Multi Channels Data Fusion Algorithm on Quantum Genetic Algorithm for Sealed Relays

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Abstract. Particle Impact Noise Detection (PIND) is a screening test that must be done before the sealed relay is released. PIND signals are mostly occasional weak, which are difficult to measure and identify. In this paper, the three channel sensor is used to detect the remainder signals, and the weak signal is enhanced by weighted data fusion. For the first time, quantum genetic algorithm (QGA) is used to self-adaptively configure the weight, taking the place of arti-ficial settings. Experiments show that after data fusion, and the variance is only about 20% of the single input signal, which verifies the effectiveness of the algorithm. The computational complexity of QGA is offered.

1. Introduction

The reliability in the aerospace system is extraordinary important. The remainder in the sealed relay is the main damage of the reliability. They are produced and remained during the processes such as manufacturing, sealing and application of the sealed relays. They are excited at the extreme mechanic condition, and move with a random motion, leading to the system failure. Most of the sealed relays can be manual produced only, easily generating the remainders. The occasional accidents caused by the remainders cannot be perceived or confirmed. This leads to a particularly serious hazard. The moving remainder particles in the sealed relays cause the failure in the launch of carrier rockets, satellites, missiles and shuttles, giving rise of immeasurable losses\(^1\). From 1996 to 2003, more than 60% of the accidents have been caused by the remainders. It demonstrates that the remainders in the relays are the main cause in the aerospace accidents.

Up to now, several methods are used to detect the remainders, including microscopic observation, X-ray photography, Matrah detecting and Particle Impact Noise Detection (PIND). PIND is widely applied because of its swiftness, convenience, low cost and high sensitivity.

PIND is first proposed by NASA as a non-destructive examination to detect the remainders in the military electronic components, semiconductor discrete devices, integrated circuit, aerospace relays. The remainders are excited according to the shock and vibration by the shaker, and then they may impact upon the cavity wall. The acoustic emission sensor transfer the impact energy to the voltage signal and export, determining if the remainders exist\(^2\),\(^3\).

Because the amplitude of PIND test signal is too small, the signal captured by a single sensor is often very weak and difficult to be analyzed. In order to reduce deviation and the environmental impact, many experimental times are required. This will greatly reduces the timeliness of remainder
detection, and may probably destroy some vulnerable components. The differences among the sensors lead to the deviations, losses and distortions of the collected signals, affecting the accuracy of the remainders detection. In addition, as the reproducibility of PIND test is poor, multi measurements will not achieve better results.

A multi-channels testing can effectively utilize the complementarities of signals to make the remaining signals stronger and more reality. This is an important way to improve the sensibility, accuracy and efficiency of the remainder test[4]-[6]. To integrate sampling signals from multiple channels, data fusion technology is introduced in this paper.

The data fusion technique is first proposed by the American army and applied in the military system. The systems became more and more complex with the industry development. Various kinds of sensors get more and more extensive applications. Then the data fusion technique for the sensors was developed rapidly[7]. Data fusion for multi sensors is a data processing technique. The data can be configured more effectively in multi ranks by the data fusion technique, including pixel fusion, feature fusion and decision fusion[8]-[10]. In this paper, the weak remainder signals were collected by three channels of acoustic emission sensor in the PIND. The channels were homogeneity. The waveforms of the output and the input were similar PIND signals, therefore, the pixel fusion was chosen.

The pixel fusion algorithm included principal component analysis, wavelet analysis, weighted fusion, the particle filters, Kalman filter[11]-[13], etc. In this paper, the ideal condition in the test is that the performance parameters of the three channels are the same. The arithmetic average method can be used for data fusion, therefore, the weighted fusion was chosen during the data fusion.

The weighted advantage is the real time processing, small amount of calculation and low mean square deviation[14]. During the weighted fusion, the results are closely related with the algorithm and the weights. Although the commonly used method of determining weights manually meets the requirements of real time dynamic data processing, it is hard to achieve the optimal fusion results when the accuracy requirement is high. In this paper, a weighted fusion algorithm based on quantum genetic algorithm (QGA) is introduced to realize self-adaptive weight determination.

In order to extract the weak remainder signals, an acoustic emission sensor with three channels is applied. Quantum genetic algorithm is first implemented to achieve the weights of the three signals after synchronization. Experiments show that the variance of the weighted average remainder signal is cut down to about only 20% of the original. Finally, the complexity of quantum genetic algorithm is discussed.

2. Computation scheme

2.1 Multi channels data fusion based on QGA

In the experiment, three independent crystals for detecting sound emitting were placed as shown in figure 1. As these positions were the most sensitive, the relays were fixed if they were small.

When multi-channel homogeneous sensor sampling, the sample variance comes from the slight difference among the channels, or the random influence of noise on the signal in data measurement. It reflects the consistency and concentration of the measured data of each sensor and can be used to represent the performance of the measurement method. The larger the variance of the samples, the more discrete the data, the greater the randomness, the greater the difference among the channels, and vice versa. The size of the total sample variance directly determines the rationality of the fusion algorithm and the reliability of the fusion data[8],[10].

In this paper, we take the sample variance as the fitness function, find its minimum value, take the channel weighted factors as the variables, and use QGA to calculate.

The algorithm does not need to provide guidance to the calculation of the weighted factor through the parameters of the sensor itself. Based on the data collected by each channel, the data can be fused according to the minimum variance of the samples. The multichannel data weighted fusion algorithm model is shown in figure 2.
In the same signal measurement, the weighted factor for each channel in weighted fusion satisfies

$$\sum_{i=1}^{l} W_i = 1$$  \hspace{1cm} (1)$$

Here $l$ is the channel amount, and $W_i$ is the weighted factor for the respective channel.

2.2 Data synchronization test

It is assumed that $n$ data collections will be performed in a PIND test. The $j$th ($1 \leq j \leq n$) data collection results in the $i$th channel are recorded as $S_{ij}$. Ideally, all $n \cdot j$ data are valid data. However, in the actual PIND detection process, if a channel has a large interference or a sudden failure in a certain collection without checking, there will be large errors or even faults. Then these will have a catastrophic effect on the results, resulting in the failure of the fusion. Therefore, after the data collection is completed, the synchronization of data collected by each channel should be checked before the data is fused. Here, "synchronization" has two meanings. First, the pulse numbers and the appearance time in each channel are basically the same; the second is similar waveforms. The so-called similarity refers to the pulse amplitude collected by each channel, which is very approximate in the same position and proportional to different positions. The purpose of synchronization test is to preprocess signals, remove error data and faults in multiple channels, and provide assurance for the accuracy of data fusion results.

Two data synchronization indicators are presented in this paper

(1) Synchronization of pulses.

Compare the number of pulses in each channel, and whether the beginning and ending point of the same position is basically the same. According to the signal sampling rate of the detection system is 500kHz, the difference threshold of the synchronization of the pulse is set to $\sigma_s \leq 1000$ at the beginning position and $\sigma_s \leq 1000$ at the ending position. If the difference between the two channels exceeds the threshold value at the same time, it is determined that the pulse is not synchronous.
2) Similarity of pulses.
Determine whether the difference between the amplitude of the pulse at the same location is smaller than the threshold $\epsilon$ determined by the sensor's precision.

$$|S_{i1}(j) - S_i(j)| \leq \epsilon \quad i = 1, 2, \ldots, l - 1$$  \hspace{1cm} (2)

If equation (2) is satisfied, the ratio of pulse amplitude to different positions of each channel will be verified. The similarity judgment function is

$$\eta = \frac{A_{m,n}}{A_{m+1,n}} - \frac{A_{m,n+1}}{A_{m+1,n+1}}$$  \hspace{1cm} (3)

Because of the homogeneity of the sensitive elements, if equation (1) is satisfied and the pulse matches, the ratio of the amplitude of the waveform pulse of each channel should be close to the fixed value at the same time, and the similarity judgment function should be close to zero. In the same test, if the value of $\eta$ does not fluctuate within the neighbourhood $U(0, \delta)$ with the different values of $m$ and $n$, the pulse asynchrony is determined. The value of neighbourhood radius $\delta$ varies with the type of relay and the size of remainders.

2.3 The fusion algorithm
After the synchronization test, the multichannel remainder signals are weighted. In the same PIND test, $n$ signals are collected, and each channel data is assigned after each sampling. Weighted fusion gives an estimate of the current measurement

$$H'S(j) = \sum_{i=1}^{l} \mathcal{W}_i S_i(j)$$  \hspace{1cm} (4)

The total estimate of the experiment is obtained by arithmetic averaging $n$ estimates

$$\bar{H} = \frac{1}{n} \sum_{j=1}^{n} H'S(j)$$  \hspace{1cm} (5)

The total sample variance is the following equation

$$\delta^2 = \frac{1}{n-1} \sum_{j=1}^{n} (H'S(j) - \bar{H})^2$$  \hspace{1cm} (6)

It can be seen from equation (6) that the variance of the total sample is a quadratic function, and its independent variable is the weight value of each channel. When the function is minimized, the estimated value of data fusion is optimized. At this point, the task of finding the optimal data fusion is transformed into the process of minimizing $\delta^2$ by the weight of each channel under the constraint of equation (1). The optimization of weight depends on the measurement value of each channel and QGA. After calculating the optimal weight of each channel, the optimal estimate value of $H'S(j)$ for each measurement can be obtained according to equation (4), and the final data fusion optimal estimate value $\delta^2$ can be obtained.

The three-channel $S_1$, $S_2$, $S_3$ detect the sound signal during the weak signal detection of multiple residues. In repeated experiments, each channel can measure $n$ data, denoted as $S_i(1)$, $S_i(2)$, $S_i(3)$, $S_i(n)$. In the process of using QGA for weight optimization distribution, due to $W_1 + W_2 + W_3 = 1$, this paper makes $W_3 = 1 - W_1 - W_2$ to change the optimization variable from 3 variables $(W_1, W_2, W_3)$ to 2 variables $(W_1, W_2)$, reducing the randomness of the variable and the complexity of the algorithm. Since $W_1, W_2$ needs to satisfy $W_1 + W_2 < 1$, not two unrelated free variables are inconvenient to implement in QGA. For the simplicity of the calculation, $a_i, a_2 \in (0,1)$, $W_1 = a_1$, $W_2 = a_2(1-a_1) \cdot W_3 = 1 - W_1 - W_2$ can be made.

The flow chart of multichannel data fusion based on QGA is shown in figure 3. The final result can be obtained through the continuous cycle of parameter setting, quantum gate operation, fitness function calculation and selection.
QGA is developed from traditional genetic algorithm combined with quantum computing. Of course, it also inherits the algorithm method of genetic algorithm, which mainly includes steps such as coding, evaluation, selection, crossover, and variation[15],[16]. Compared with the traditional optimization method, QGA only focuses on global optimization of the objective function according to the established constraints, and is not affected by other conditions. Therefore, QGA is more widely applicable.

The proposed QGA-based multi-channel data fusion steps are as follows:
(1) Complete the data synchronization test.
(2) Initialization of the population.
Random numbers between 0 and 1 are generated as initial weight populations, and each weight individual represents the gene code of the quantum chromosome. In order to reduce the population size and complexity of the algorithm, and to improve reliability, all genes \((\alpha_{ij}, \beta_{ij})\) of all chromosomes in the \(P(t)=\{P_1, P_2\}\) population containing two parameters are initialized into quantum probability coding so that all possible states are superimposed with equal probability on the same chromosome.

(3) Detect individuals.
The qubit probability \(|\alpha_{ij}|^2\) or \(|\beta_{ij}|^2\) is measured first. Generate a random number between 0 and 1 and compare it with the square of the probability range. If the random number is large, take 1, otherwise take 0 and record it as \(x_{ij}\). The \(m\) individual values contained in the initial weight population are measured as \(R(t)\)\(=\{r_{11}, r_{12}, \ldots, r_{1m}\}\), where \(r_{ij}\) \( (j=1,2,\ldots,m)\) is the measurement value of the \(j\)th individual in the \(t\)th generation population represented by binary numbers, each of which corresponds to \(x_{ij}\).

(4) Evaluate individuals.
The fitness of individual weights is calculated. Determine whether the total variance has been minimized. When the condition is satisfied, output the best weight, otherwise continue to iterate.

(5) Selection.
According to the calculation results, if the iteration is continued, the individuals with high fitness will be selected to produce the offspring.

(6) Generation of offspring
Using quantum rotation gate to realize chromosome evolution.

(7) Output results
If the condition of minimum variance is satisfied, the best weight estimate and total variance are output, otherwise return to step (4).

3. Experimental results and analysis
First, data synchronization test is carried out. The PIND acoustic emission signals collected from three channels are extracted, and the results of two channels are shown in figure 4. By comparison, the difference between the beginning and ending points of the two signals is less than the threshold set, and the two waveforms are similar. The collected signal can be checked by data synchronization.

Data fusion is done after completion of synchronization test. Increasing the sampling scale can reduce the effect of accidental error. The number of \(n=200\) in the PIND test is set, and the algorithm is iterated 300 times. QGA is used to optimize the weight distribution of three channels, and the optimal estimates of sample variance and data fusion are obtained. Table 1 lists the optimized weights of each channel, the sample variances of each channel and the total sample variance after data fusion.
After analysis, we get the following conclusions.

1. In this experiment, the weights optimized by the algorithm are close to the arithmetic average value of 0.3333, which shows that the sensor has good consistency and no fault occurs in the PIND detection process.

2. Comparing the three-channel sample variance data with its assigned weight, it is found that the weight allocation is inversely proportional to the sample variance, which verifies the correctness of the algorithm.

3. Comparing the total sample variance and single channel sample variance after data fusion, it is found that the total variance is less than any single channel variance, which verifies the effectiveness of the algorithm.

After getting the corresponding weights of the three channels, we can fuse the collected three-channel sound signals to get the optimal fusion estimation, which is convenient for subsequent data processing. The signal collected by the three sensors is shown in figure 5(a)-(c), and the result of signal fusion is shown in figure 5(d).
4. The complexity of algorithm

The complexity of algorithm can reflect the efficiency of the algorithm, and it is mainly analyzed by the execution steps of the algorithm. This is analyzed by the incremental method. In this way, the operating steps executed by the programs to roughly estimate the implementation efficiency of the algorithm. Let \( N_c \) be the number of populations in the quantum genetic algorithm, \( n \) the length of the sending sequence of the population, and \( G \) the number of iterations (Generation_num). The time complexity of the entire iterative process is as follows.

| Step | Flow of Quantum Genetic Algorithm | Time-Complexity |
|------|----------------------------------|-----------------|
| 1    | Initial Population               | \( O(1) \)      |
| 2    | Calculate the Fitness Function Value of each individual | \( O(N_c \cdot n \cdot G) \) |
| 3    | Quantum Cross Operation          | \( O(N_c \cdot n \cdot G) \) |
| 4    | Quantum Rotary Gate Mutation Operation | \( O(N_c \cdot G) \) |
| 5    | Comparison the Result, and Saving the Current Optimal Individual | \( O(N_c \cdot G) \) |
| 6    | Judge whether or not to Satisfy the condition | \( O(G) \) |
| 7    | Regeneration Population          | \( O(N_c \cdot n \cdot G) \) |
| 8    | Output the Result                | \( O(1) \)      |

According to Table 2, the time-complexity of QGA was

\[
T_{QGA}(n) = O(4 \cdot N_c \cdot n \cdot G + N_c \cdot G + G + 2) .
\]

When \( n \) was big enough, the influence of low power term could be ignored. So the time-complexity of QGA approximate to

\[
T_{QGA}(n) \approx O(4 \cdot N_c \cdot n \cdot G) .
\]

5. Conclusions

In this paper, the three channel acoustic emission sensor is used to test the sealed relay by PIND. The three channel signal is detected through synchronization test, including the synchronization and similarity of pulses. According to the homogeneity of sensitive components, the weighted average method is used for data fusion. For the first time, QGA is used to adaptively configure the weight of each channel signal. The test was carried out 200 times, and the algorithm was iterated for 300 generations. Experiments show that after data fusion, and the variance is only about 20% of the single
input signal, which verifies the effectiveness of the algorithm. The computational complexity of QGA is about $O(4 \cdot N_c \cdot n \cdot G)$.

Acknowledgments
This study was co-supported by the National Natural Science Foundation of China (Nos. 51607059, 51077022 and 61271347); the National Natural Science Foundation of Heilongjiang Province (QC2017059); Postdoctoral Fund in Heilongjiang Province (LBH-Z16169); Science and Technology Innovative Research Team in Higher Educational Institutions of Heilongjiang Province (No.2012TD007); Heilongjiang University Youth Science Fund Project (QL201505).

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