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An Intelligent Quality Inspection Sytem for the Riveting Process

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***Abstract* – The rivet assembly is an essential work for the aircraft manufacturing. Its quality is highly related with the flight safety. This paper presents an intelligent quality inspection system which is constructed by a fuzzy mechanism and a neural network (NN) for the riveting work. The fuzzy mechanism plays the role of signal processor which is used to enhance the significant features of the impact signals so that the neural network could make the immediate diagnosis of the riveting quality based on the processed signals. The intelligent inspection system is expected to give the assistance for the verification of rivet quality. It can not only monitor the real time riveting process, but also greatly decrease the inspection inaccuracy caused by the visual examination. The experimental data provided by Chinese Air Force Institute of Technology were simulated and studied. In order to demonstrate the superiority of the intelligent inspection system developed, the pure neural network model with no fuzzy mechanism was also performed as the comparison.**

***Keywords* – Intelligent, Quality Inspection, Riveting Process, Fuzzy, Neural Network.**

I. Introduction

It is well known that the sheet metal parts are mostly joined by the rivets in the aircraft manufacturing. The rivet assembly plays a very important role for the aircraft manufacturing business. The flight safety is highly related with the quality of the rivet assembly. The failure of riveting work will cause the serious safety problem of the aircraft [1]-[4].

Basically, riveting is a mechanical fastening process which is used to accomplish the rivet assembly. Bajracharya [5] and Cheraghi [6] have indicated that thermal fatigue, vibration and induced stresses are three main factors cause the rivet failure. In which, thermal fatigue and vibration are easily affected by the surroundings and hardly to be controlled. Hence, how to control the induced stresses effectively becomes an important and essential work for the rivet assembly [6]-[9]. Bajracharya [5] and Cheraghi [6] also pointed at the relevant parameters such as the squeeze force, the length and diameter of rivet, the diameter of sheet hole and the depth of countersink must be carefully considered and precisely controlled, if the induced stresses would be reduced effectively. These parameters could determine the stresses induced on the joint and the final geometry of the rivet buck tail. Generally, the information about the length and the diameter of rivet, the diameter sheet hole and the depth of countersink could be guided by the standard handbook [10]. But, the squeeze force must be exerted adequately in accordance with the size and the type of rivet, riveting gun and riveting force.

The proper riveting tool, the control of squeeze force and the rivet quality verification are three indispensable parts for accomplishing a successful fastener installation. The air-pressurized pneumatic riveter is the riveting tool commonly used in the industry of aircraft for the structural fastening and repairing works due to its fast installation speed and low manufacturing cost. In addition, the visual examination is the common inspection way taken by the full experienced technician for judging the rivet joint good or not. Undoubtedly, the human-made judging mistake is still unavoidable, especially when the technician is working in the case of eyestrain.

Several systematic and reliable evaluation methods have been studied and proposed in order to do the quality control on riveting process and improve the lacks of visual examination [3]-[6], [11], [12]. Wang et al. also proposed an indicator, called riveting quality index (RQI) to evaluate the quality of riveting process [11], [13], [14]. The idea of RQI is taken by the assumption which the impact signals of a good riveting process must have the different and distinguishable features from the signals of an inferior riveting process. Through the analysis of impact signals sensed, the judging rule of RQI could determine the rivet joint is “Good” or “No-good”, which also means the riveting process is qualified or disqualified.

Recently, due to the abilities of self-learning and self-organization, neural network (NN) has been widely employed in the application of fault diagnosis [15]-[19]. Through an appropriate training process, the fault signature could be classified into a particular vector by NN. The well-trained neural model then can be used to execute the fault detection work. In fact, the NN technique used for judging the riveting work has been studied and presented [20]-[22]. The research results have showed that the technique of NN has the outperformance in comparison with the statistical RQI method.

In this research, an intelligent inspection system with the combination of fuzzy mechanism and NN model is developed to verify the structural damage of the rivet based on the impact signals sensed. Its diagram is illustrated in Fig. 1. All impact signals that might be sensed in the different time periods and experimented by different riveting forces are pre-processed by a fuzzy mechanism firstly. The purpose of signal pre-processing is to make the significant features of the original impact signal could be enhanced and modified so that the NN model could have more efficient learning and more precise verification based on the pre-processed signal.

Section II presents the experimental equipment setup for this research briefly. Section III describes the inspection methods, including Fussy mechanism and NN model. The

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study results are reported in Section IV and the conclusion is given in Section V.

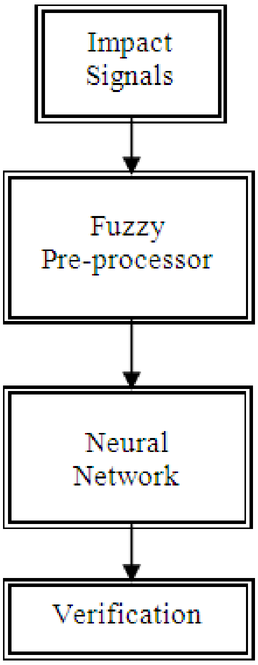

Fig.1. The diagram of hybrid fuzzy neural network.

II. Equipment Setup and Experiment

In the experiments, the aluminum panels riveted by the pneumatic, handheld riveting gun were experimented. All panels have the zigzag pattern which has eighteen rivets. The basic panel structure is shown in Fig. 2. A riveting control consists of the air-pressure regulator; AD converter and microprocessor are utilized in order to reduce the human operational deviations [20]-[22]. The laptop is used to be the master-controlling computer. The changes of signal are from low level (0V) to high level (5V) when the riveting process is executed. The whole experimental setup of the riveting process is illustrated in Fig. 3.

324 rivets (18 panels) were experimented and collected for this research. The overall 324 rivets were visually verified by a senior engineer with more than 5 years of experience to judge the rivet work is qualified or disqualified.

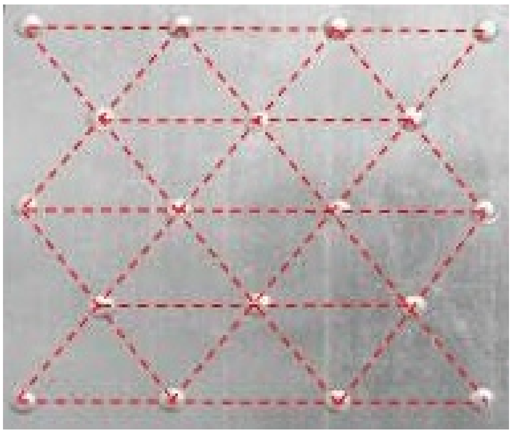

Fig. 2 Panel picture

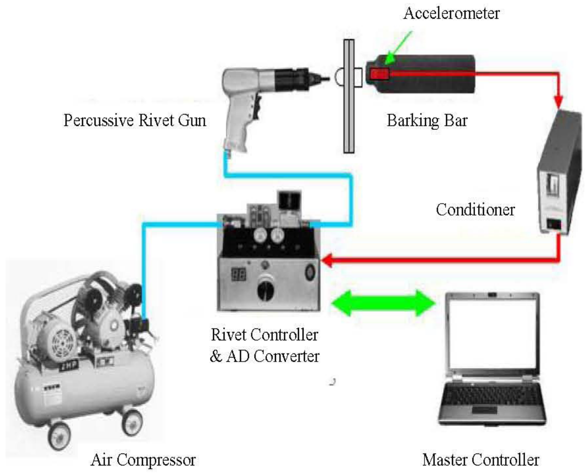

Fig.3. The experimental setup of the riveting process.

For each rivet pattern, 15000 voltage signals are sensed in 1.5 seconds. The example of signals of one rivet pattern is shown in Fig. 4 [20]-[21]. However, it is impossible to use such large number of signals to be the inputs of NN model for learning and doing the inspection. In order to solve this problem, we divided 1.5 seconds into 15 segments and took the maximum voltage in each segment to be the impact signal. Thus, each rivet pattern has 15 impact signals and these 15 signals are then used as the inputs of NN model for rivet quality verification.

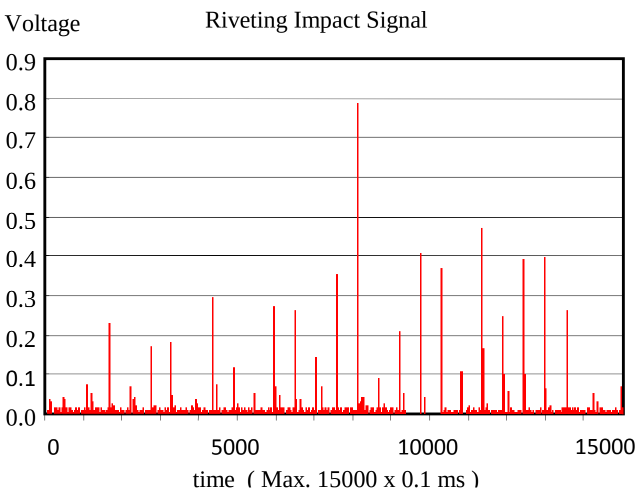

Fig.4. The voltage signals sensed for a rivet pattern.

III. Inspection Methods

Two inspection methods, including pure NN model and NN model with fuzzy processor were used to perform the rivet quality verification. As mentioned, the related researches about the verification of riveting process by NN techniques have been studied in the past years [20]-[22]. The research results also show the advantage of NN in this application. However, in these researches, the impact signals were not pre-processed by a signal processor. They were sent to NN model to do the learning and verification directly. In our study, the impact signals were pre-processed by a fuzzy processor to make the significant features of the signals could be easily learned by NN model. Both NN and fuzzy mechanism are described as follows.

A. Neural Network

A three-layer feed-forward NN is taken as the verification model. Its size is 15-16-1 which means the network is composed of one input layer with fifteen nodes, one hidden layer with sixteen nodes and one output layer with one node. The activation function for all nodes is sigmoid function. The error back-propagation (BP) algorithm is the learning rule adopted for network's training [21], [23]. Let $\omega_{ij}(\mathrm{n})$ be the value of synaptic weight ω_{ij} of node j excited by input node $X_i(\mathrm{n})$ and $O_{output}(\mathrm{n})$ denotes the computed value of output node, the weights of the network can be adjusted by

$$\omega_{ij}(\mathrm{n}+1)=\omega_{ij}(\mathrm{n}),$$

if $O_{output}(\mathrm{n})$ belongs to the correct class (1)

$$\omega_{ij}(\mathrm{n}+1)=\omega_{ij}(\mathrm{n})+\alpha\delta_j(\mathrm{n})X_i(\mathrm{n}),$$

if $O_{output}(\mathrm{n})$ belongs to the incorrect class (2)

where n+1 and n are the next and present iteration numbers, respectively. $\delta_j(\mathrm{n})$ is the error of node j and α is the learning rate.

B. Fuzzy Pre-processor

It is known that the riveting work could be possibly done by several technicians (different squeeze forces) in different time periods. Thus, the impact signals of all rivet patterns could be different. For instance, the impact signals shown in Fig. 5 and Fig. 6 are two "Good" rivet patterns (pattern 1 and pattern 2). Clearly, the signal ranges of two patterns are quite different. In other words, the features of the impact signals of two "Good" rivets are hardly distinguished. Such a phenomenon might cause NN to have an incorrect learning.

In order to let the features of impact signals for different rivets could be more enhanced and clearer so that the NN model could have more efficient learning, a fuzzy mechanism is designed to do the transformation and normalization of the signals. All signals are transformed into the range of [0, 1]. It stands that the whole riveting work accomplished by different technicians in different time periods is assumed to be carried out by a technician only and the squeeze forces to all rivets are given by the same person. This assumption aims to make the features of the impact signals of "Good" and "No-good" rivets could be clearer. Thus, the NN model is able to catch the features more easily and make the diagnosis of the riveting quality more precisely.

Fig. 7 is the membership function of the fuzzy mechanism developed. *Max* and *Min* are maximum and minimum values of the original impact signals on each rivet pattern (15 voltages). *a*, *b*, *c* are three values which can be calculated by the following equations:

$$a = Min + (Max - Min)/4 \quad (3)$$

$$b = Min + 2(Max - Min)/4 \quad (4)$$

$$c = Min + 3(Max - Min)/4 \quad (5)$$

The fuzzy rule base comprises the fuzzy IF-THEN rules. Two examples of fuzzy IF-THEN rules are listed as follows [24].

$Ru^{(i)}$: IF the original impact signal has the degree μ_1 of VS and the degree μ_2 of S,

THEN the value of the transformed impact signal is $(\mu_1\mathrm{VS}+\mu_2\mathrm{S})/(\mu_1+\mu_2)$.

$Ru^{(l)}$: IF the original impact signal has the degree μ_3 of L and the degree μ_4 of VL,

THEN the value of the transformed impact signal is $(\mu_3\mathrm{L}+\mu_4\mathrm{VL})/(\mu_3+\mu_4)$.

The value of impact signal as a linguistic variable that can take fuzzy sets "very small (VS)", "small (S)", "medium (M)", "large (L)", and "very large (VL)" as its values. Fig. 8 is the singleton membership function for defuzzification. Fig. 9 and Fig. 10 are the transformed impact signals of the patterns 1 and 2 shown in Fig. 5 and Fig. 6.

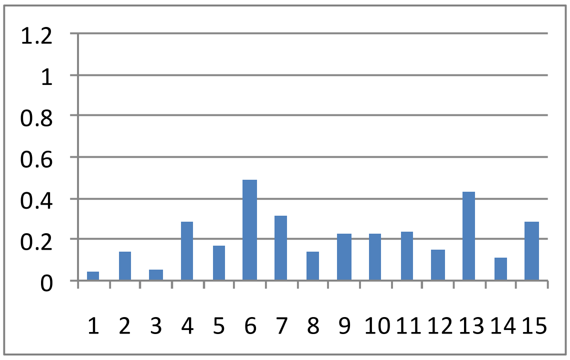

Fig.5. The example of 15 impact signals of rivet pattern 1.

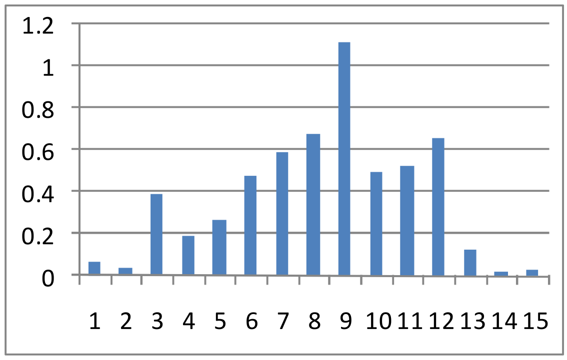

Fig.6. The example of 15 impact signals of rivet pattern 2.

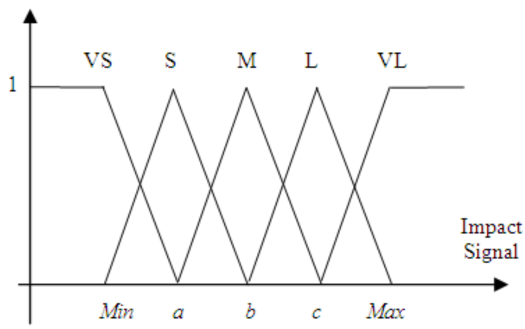

Fig.7. The membership function of each rivet pattern

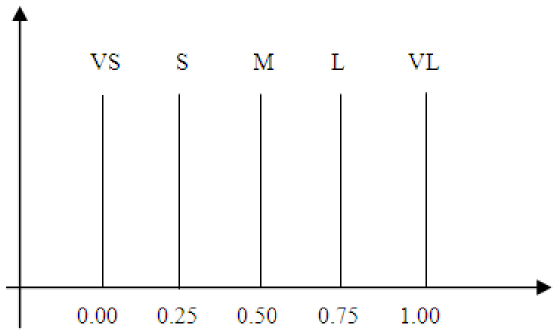

Fig.8. The singleton membership function of defuzzifier.

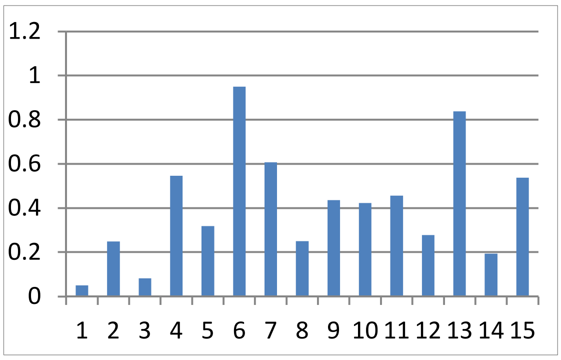

Fig.9. The example of 15 transformed impact signals of rivet pattern 1.

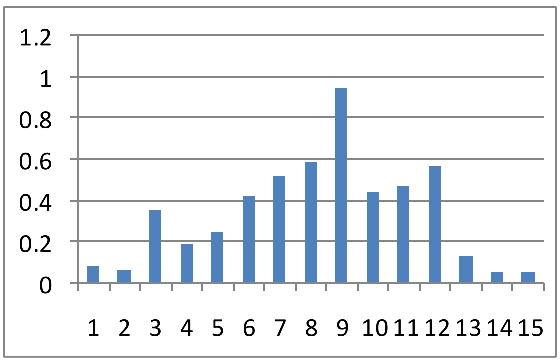

Fig.10. The example of 15 transformed impact signals of rivet pattern 2.

IV. Simulations

In this research, 324 rivet patterns were experimented and collected. In which, 216 patterns were used for network's training and 108 patterns were used for testing. All verification methods are used to verify the rivet patterns to be "Good" or "No-good". "Good" stands the quality of rivet is qualified and "No-good" stands the quality of rivet is disqualified.

In our experiments, the pure NN model with no fuzzy processor was also performed as the comparison with the model proposed. For demonstrating the superiority of the intelligent inspection system developed and having a fair comparison with the pure NN model, six different data sets; Set-1, Set-2, Set-3, Set-4, Set-5 and Set-6, are randomly re-organized based on the original data. For each data set, 216 patterns were used for model's training and 108 patterns were used for testing. Table 1 lists the verification accuracies of rivet quality by using two inspection methods. From the results shown, it is clearly found that the average accuracy of quality verification carried out by the intelligent model developed is 91.97% which is more accurate than 86.73% carried out by the pure NN model.

Table 1: The verification accuracies by two NN models.

Data	NN Model	Intelligent Model
Set-1	87.04% (94/108)	92.59% (100/108)
Set-2	87.96% (95/108)	92.59% (100/108)
Set-3	84.26% (91/108)	89.81% (97/108)
Set-4	86.11% (93/108)	91.67% (99/108)
Set-5	85.19% (92/108)	90.74% (98/108)
Set-6	89.81% (97/108)	94.44% (102/108)
Avg.	**86.73%**	**91.97%**

V. Conclusion

In this study, an intelligent quality inspection system for riveting process by using fuzzy mechanism and NN model was developed and proposed. In order to make the impact signals for different rivets have the consistent condition, a fuzzy mechanism is designed to execute the transformation and normalization of the signals. Its aim is to let the impact signals of the rivets carried out by different technicians (different forces) in different time periods could have the consistency. All rivet joints are assumed to be done by the same technician. In other words, the signal processing by fuzzy transformation aims to enhance the features of the original impact signals sensed so that the NN model is able to catch the features of signals and perform the verification easily and precisely. From the simulation results shown, the transformed impact signals indeed make NN model have the more efficient and accurate verification. In other words, the inspection system developed has the more powerful ability to verify the quality of riveting process. Thus, we conclude that the intelligent inspection system can not only used to monitor the real time process, but also give assistance on the riveting quality verification for the experienced technician. The research result is very promising and shows that such an intelligent inspection system has the great potential in the real application.

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