Multisensor Data Fusion Based on Fuzzy Logic in Non-Destructive Testing

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Abstract: Fuzzy logic has been widely used in data fusion, but data fusion based on fuzzy logic in NDT (Non-destructive testing) is a new topic. This paper gives a new fuzzy logic architecture for multisensor data fusion in NDT. The definition methods of the membership functions and operators are presented. It also gives an example to illustrate the use of this architecture in NDT.

Key words: multisensor data fusion; fuzzy logic; NDT

无损检测中基于模糊逻辑的多传感器数据融合

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摘要: 模糊逻辑在多传感器数据融合中得到广泛的应用,但是基于模糊逻辑的多传感器数据融合在无损检测中的应用还是一个崭新的课题.本文给出了一种新的用于无损检测数据融合的模糊逻辑结构,并且给出了隶属度函数以及运算符的定义方法.最后给出了例子阐明了这种结构在无损检测中的应用.

关键词: 多传感器数据融合; 模糊逻辑; 无损检测

1 Introduction

In recent years, multisensor data fusion technology has evolved rapidly. Various kinds of approaches have been used for it, such as evidence reasoning theory, statistic theory, fuzzy logic and neural network, etc. The fuzzy logic is suitable for data fusion when the system has incomplete information. Fuzzy logic techniques have become popular to address various processes for multisensor data fusion. Examples include[1]: 1) Fuzzy membership functions for data association; 2) Evaluation of alternative hypotheses in multiple hypothesis trackers; 3) Fuzzy-logic-based pattern recognition; 4) Fuzzy inference schemes for sensor resource allocation.

Researchers in different countries have shown a great interest in data fusion based on fuzzy logic. But they use it mostly in battlefield, such as surveillance and strategic warning[2], object detector[3] and tracking[4]. In addition, some of them use it in intelligent robot[5]. Therefore, the data fusion based on fuzzy logic used in NDT is a new topic. NDT itself is an old topic. It has a lot of realization methods. But those methods mostly use one sensor to determine the situation, and even if there are lots of sensors they also use the Boolean logic to judge the situation. In fact, many properties can not be measured by Boolean logic, for example we say a person is "young" or "beautiful". In those cases we must use fuzzy logic, especially in multisensor data fusion for NDT. In this paper we propose a new data fusion structure based on the fuzzy logic and its application in NDT.

In section 2, we define the membership functions and give the basic operators in the new architecture. In section 3, we give the new fuzzy logic architecture and its application in NDT. In section 4, we draw the conclusions.

2 Membership functions and basic operators in fuzzy logic

The basis for the multisensor data fusion based on fuzzy logic involves the definition of the fuzzy membership functions and the fuzzy logic operators. In this section, the ways to decide the membership functions and operators are presented.

2.1 The definition of the memership functions

Fuzzy logic involves the extension of Boolean set theory and Boolean logic to a continuous-valued logic via

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the concept of membership functions. Membership functions are continuous functions defined on the interval [0,1]. It is used to quantify the "fuzziness" or imprecise concept. So the fuzzy membership functions quantify the extent to which a concept or attribute is inherently imprecise. By contrast, other techniques, such as probability, quantify the extent to which a precise concept. In multisensor data fusion, the multiple sensors get the information from a particular aspect of the object tested. The outputs of each sensor are variables that represent the extrinsic physical attribute. These form the set of physical properties of the object represented. But the fuzzy properties are inferred from the values of the physical properties since they can not be detected directly by the sensors. In this situation, we must define the fuzziness of the physical variables. The membership functions finish this work. They make the subspace $\mathbb{R}^n$ into the interval [0,1].

There are lots of methods to define the membership functions. The method we suggest here includes four kinds of forms. The four forms are named "highpass", "lowpass", "bandpass", and "bandstop" apart. They are shown in Fig.1.

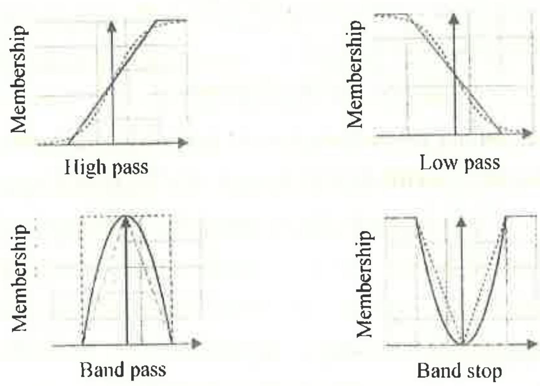

Fig. 1 Membership functions

As shown in Fig. 1, the four forms contain all kinds of membership functions. We can define the membership functions according to the real situation. Of course, the sharps of the membership functions can be arbitrarily selected and they are not limited by the sharps shown above. Those sharps are only some examples.

2.2 The basic operators of the fuzzy logic

The basic operators in fuzzy logic and Boolean logic are "AND", "OR" and "NOT". They can be used to build up all kinds of fuzzy functions. So we can use them to complete our fusion task in random situations. Because membership functions are not equally important, the weight vector is presented. The weights control the relative significance of the sub-properties.

Now we will give the definitions of those operators in the fuzzy logic.

The AND operator models a necessity condition. For example, the output property, P, exists only if each of a collection $\{Q_1, Q_2, \cdots, Q_N\}$ of sub-properties exists. In addition, the function AND should also have the capability of combining information of various degrees of significance as well as of various degrees of existence. In accordance with this, the truth value or confidence of varying factor for the existence of P, CF(P), is computed by

$$\mathrm{CF}(P) = \mathrm{AND}(w_1\mathrm{CF}(Q_1), w_1\mathrm{CF}(Q_2), \cdots, w_n\mathrm{CF}(Q_N)). \tag{1}$$

The operator OR can be established as the operator AND. The difference is in the intuitive meaning. The OR operator is a sufficiency condition. Just like the AND operator, the compute formula is:

$$\mathrm{CF}(P) = \mathrm{OR}(w_1\mathrm{CF}(Q_1), w_2\mathrm{CF}(Q_2), \cdots, w_n\mathrm{CF}(Q_N)). \tag{2}$$

According to these specifications, there are many ways to model the "AND" and the "OR" operators, such as the Min-max model, Hamacher model, Yager model and the Dubois models and so on.

Gibson and Hall[1] gave a new kind of model as follows:

$$\mathrm{AND}(C, W, N) = \left[\prod_{i=1}^{N}(1 - W_i + W_i C)\right]^u, \tag{3}$$

where

$$C = (C_1, C_2, \cdots, C_N)$$

is the input confidence vector,

$$W = (W_1, W_2, \cdots, W_N)$$

is the weight vector, N is the number of onputs (sub-properties).

$$\mathrm{OR}(C, W, N) = \begin{cases} b, & \text{if } e \leq a, \\ 1, & \text{if } e \geq c, \\ 0.5\left[d+b+(d-b)\sin\left(\pi\left(\frac{e-a}{c-a}-0.5\right)\right)\right], & \text{otherwise}, \end{cases} \tag{4}$$

where

$$e = \sqrt{\sum_{i=1}^{N} (W_i C_i)^2},$$

$$u = \max\{W_i C_i,\ i = 1,2,\cdots N\},$$

$$a = 2u - \sqrt{N}, \quad b = 2u - 1,$$

W and C are vectors defined in AND operator.

In terms of the practical condition in NDT, the AND model is retained and the OR operator is defined as follows:

$$\mathrm{OR}(C, W, N) = \max\{W_i C_i,\ i = 1,2,\cdots,N\}. \tag{5}$$

The reason that we select this will be given in the next section. Because the "NOT" operator is not used in this paper, we will not discuss it.

3 The new multisensor data fusion based on fuzzy logic architectrue in NDT

NDT is a wide area. In this paper the example is to detect the crackle or bubble in a large ingot. In some huge vehicle, the main axis is the most important part. If there are some flaws such as crackle or bubble in it, the result will be very severe. So it must be detected before it is used and can not be destroyed. It is called NDT. In this paper, the multisensor data fusion NDT system is presented. It is shown in Fig.2.

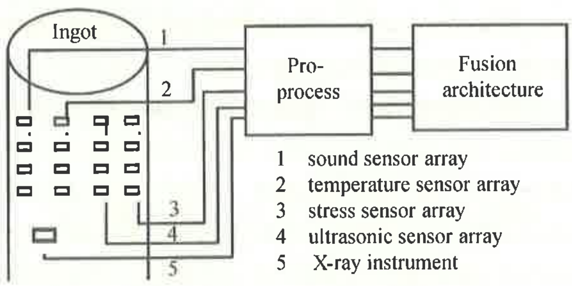

Fig. 2 Multisensor data fusion system in NDT

From this figure, we know that this system has five kinds of sensor arrays. They are stress sensor array, sound wave sensor array, temperature sensor array, ultrasonic sensor array and X-ray instrument. For these five sensor arrays, five experiments have been conducted in the following ways:

1) Using one small hammer to peen the ingot, if there is flaw in it, the sound wave must be different from that no flaw. By knocking different places, the salted worker can estimate whether the ingot has a flaw or not and decide the position of the flaw probably.

2) Heating one end of the ingot, the temperature of the ingot surface satisfies the thermodynamic conduction equation. If there is a flaw in the ingot, the outputs of the temperature sensors must be different from that no flaw.

3) Exerting a leverage to the ingot, the outputs of the stress sensor array must be different from the flawless one.

4) Emitting ultrasonic to the ingot, the reflex and the transmission of the ultrasonic can be used to find the flaw. But it can not give a complete and true answer.

5) Using the X-ray instrument. This experiment has the highest reliability. So we select the formula (5).

In these five experiments, the outputs of those five kinds of sensor array can not decide the flaw in the ingot separately. They only give a fuzzy concept. But we can fuse them together and make a credible decision. The fusion architecture is shown in Fig.3.

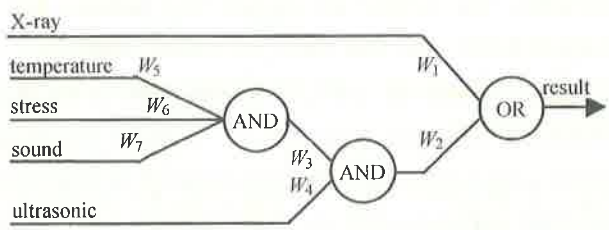

Fig. 3 Fusion architecture

According to the formula (3) and (5), we have:

$$\mathrm{CF(FLAW)} = \mathrm{OR}(W_1\mathrm{CF(X\text{-}ray)}, W_2\mathrm{CF(TSSU)}) = \max(W_1\mathrm{CF(X\text{-}ray)}, W_2\mathrm{CF(TSSU)}), \tag{6}$$

where

$$\mathrm{CF(TSSU)} = \{\{(1 - W_3 + W_3 * [(1 - W_5 + W_5 * \mathrm{CF(Temperature)}) * (1 - W_6 + W_6 * \mathrm{CF(Stress)}) * (1 - W_7 + W_7 * \mathrm{CF(Sound)})]^U\} * ((1 - W_4 + W_4 * \mathrm{CF(Ultrasonic)})\}^V,$$

$$U = 0.1 + 0.9\exp(-0.3(W_5 + W_6 + W_7 - 1)),$$

$$V = 0.1 + 0.9\exp(-0.3(W_3 + W_4)), \tag{7}$$

$W_1, W_2, W_3, W_4, W_5, W_6, W_7$ are adaptive parameters.

According to the formula (6) and (7), we can fuse the sensor data together. It is more reliable than any one kind of sensor. Using this system, we can not only judge the existence of the flaw but also can estimate the position of the flaw approximately.

4 Conclusion

In this paper, a new multisensor data fusion based on fuzzy logic architecture for NDT is presented. The ways to decide the membership functions and the operators of fuzzy logic are given. The architecture introduced is being used now. It also can be used in other fields. This research can be improved by adopting the neural network to decide the weight automatically.

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王 祁 见本刊 1999 年第 2 期第 264 页.

孙圣和 见本刊 1999 年第 2 期第 264 页.

(Continued from page 923)

have shown that the proposed method for controlling the weld pool depth yields superior performance.

4 Conclusion

Within this paper the neural network for modeling the GTAW and controlling the weld pool depth has been investigated. The neural network offers significant abilities in the development of welding process models and control. The weld pool depth is estimated by using the information obtained from the welding pool and the seam gap. The depth can be kept constant during the welding process. It is demonstrated that the proposed neural network can produce highly complex nonlinear multi-variable models of the GTAW process that offer accurate prediction of weld properties from control parameter values.

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