Support vector machine (SVM): the method can implement the good recognition rate derived from a few training samples, and it is based on statistical learning theory [35]. Kernel function is a key parameter for SVM, which includes linear, polynomial, Gaussian RBF, and sigmoid.

(2) C4.5: the algorithm implements "If-Then" rules derived from the training data set [36]. These rules are used to classify the "unseen" data.

(3) k nearest neighbor (k-NN): the classifier is very simple and effective [37]. The k nearest neighbors of the unidentified test pattern are searched within a hypersphere of predefined radius in order to determine its true class, which is the most class in the k samples. If only one nearest neighbor is detected, k-NN is the minimum-distance classification.

(4) Improved iterative scaling (IIS): IIS is one of the major algorithms for finding the optimal parameters for the conditional exponential model [38]. Its underlying idea is that by approximating the log-likelihood function of the conditional exponential model as some kind of "simple" auxiliary function, it is able to decouple the correlation between the parameters and search for the maximum point along many directions simultaneously. By carrying out this procedure iteratively, the approximated optimal point found over the "simplified" function is guaranteed to converge to the true optimal point due to the convexity of the objective function.

(5) Gaussian mixture model (GMM): the classifier is based on Gaussian component functions [39]. The linear combination of Gaussian functions is capable of representing a large class of the sample distribution. In principle, it is a compromise between the performance and the complexity. Gaussian mixture has remarkable capability to model the irregular data.

(6) Learning vector quantization (LVQ): it is a neural network classifier proposed by Villmann et al. [40]. It combines the simplicity of competitive learning with the accuracy of supervision. It is a simple and intuitive prototype-based clustering algorithm.

4. Results and Discussion

This section describes the result of an experiment of the bolted joint monitoring using the proposed decision fusion system. Then, comparison and discussion are given for each part of the presented system.

Table 2: Classification results.

Classifier	SVM	C4.5	k-NN	IIS	GMM	LVQ
Accuracy	0.8952	0.5385	0.8571	0.1904	0.7524	0.3077

Table 3: Result of optimal sequence of classifiers fused.

Number of classifiers selected	Serial number of classifiers						Entropy-based diversity measure
1	1						—
2	1	4					1.127
3	1	4	6				0.978
4	1	4	6	2			0.878
5	1	4	6	2	3		0.826
6	1	4	6	2	3	5	0.596

4.1. Individual Classification. Next, six classifiers are utilized to classify the calculated features of the bolt loosening. The relevant parameters setup for these classifiers can be found in Table 1. Table 2 gives the test accuracy of the six classifiers. In the experiment, the classification accuracy is evaluated using a ratio of the number of the samples classified correctly to the total sample. It can be seen that the best classification accuracy is 0.8952 and 0.8571 of SVM and k-NN agents. As far as performance of the six classifiers is concerned, SVM and k-NN produce superior results followed by GMM agent. LVQ and IIS are not suitable in this work for joint failure. It implies that the two types of classifiers do not fit for the scatter of training samples. But in practice, it is almost impossible that all the predetermined classifiers will achieve the best performance at the same time. Otherwise, the fusion of pure good or bad classifiers group may not necessarily improve the accuracy [24]. Therefore, LVQ and IIS are still reserved for the fusion method.

4.2. Selection of Classifiers. Based on the individual classification decisions acquired in the first step, the entropy-based diversity measure method introduced in Section 2.1 is used for sequence selection of six classifiers. The optimized selected results for different numbers of classifiers and the entropy-based diversity degrees are shown in Table 3.

To evaluate the effect of classifier selection, Bayesian fusion method with classifier selection is compared with the one without classifier selection as shown in Figure 9.

Table 4: Relationship of accordance criterion, number of classifiers fused, and accuracy.

Accordance criterion ρ	Number of classifiers fused					
	1	2	3	4	5	6
	Accuracy					
0.50	0.895	0.933	0.962	0.952	0.949	0.956
0.55	0.895	0.933	0.962	0.952	0.949	0.956
0.60	0.895	0.933	0.962	0.952	0.949	0.956
0.65	0.895	0.933	0.962	0.952	0.949	0.956
0.70	0.895	0.933	0.962	0.952	0.971	0.971
0.75	0.895	0.933	0.962	0.952	0.971	0.971
0.80	0.895	0.933	0.962	0.952	0.971	0.971
0.85	0.895	0.933	0.962	0.952	0.971	0.971
0.90	0.895	0.933	0.962	0.952	0.971	0.971
0.95	0.895	0.933	0.962	0.952	0.971	0.971

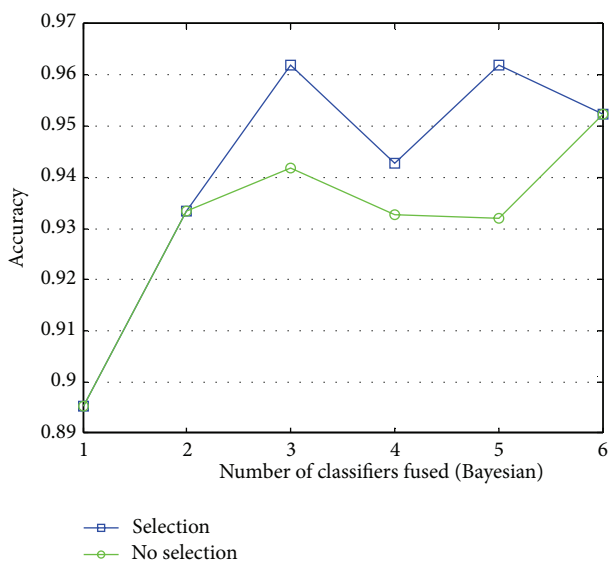


Figure 9: Effect of classifiers selection (Bayesian method).

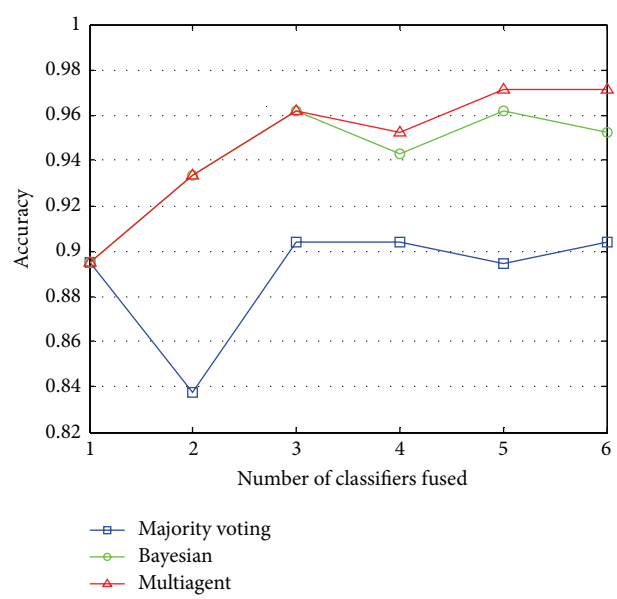


Figure 10: Fusion performances of three algorithms for current data.

The results show that the fusion accuracy rate with the selection process is higher than that of the no selection process. Therefore, selection of classifiers is proposed as a potential optimization process before the final decision fusion.

4.3. Decision Fusion. After the six classifiers are sequentially selected, the decision vectors of multiclassifiers are fused using three fusion methods, namely, majority voting, Bayesian belief, and multiagent method. In the multiagent method, accordance criterion is a vital parameter. The larger the value is configured, the longer computation time it takes and the better accuracy rate it produces. In order to search the optimization value, the value is traversed from 0.5 to 1 with a step size of 0.05 and the corresponding fusion results are shown in Table 4. When the value is 0.7 and the number of classifiers fused is 5, there is the optimization in the cost of time and the accuracy. While the accordance criterion is gradually increased from 0.7 to 0.9, the fusion result is not much improved.

The performance of the three fusion algorithms is compared as shown in Figure 10. It can be seen that multiagent method is better than Bayesian method when the number of classifiers fused is more than 3. The maximum fusion accuracy for multiagent method is 0.971, while it needs fusing 5 classifiers. While the maximum accuracy using Bayesian method is 0.962, it only needs 3 classifiers. The minimum accuracy for the two methods is 0.895. Compared with the other two methods, the maximum and minimum fusion accuracy for majority voting method are 0.904 and 0.838, and it gives the worst fusion performance. The reason is that multiagent and Bayesian methods involve soft dynamic fusion, and majority voting is only a static fusion process. Since multiagent method includes two-order correlation

degree between the classifiers, it provides better performance than Bayesian method.

5. Conclusions

In this paper, a decision system for bolted joint monitoring is presented which consists of individual classification, classifier selection, and decision fusion. The effectiveness of the proposed methodology is tested with examples of the large aviation aluminum plate structure. In the process, classification accuracy considering the classifier selection is superior to the ones without the step. To compare three fusion methods, the multiagent method is the best since the method not only considers the character of individual classifiers, but also the information exchange between the classifiers. Decision fusion strategy can improve the classification accuracy remarkable.

Based on the decision fusion framework, further studies are required concentrating on the following three parts:

(1) investigating more joint failure modes including the level of the bolt loosening and validating the effectiveness of the presented method; more studies are needed with complex structures to fully validate the new method;

(2) comparing other different methods of classifier selection and evaluating these methods;

(3) studying deeply the relation among the individual classifier, classifier selection, and fusion method.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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