Paper

Quality Evaluation of Transmission Devices Using the GA

Bingchen Wang* Student Member
Sigeru Omatu* Member
Toshiro Abe** Non-member

In this paper, we propose a new method of evaluating the quality of a transmission device according to the acoustic data by using the genetic algorithm (GA). We consider that the "spectrum average" and the "frequency variation" reflect the characteristic of acoustic data. In this paper, we first extract the "spectrum average" and the "frequency variation" from the acoustic data of operating transmission device. Then we use the GA to select the "significant frequencies" and determine the boundary between good and no good products. The experimental results show that the proposed method can perform the quality evaluation of transmission devices successfully.

Keywords: GA, quality evaluation, acoustic data, spectral feature extraction

1. Introduction

As is well known, transmission devices have been widely used in many kinds of machines. At present, most factories depend on skilled workers to test the quality of transmission devices by listening to the sound. This inevitably causes some problems. For example, the results of testing will sometimes vary according to the worker, and even the same worker may obtain different results for the same machine on different occasions. Thus, developing a means of automatic and quantitative testing becomes an important problem. Moreover, skilled workers have to continuously learn new knowledge in order to test new products effectively. To reduce the training time, an intelligent testing system is required.

Research on acoustic recognition has made rapid progress in recent years[(1)~(3)]. Teranishi *et al*[(4)]. have classified new and used bills using the acoustic data from a bank machine. In their research, they checked whether the bill is new or old according to the acoustic energy pattern by using a competitive neural network. Kamimoto *et al*[(5)]. proposed a method of performing the quality recognition of interphones by a learning vector quantization (LVQ) method. In a previous study, Wang *et al*[(6)]. proposed a method of testing the quality of machines automatically by using a neuro-classifier trained by the LVQ. In that paper, we have tested the quality of machines by only using the "frequency variation". But in the practical production, we have found that the "spectrum average" was also important where the definition of "spectrum average" and "frequency variation" will be stated in the next Section. From the abnormal power spectrum, we can estimate the cause of trouble easily. For such no good products as "LS" and "HS", it seems that using the "spectrum average" is more effective than the "frequency variation" in quality evaluation where "LS" denotes the sound is too loud and "HS" denotes the sound has a high tone. However, it is difficult to use the whole "spectrum average" to test the quality of a transmission device. We should determine some "significant frequencies" and use them to evaluate the quality of transmission devices.

In this paper, we propose a new method of evaluating the quality of a transmission device according to the acoustic data by using the genetic algorithm (GA). The contents of this paper are as follows: In Section 2. we introduce the quality evaluation system. In Section 3. we explain how to get the "spectrum average" and the "frequency variation". In Section 4. we introduce how to select the "significant frequencies" and how to determine the boundary according to the spectral data by using the GA. In Section 5. we test some new data and show the results. The last Section is the conclusion.

2. Quality Evaluation System

Figure 1 shows the quality evaluation system. We first record the acoustic data while good and no good products are running. Then we compute the "spectrum average" and the "frequency variation" in the process of feature extraction. Next, we select some "significant frequencies" from the whole frequency field by using the GA. Then we use the GA to determine the boundary between good and no good products according to the selected

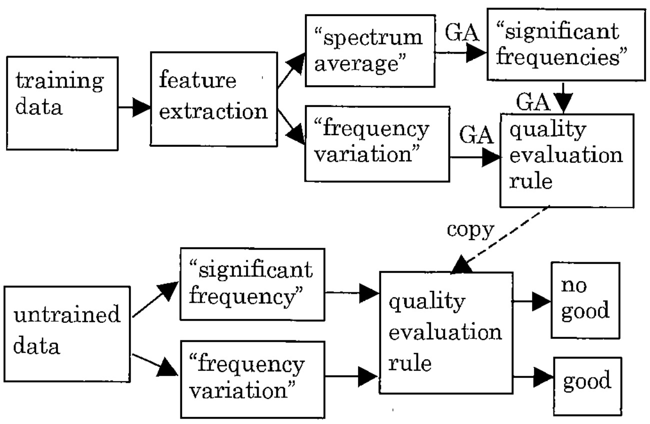


Fig. 1. Quality evaluation system.

* Division of Computer and Systems Sciences, Graduate School of Engineering, Osaka Prefecture University
Sakai, Osaka 599-8531
** The foundation of Osaka Science & Technology Center
8-4, 1choume, Utsubohonmachi, Nishi-ku, Osaka 550-0004

frequencies and the periodicity of "frequency variation". At last, in order to verify the effect of the proposed method we test some untrained data by using this boundary. The testing results show that the proposed method can perform the quality evaluation of transmission devices successfully.

3. Feature Extraction of Spectrum

In this paper, the transmission device is driven with a constant load in a sound booth. We use a microphone, which is located near the motor, to record the acoustic data of the transmission device. After amplification, it is digitized to 16-bit data by an analog-digital converter. Then the data are stored in a personal computer. As an example, Fig. 2 shows the acoustic data wave of a good product. The sampling rate is 44.1kHz and the recording time of each acoustic data is about 11 seconds.

Figure 3 shows the computation process of "spectrum average" where ①, ②, and ③ denote the acoustic data, the spectrum, and the "spectrum average", respectively. First, we apply the fast Fourier transform (FFT) to the acoustic data. In consideration of frequency resolution, we set the length of each frame as 4,096 and apply the Hamming window. From the acoustic data, we take 4,096 data in order and compute their spectra. If we take Nx4,096 data, we can obtain N spectra. We compute the average of these N spectra which are called "spectrum average". In what follows, all the data denoted in figures are normalized by suitable values. Figure 4 shows an example of "spectrum average" of good and no good products. The horizontal axis denotes the frequency and the vertical axis denotes the amplitude.

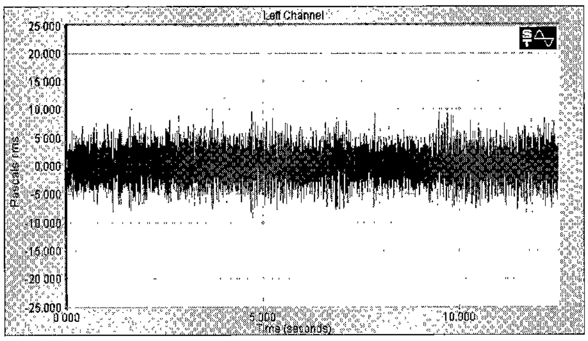


Fig. 2. Acoustic data wave of a good product.

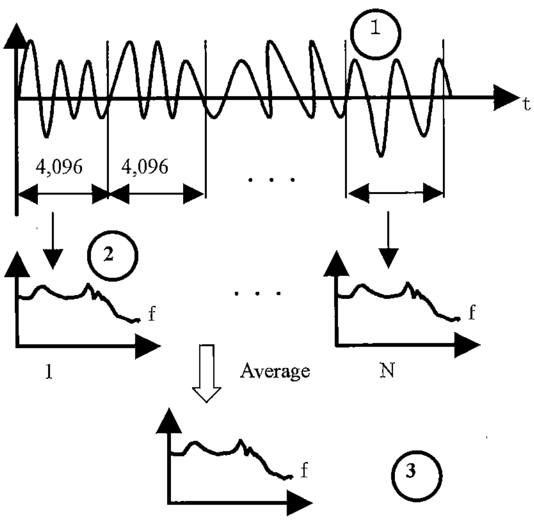


Fig. 3. Computation process of "spectrum average".

Next, we compute the feature vector of "frequency variation". Figure 5 shows the computation process of the feature vector of "frequency variation" where ①, ②, ③, and ④ show the acoustic data, the spectrum, the "frequency variation", and the feature vector, respectively. Since we take an interest in the frequency variations with time, we set the length of each frame as 1,024 and apply a 50% overlap to improve the time resolution. Instead of studying the entire frequency field, a frequency range [m[Hz], n[Hz]] is selected based on the expert's knowledge and the "spectrum average". We compute the average value of amplitude in the selected frequency range and draw the variation of the average value with time. In this paper, we call it "frequency variation".

Figure 6 shows an example of "frequency variation" for good and no good products. The horizontal axis denotes the time and the vertical axis denotes the amplitude. It can be seen that the "frequency variation" of the good product is different from that of the no good product, but it is difficult to classify them. From Fig. 6, we observe that both good and no good products have

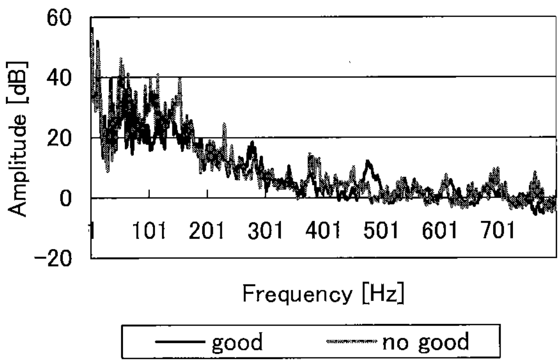


Fig. 4. "Spectrum average" of good and no good products.

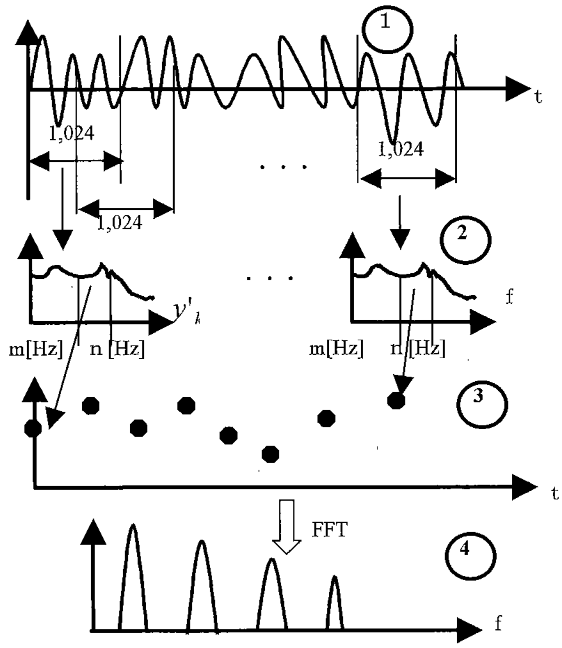


Fig. 5. Computation process of feature vector of "frequency variation".

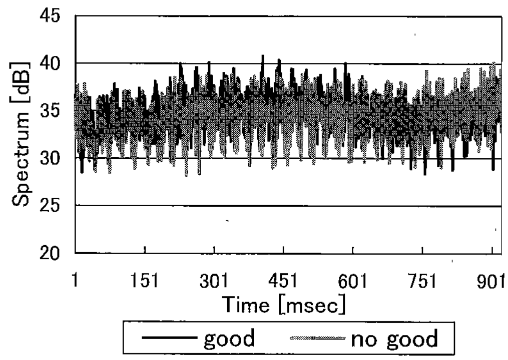


Fig. 6: "Frequency variation" of good and no good products.

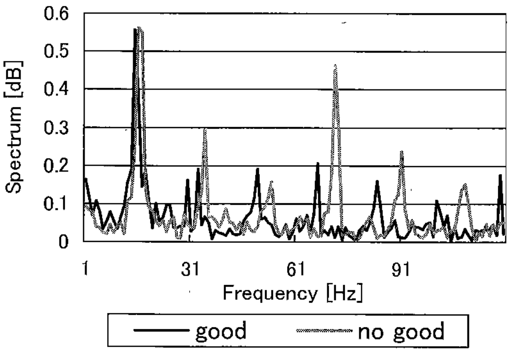


Fig. 7. Feature vectors for good and no good products.

periodicities. From the mechanical structure of the machine, it can also be concluded that the acoustic data of the operating machine have periodicity. Thus, we consider the "frequency variation" as a time series, and apply the FFT to it again. Then we select a part of the FFT result as the feature vector of "frequency variation".

Figure 7 shows the feature vectors of good and no good products where the samples are the same as those in Fig. 6. The horizontal axis denotes the frequency and the vertical axis denotes the amplitude. It is obviously that the feature vectors of good and no good products have different characteristics.

4. Quality Evaluation with the GA

In this paper, we construct an intelligent test system that is able to give a correct classification result for the acoustic data of any input product and this result must be as near as possible with those given by skilled workers. This system must have the ability that can learn the difference between good and no good products by itself. In Ref. (6), we have used the LVQ algorithm to classify the good and no good products successfully according to the feature vector. But as mentioned above, in the practical production we find that the frequency characteristic is also important. Especially, for such no good products as "LS" and "HS", they have large values in some particular frequencies but there are no obvious features in their "frequency variation". For these kinds of no good products, it seems that using the "spectrum average" is more effective than the "frequency variation" in quality evaluation. Moreover, from the "spectrum average" we can estimate the cause of trouble based on the abnormal power spectrum in some frequency ranges from theoretical viewpoint. Thus, we consider that the characteristic of acoustic data is determined by two factors: One is the "spectrum average", and the other is the "frequency variation". For the "spectrum frequency", it is unreasonable and not necessary to apply the entire frequency field to the classification of good and no good products. In our case, the length of each frame is 4,098 in FFT processing, which means even using only the frequency range [0,8[kHz]], there are about 800 data. It is difficult for applying these data to the classification of good and no good products using the LVQ. Since the GA performs a multi-directional global search, it has been quite successfully applied to an optimization problem. In this paper, we select some "significant frequencies" from the entire frequency field and determine the boundary between good and no good products by using the GA.

We select 18 good products and 22 no good products as the training data where good or no good products are inspected by a skilled worker. We use her inspection results as the evaluation standard. Since the inspection results are determined by the skilled worker with good state of mind in quiet environment, we consider that the results are trusty. In practical production, more than one skilled worker is recommended. The number of individuals in each generation is 20. The crossover rate is set to 0.4 and the probability of mutation is set to 0.01.

4.1 Evaluation of the "Spectrum Average"

In this paper, we have confirmed that those high frequencies, which are larger than 8kHz, have little effect on the characteristic of acoustic data by using the low-pass filter. Thus, we adopt the frequency range [0,8[kHz]] as the input of the GA. Since the FFT result is discrete, we can represent this frequency range as $\{x_1,\cdots,x_n\}$,, and the corresponding power spectrum is stated as $\{y_1,\cdots,y_n\}$. In this paper, n is 780. Fig. 8 shows the process of extraction the quality evaluation rule from the "average spectrum" by using the GA where f_i denotes the fitness of each frequency, O_i denotes the ranking of each frequency based on f_i and F_i denotes the ability of quality evaluation of the selected "significant frequencies".

4.1.1 Stage 1: Selecting "significant frequencies"

In this stage, we evaluate the classification ability f_i of each frequency x_i by using the GA and select the "significant frequencies" according to f_i.

For each frequency x_i, the input data of GA is the amplitude y_i, the output data is optimum amplitude y'_i and the corresponding fitness f_i which denotes the ability of classifying good and no good products. Since the amplitude of each frequency x_i varies between –20 and 80 [dB], we set the domain as [-20,80]. The required precision is 2 places after the decimal point. This means that 14 bits are required as a binary vector:

$$8{,}192 = 2^{13} < 10{,}000 < 2^{14} = 16{,}384 .$$

For each frequency x_i between 0 and 8kHz:

1) Producing initial individuals. We compute the average amplitude y_i of all good and no good products on each frequency x_i. Then we produce 20 individuals $\{x_i,(y_{i1},\cdots,y_{i20})\}$ by adding the random value to the average amplitude y_i.

2) Evaluation. We apply the teaching data to evaluation of each frequency. For the frequency x_i, if its amplitude y_i is larger than that of a good product, or its amplitude y_i is smaller than that of a no good product, we add one to its fitness.

3) Selection. We use the elitist model to select the parents group. We preserve the best individual in each generation, and select the other individuals in a roulette wheel with slots sized according to fitness.

4) Crossover and mutation. The amplitude of each frequency can be represented as a 14 bits binary vector, we decide the crossover point randomly and apply the one point crossover. The mutation operation is treated by selecting one gene at random from the binary vector and inverting it.

We repeat steps 2)～4), until the number of generation is larger than 2,000. Thus, for each frequency x_i we obtain a fitness f_i, which denotes its recognition ability of good and no good products. Then we order the frequencies $\{x_1,\cdots,x_n\}$ according to the fitness f_i. From the frequency range $\{x_1,\cdots,x_n\}$, we select the best 20 of x_i as the "significant frequencies".

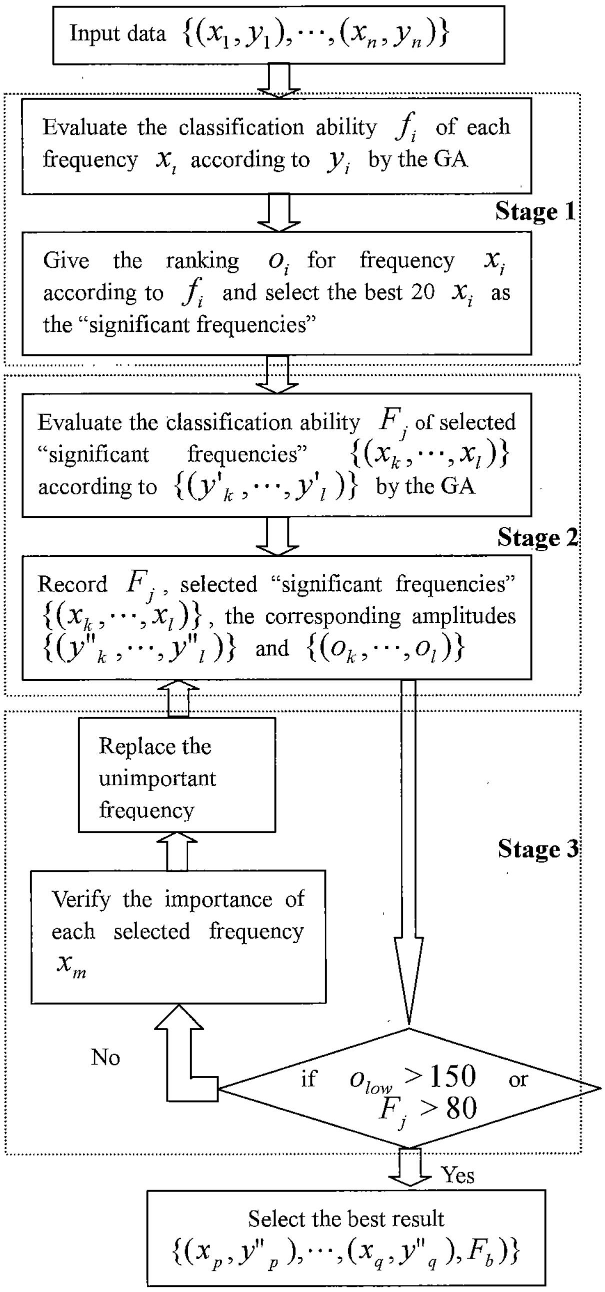


Fig. 8. Extraction of the quality evaluation rule from the "average spectrum" by using the GA.

4.1.2 Stage 2: Determining the Optimum Values of Amplitude for the Selected "Significant Frequencies"

In this stage, we use the GA to adjust the power spectrum of selected "significant frequencies". In stage 1, we get the optimum amplitude for each frequency x_i. However, when we use them together we need adjusting the amplitudes of select "significant frequencies". The input of the GA is $\{y'_k,\cdots,y'_l\}$, the output of the GA is $\{y''_k,\cdots,y''_l\}$ and the corresponding fitness F_j where subscript j denotes the repeating times of stage 2.

i) Producing initial individuals. We produce the 20 initial individuals $\{(x_k,\cdots,x_l),[(y'_{k1},\cdots,y'_{l1}),\cdots,(y'_{k20},\cdots,y'_{l20})]\}$ by adding the random value to the present amplitudes $\{y'_k,\cdots,y'_l\}$ of selected "significant frequencies". The individual is represented as a series of 14 bits binary vectors.

ii) Evaluation. For the "significant frequencies", if their all amplitudes are larger than those of a good product, or if the amplitude of any frequency is smaller than that of a no good product, we add one to the fitness F_j. We adopt two conditions: "spectrum average" and "frequency variation" to test the quality of products. Only the recognition results of both "spectrum average" and "frequency variation" are good, the product will be looked as a good product. For no good products, even if we cannot recognize them, we still have a chance to be corrected in the next recognition. But for the good products, if we make a mistake, we cannot correct it anymore. Moreover, not all the products which have large amplitudes are no good. For some frequencies, their amplitudes have no relationship with classification of good and no good products. In order to avoid this kind of misclassification, we subtract one from the fitness F_j if the good product is misclassified as a no good product. We set the initial value of fitness be the equal of the number of training data to ensure that the fitness F_j is always large than zero.

iii) Selection. We use the elitist model as described above.

iv) Crossover and mutation. The processes of crossover and mutation are showed in Fig. 9.

We repeat steps ii), iii), and iv), until the number of generation is larger than 20,000. Here, we increase the number of generation, since each individual includes 20 real numbers. After evolution, we record the best individual $\{(y''_k,\cdots,y''_l)\}$, the best fitness F_J, the selected "significant frequencies" $\{(x_k,\cdots,x_l)\}$ and corresponding ranking $\{(o_k,\cdots,o_l)\}$.

4.1.3 Stage 3: Replacing the Unimportant Frequencies

In the above stage, we obtain the best amplitudes of selected "significant frequencies". But we cannot ensure that all the "significant frequencies" play an important role in the classification of good and no good products. When we use the

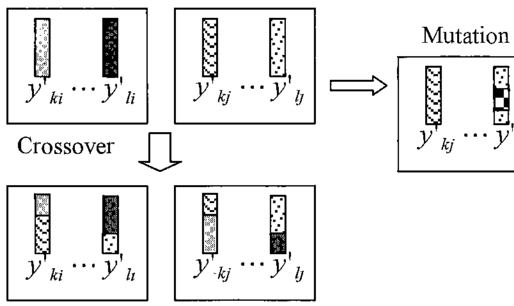


Fig. 9. Process of the crossover and mutation.

"significant frequencies" as a whole, it is possible that each frequency will conflict each other. This confliction will lead up to the result that some frequencies have no effect on recognition of good and no good products. Therefore, we check each frequency x_i of present "significant frequencies", if the amplitude of any frequency x_i is larger than the amplitude of all no good products, we consider that the frequency x_i is not necessary to the quality evaluation. We discard this frequency x_i, and select the frequency which has the best fitness from the remaining frequencies. Repeat the operation of stage 2, until the best 150 in the remaining frequencies are used or all good and no good products are classified correctly.

4.1.4 Final selection In stage 2, we record the "significant frequencies", their amplitudes and the corresponding fitness. If we repeat stage 2 N times as described in stage 3, we can obtain N series "significant frequencies", amplitudes and the corresponding fitness where N is determined by the inputting good and no good samples. In this paper, N is 5. From these N series "significant frequencies", we select the one, which have the largest fitness value F_b as the quality evaluation rule.

4.2 Evaluation of the "Frequency Variation" As we mentioned, in the previous study we use the feature vector of "frequency variation" to classify good and no good products. But it seems that using the GA to evaluate the "frequency variation" is more efficient since we have used the GA to evaluate the "spectrum average". From Fig. 7, we can see that the peaks of feature vectors play an important role in discriminating between good and no good products. We have also obtained the same conclusion from the classification results by the LVQ in the previous study[6]. Figure 10 shows these peaks.

As a good product, it must satisfy the following two conditions: One is that the value of each peak must be smaller than some value. The other is that the value of p4 cannot be too large comparing with the values of neighbor peaks p3 and p5, which are concluded from the classification results of previous study. Here, we define a variable p7=p4/max(p3,p5). For a good product, its value must be smaller than some value. We use the GA to search the optimum value of data series {p1, p2, p3, p4, p5, p6, and p7}. The process of the GA is described as follows:

Step 1. Representation. Since each data varies between the range [0,2] and the required precision is three decimal places for each variable, we select the length of bits as 11 for one chromosome.

Step 2. Initiation. We first compute the averages of all good and no good products, and then we produce the initial individuals randomly according to these averages.

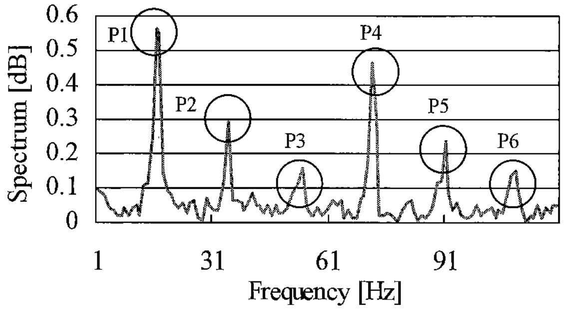


Fig. 10. The peaks of feature vector.

Step 3. Evaluation. If any value of the data series is smaller than that of a no good product, or if all the values of the data series are larger than those of a good product, we add one to the fitness. If the good product is misclassified as bad product, we subtract two from the fitness.

Step 4. Selection. We use the elitist model to select the parents group.

Step 5. Crossover and mutation. The process of crossover and mutation is same as shown in Fig.9.

Repeat Steps 3, 4 and 5, until the number of generation becomes larger than 10,000. We record the value of the best individual, and use it to classify the good and no good products.

5. Experimental Results

Table 1 shows the evaluation results of teaching data by using "spectrum average" and "frequency variation", respectively where 1 means good and 0 means no good. Because of the limit of space, we cannot list all the evaluation results. We select 8 good products and 12 no good products from the teaching data. Here, G denotes good product, and B denotes no good product. From Table 1, we can see that all the good products are recognized correctly as we expect. We also notice that sample B7 is evaluated as a good product while using "spectrum average".

Figures 11 and 12 show the "spectrum average" and the feature vectors of "frequency variation" of samples G3 and B7, respectively. From Fig. 11 we can see that the "spectrum average" of B7 is similar with that of G3. Thus, we cannot classify them by using the "spectrum average". But we can classify them by using the feature vector as shown in Fig. 12.

Tables 2 and 3 show the evolution results of "spectrum average" and "frequency variation", respectively.

In order to verify the effectiveness of our proposed method, we use above evolution results to test 40 new data. Table 4 shows the

Table 1. Training result.

File No.	Teaching	Average	Variation
G1	1	1	1
G2	1	1	1
G3	1	1	1
G4	1	1	1
G5	1	1	1
G6	1	1	1
G7	1	1	1
G8	1	1	1
B1	0	0	0
B2	0	0	0
B3	0	0	0
B4	0	0	0
B5	0	0	0
B6	0	0	0
B7	0	1	0
B8	0	0	0
B9	0	0	0
B10	0	0	0
B11	0	0	0
B12	0	0	0

part of their results which include 8 good products and 12 no good products where Human denotes the test results by a skilled worker, Computer denotes the test results by a computer, Ave. denotes the "spectrum average", and Var. denotes the "frequency variation". In order to distinguish the samples from those in Table 1, we name the samples as GN or BN. From Table 4, it can be found that all the good and no good products are classified correctly. Sample BN10 is a no good product. The test result of the skilled worker is "LS". But as shown in Table 4, the test result of the "frequency variation" gives a wrong message.

Figure 13 shows the feature vectors of "frequency variation" of samples GN6 and BN10. It can be seen that these two vectors are similar. As a matter of fact, "LS" has no any relation with "frequency variation". Figure 14 shows the "spectrum average" of

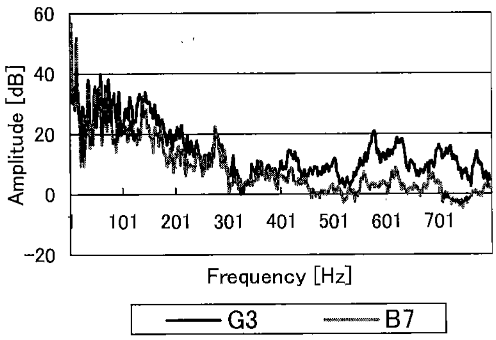


Fig. 11. "Spectrum average" of samples G3 and B7.

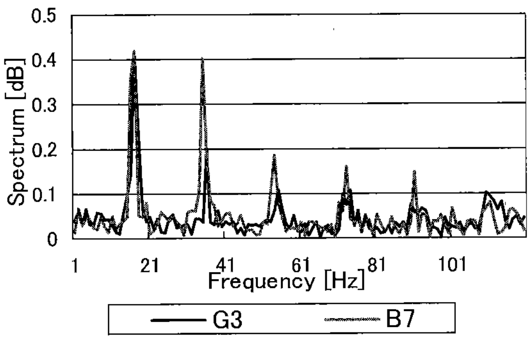


Fig. 12. Feature vectors of samples G3 and B7.

Table 2. Evolution result 1.

Frequency	Amplitude
52	34.184
99	26.267
115	36.998
166	30.760
194	15.964
353	12.839
425	19.993
760	7.144

Table 3. Evolution result 2.

Frequency	Amplitude
P1	0.559
P2	0.401
P3	0.307
P4	0.366
P5	0.340
P6	0.217
P7	1.320

Table 4. Test results.

File No.	Human	Computer	Ave.	Var.
GN1	1	1	1	1
GN2	1	1	1	1
GN3	1	1	1	1
GN4	1	1	1	1
GN5	1	1	1	1
GN6	1	1	1	1
GN7	1	1	1	1
GN8	1	1	1	1
BN1	0	0	0	0
BN2	0	0	0	0
BN3	0	0	0	0
BN4	0	0	0	0
BN5	0	0	0	0
BN6	0	0	0	0
BN7	0	0	0	0
BN8	0	0	0	0
BN9	0	0	0	0
BN10	0	0	0	1
BN11	0	0	0	0
BN12	0	0	0	0

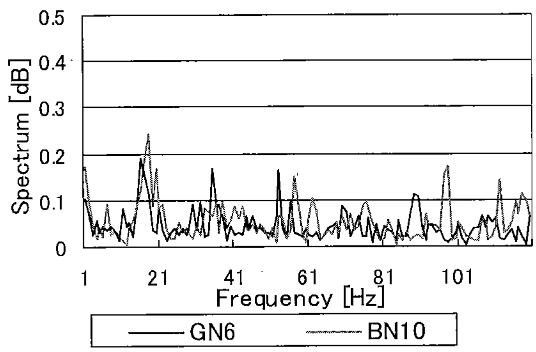


Fig. 13. Feature vectors of samples GN6 and BN10.

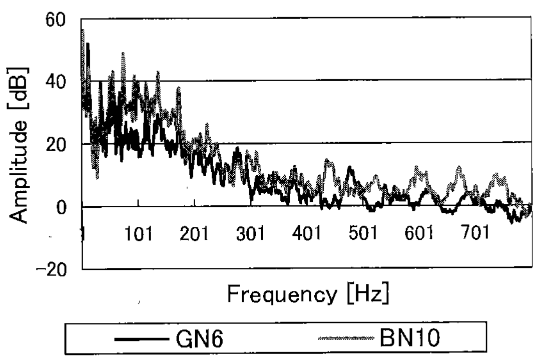


Fig. 14. "Spectrum average" of samples GN6 and BN10.

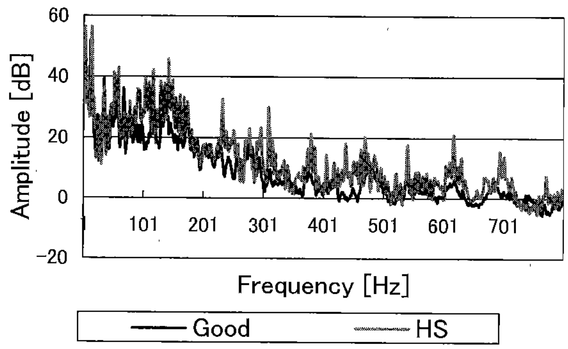


Fig. 15. "Spectrum average" of good and "HS" products.

samples GN6 and BN10. From Fig. 14, evidently we can get the conclusion that the problem of sample BN10 is too loud. Similarly, since the no good products of "HS" have a high tone, it have large amplitudes in high frequency and can be inspected by the "spectrum average". Figure 15 shows an example of "spectrum average" of good and "HS" products.

From above results, it can be seen that the no good product must have abnormal feature on either the "spectrum average" or "frequency variation". Only using the "spectrum average" or "frequency variation" might lead up to wrong results. However, we can ensure the final quality by using both "frequency variation" and "spectrum average". The experimental results also prove it. Actually, in the previous study we inspect the most of no good products by only using "frequency variation".

6. Conclusion

In this paper, we have proposed a new method of evaluating the quality of a transmission device according to the acoustic data by using the GA. In the manufacture site, each batch of transmission devices may have little difference in frequency characteristics and the evaluation rule of good products will be adjusted according to the different conditions. From the above results, it can be seen that as long as we have enough good and no good samples, the proposed method can automatically make a proper evaluation rule to classify the good and no good product correctly. By using the proposed method, we consider that we can construct an intelligent system, which is able to give the proper quality evaluation for some transmission devices automatically and have a self-learning ability to learn the new information while the environment is changing.

(Manuscript received October 30,2002, revised April 30, 2003)

References

(1) A.V. Oppenheim and R.W. Schafer . "Digital Signal Processing", Prentice-Hall, New Jersey (1975)

(2) S. Furui : "Digital Speech Processing", Synthesis, and Recognition, Marcel Dekker, New York (1989)

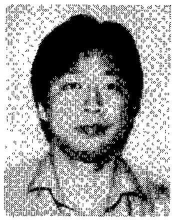
(3) A. Gersho and R.M. Gray : "Vector Quantization and Signal Compression", Kluwer Academic Publishers (1991)

(4) M. Teranishi, S. Omatu, and T. Kosaka : "New and used bill money classification using spectral information based on acoustic data of banking machine", *Trans. on IEE Japan*, Vol 117-C, No 11, pp. 1677-1681 (1997-11)

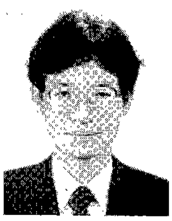
(5) N. Kamimoto, T. Abe, L Ken, and S. Omatu : "Quality verification of interphones by the LVQ method", *Trans. on IEE Japan*, Vol. 122-C, No. 4, pp. 648-654 (1997-4)

(6) B Wang, S. Omatu, and T. Abe · "Quality evaluation of machines using the LVQ", *Journal of Signal Processing*, Vol. 7, No. 1, pp.61-68 (2002-1)

Bingchen Wang (Student Member) was born on July 22, 1976. He received his B.S. degree in mechanical engineering from Zhejiang University, China in 1998 and the M.S. degree in mechanical engineering from the University of the Ryukyus, Okinawa, Japan in 2001. He is now a Ph. D. student at Osaka Prefecture University, in Japan. His research interests include signal processing and artificial intelligent control.



Sigeru Omatu (Member) received his Ph.D. degree from Osaka Prefecture University in Electrical Engineering in 1974. From 1988 to 1995, he was Professor at the University of Tokushima, Tokushima, Japan, and then he was appointed Professor at Osaka Prefecture University, Osaka, Japan. He has been a Regional Editor of Engineering Application for AI (IFAC) and Associate Editors of IEEE Transaction on Neural Networks since 1994, the IMA Journal of Mathematical Control and Information (Oxford University Press), and Engineering Application of Artificial Intelligence (Pergamon).



Toshiro Abe (Non-member) received his B.S., M.S., and Ph.D. degrees in Electronics Engineering from Osaka Prefecture University in 1965, 1967, and 1977, respectively. In 1967, he joined the Research and Development Division, Matsushita Electric Works, Osaka, Japan. He has been engaged in the research and development of power semiconductor devices, MOS-ICs, semiconductor-relays, lighting circuits and neural networks. He has been a Director of the Semiconductor Research & Development Laboratory and Research Director of the Central Research Laboratory, since 1990. In 2001, he joined the Foundation of the Osaka Science & Technology Center, Japan. He is a Visiting Professor at the Osaka Prefecture University from 2002. He received a General Director Award of Science and Technology Agency of Japan in 1991. He is a member of the Institute of Electrical Engineers of Japan, and the Japan Society of Applied Physics.