Rough Set Based Intelligent Welding Quality Classification

L. Tao, T. J. Sun, and Z. H. Li

***Abstract*—**The knowledge base of welding defect recognition is essentially incomplete. This characteristic determines that the recognition results do not reflect the actual situation. It also has a further influence on the classification of welding quality. This paper is concerned with the study of a rough set based method to reduce the influence and improve the classification accuracy. At first, a rough set model of welding quality intelligent classification has been built. Both condition and decision attributes have been specified. Later on, groups of the representative multiple compound defects have been chosen from the defect library and then classified correctly to form the decision table. Finally, the redundant information of the decision table has been reducted and the optimal decision rules have been reached. By this method, we are able to reclassify the misclassified defects to the right quality level. Compared with the ordinary ones, this method has higher accuracy and better robustness.

***Keywords*—**intelligent decision, rough set, welding defects, welding quality level

I. Introduction

THE ordinary method of welding quality classification has two steps. The first step is that an interested local area of the welding seam be photoed by radiographic means. The further step is that the welding defect image be judged and classified by relevant personnel according to the national standards. With the development of the digital radiographic imaging technology, the result form of non-destructive testing has changed from films to digital images [1]. The digitization makes it possible to apply intelligent methods to recognize the welding defects and classify the welding quality.

In recent years, there are many researches on the intelligent recognition of welding defects, such as threshold method[2]-[3], wavelet transform based method [4]-[5], SVM method[6]-[7], information fusion method [8], etc. By these methods, the recognition rate can reach 60-80% and sometimes over 90% by efficient methods in the ideal environment. However, with the reference parameters unadjusted, almost all the intelligent recognition methods perform unstably and have poor adaptability.

The further work of welding defects recognition is the decision of the quality level. That is to classify the welding quality according to the recognition results. This process is directly influenced by the recognition accuracy. There are targeted researches, such as online welding parameter based information fusion method [9] and fuzzy theory method[10]. All the methods have limitations. The information fusion method depends on the key parameters during the welding process which are very difficult to measure in the industrial site. The fuzzy theory method has efficient classification ability on single welding defect. But few correct results can be obtained when dealing with multiple compound defects. The existing classification methods have a common shortcoming. They all assume that the welding defect recognition was completely correct. Though the knowledge base of welding defect recognition is always incomplete, the correctness would not be assured. To deal with the problems above, this paper proposes a rough set based method including the model establishment, knowledge reduction and optimal rules. By this method, we can reclassify the defects to the right quality level. The experimental result proved satisfactory performance.

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II. Rough Characteristic of Defect Recognition

The rough characteristic of knowledge can be described as follows. $\exists U_0 \subset U$, U_0 can not be accurately defined by the knowledge $K=(U,R)$. So, set U_0 is the rough set of R , And the knowledge K is rough. Where U is the discussion domain, $R \subseteq U$ is the indiscernible relationship of knowledge K , and $R \in \text{ind}(K)$.

According to the related standards, to classify the welding quality with a specific thickness has four basis[11]-[13]. They are the existence of incomplete fusion or crack, the maximum depth of incomplete penetration, the quantity of round defects in unit area, the maximum diameter of bar defects. All above can be understood as four fundamental knowledges.

Assume that U is the welding defects discussion domain, the knowledges $K_1=(U,R_1)$ and $K_2=(U,R_2)$ may generate four kinds of error migration as follows:

1) There exists $R_1 \cap R_2 = \phi$ in fact. After intelligent recognition, the result is $R_1 \cap R_2 \neq \phi$. That is the indiscernible relationships of two knowledges has non-empty intersection. For example, round and bar defects have the possibility of ill-definition under some circumstances.
2) There exist $\exists x \in R_1$ and $x \notin R_2$ in fact. After intelligent recognition, the result is $x \notin R_1$ and $x \in R_2$. That is the element x migrates from knowledge K_1 to K_2 . For example, there can be wrong recognitions between round and bar defects.
3) There exists $\exists x \notin R_1 \cup R_2$ in fact. After intelligent recognition, the result is $x \in R_1$ or $x \in R_2$. That is the

element x migrates into the knowledge K_1 or K_2 from outside. For example, the misjudgement of defects.

4) There exists $\exists x \in R_1 \cup R_2$ in fact. After intelligent recognition, the result is $x \notin R_1$ or $x \notin R_2$. That is the element x migrates out of the knowledge K_1 or K_2 from inside. For example, the leakage judgment of defects. R_2

The four kinds of error migrations can be described as Fig. 1.

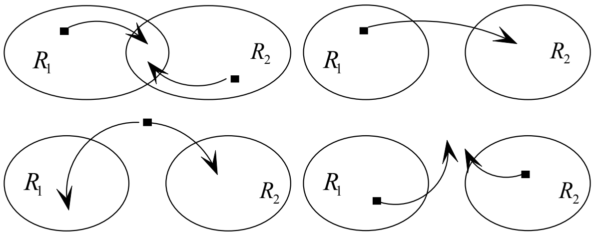
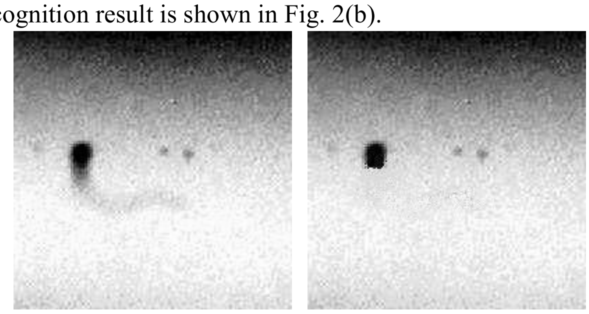


Fig.1 Four error migrations of intelligent recognition methods

Four error migrations in Fig.1 are ubiquitous and irrevocable problems of welding defect intelligent recognition methods. The element x can not be accurately defined by the knowledge base $K = (K_1, K_2, \cdots, K_n)$. So, the recognition method is rough. There is inevitable influence on further classification process. We give an example for description.

Fig. 2(a) is the original bar defect image of a welding seam by double-sided submerged arc welding. The defects are one stoma and two slags. Due to low image contrast, the airway of the stoma is removed as well as the background. The recognition result is shown in Fig. 2(b).



(a) Original image (b) Image after recognition

Fig. 2 The misjudgement of stoma

In Fig.2, the defect element migrates from stoma knowledge to round defect knowledge. According to the actual measurement, the maximum length of the stoma is 11.3mm, longer than $2T/3$, where T is the thickness of the welding seam. The defect must be classified as level IV. But it is misclassified as level III. Because it is fully accordant with the recognition result, the round defect in Fig. 2(b) has equivalently 8 points. Thus, the welding quality is misclassified.

III. Rough Set Model and Intelligent Classification

A. Rough set model

Due to the rough characteristic of defect intelligent recognition, the rough set model of welding quality classification must be build so as to reduce the influence[14]-[15].

After analysing corresponding standards, a rough set model including the attributes are built.

Def. 1: U is the welding defect library discussion domain after recognition. R is an indiscernible relationship of U. U/R indicates a set which contain all equivalent defect elements. $[X]_R$ indicates the equivalent elements of R. Given a welding quality intelligent classification decision knowledge base $K = (U, R)$, for every subset $P \subseteq R$, an equivalent relationship $\mathrm{ind}(P)$ is defined. It is called indiscernible relationship:

$$[X]_{\mathrm{ind}(p)} = \bigcap_{R \in P} [X]_R \qquad (1)$$

All equivalent elements $U/\mathrm{ind}(P)$ of $\mathrm{ind}(P)$ indicate the classification knowledge related to P. It is called the fundamental knowledge.

Def. 2: The welding quality classification decision knowledge base is $K = (U, R)$, for every subset $X \subseteq U$ and an equivalent relationship $R \in \mathrm{ind}(K)$, two subsets are defined:

$$R^-(X) = \{x \in U \mid [x]_R \cap X \neq \phi\} \qquad (2)$$

$$R_-(X) = \{x \in U \mid [x]_R \subseteq X\} \qquad (3)$$

Formula (2) and (3) are separately upper approximation and lower approximation. Set $\mathrm{BN}_R(X) = R^-(X) - R_-(X)$ is the boundary domain of R.

According to the existing knowledge, the elements which can be completely or partly described belong seperately to $R_-(X)$ and $R^-(X)$. This causes the existence of boundary domain $\mathrm{BN}_R(X)$. Obviously, $R_-(X) \neq R^-(X)$ and $\mathrm{BN}_R(X) \neq \phi$. The size of the boundary domain $\mathrm{BN}_R(X)$ is described by rough degree:

$$\rho(x) = 1 - |R_-(X)| / |R^-(X)| \qquad (4)$$

Formula (2) indicates the incomplete degree of a knowledge. The incomplete of intelligent recognition knowledge implies large boundary domain of classification knowledge, shown as Fig. 3.

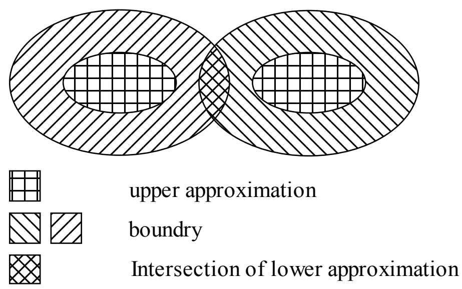


Fig. 3 Incompletement of quality classification knowledge

In Fig. 3, four kinds of error migrations can be completely described. Because the boundary domain is non-empty, different boundary domains may have intersection.

B. The establishment of fundamental knowledge

Construct four condition attributes which are treated as fundamental knowledges as follows. a - existance of incomplete fusion or crack, b - the maximum depth of incomplete penetration, c-quantity of round defect in unit area, d-maximum diameter of bar defects. Table I shows the values of four condition attributes.

TABLE I
CONDITION ATTRIBUTES AND VALUES

Condition attributes	Values
a	0— non-existing
	3— existing
b	0— 0%
	1— 0-10%
	2— 10-15%
	3— >15%
c	0— 0-1
	1— 2-3
	2— 4-6
	3— >6
d	0— 0
	1— 0-4
	2— 4-6
	3— >6

The decision attribute *e* is the final level of welding quality. The values of *e* are between level I and IV. Level I is highest and level IV is the lowest one.

C. Establishment of the decision table

According to the fundamental knowledge, several groups of representative welding defect images are chosen from the defect library. The redundant information is consolidated so as to build the decision table of knowledge $K=(U,R)$ as shown in Table II.

TABLE II
THE DECISION TABLE

U	*a*	*b*	*c*	*d*	*e*
1	3	3	3	2	IV
2	0	0	2	0	III
3	0	2	0	1	III
4	0	1	0	2	III
5	0	1	2	0	III
6	0	0	1	1	II
7	0	1	1	1	II
8	0	1	0	0	II
9	0	1	0	1	II
10	0	0	0	0	I

D. Reduction of the decision table

Firstly, the redundant information must be consolidated. Later on, it must be reducted by attributes and rules. By calculation, the final optimal decision rules is :

$$\begin{cases} a_3 \vee b_3 \vee c_3 \vee d_2 \rightarrow e_{\mathrm{IV}} \\ b_2 d_1 \vee b_1 d_2 \vee c_2 \rightarrow e_{\mathrm{III}} \\ c_1 d_1 \vee b_1 \rightarrow e_{\mathrm{II}} \\ a_0 b_0 c_0 d_0 \rightarrow e_{\mathrm{I}} \end{cases} \tag{5}$$

By the combination of ordinary and rough set based decision methods, a process of classification is shown in Fig. 4.

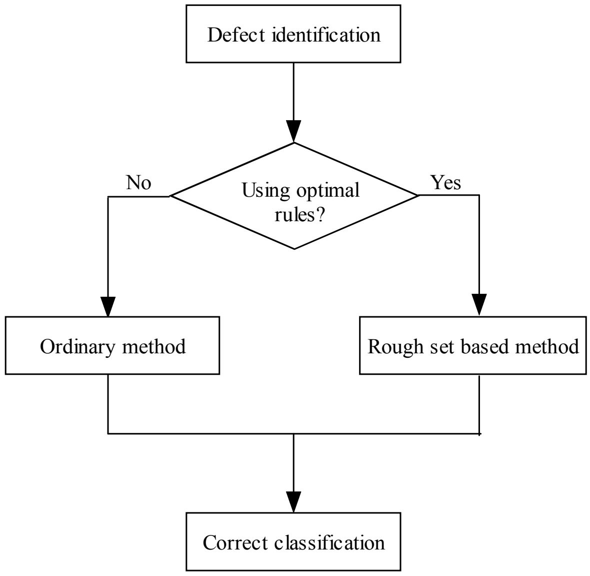
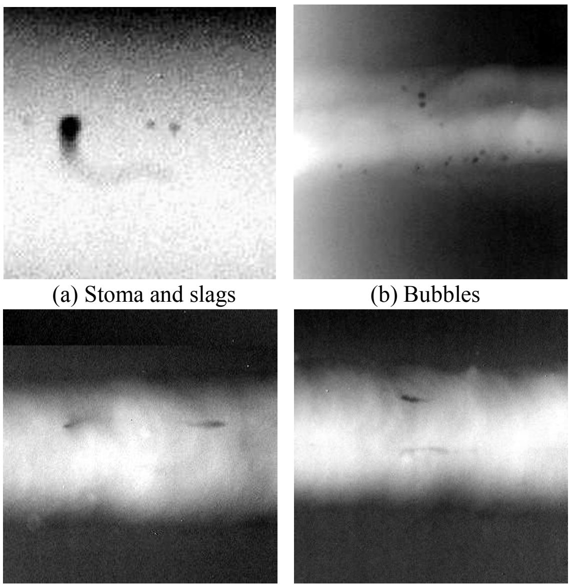


Fig. 4 Flowchart of intelligent classification

In Fig.4, if the defect feature can be described by the optimal rules, the rough set based method is adopted. Otherwise, we still take the ordinary classification process.

IV. EXPERIMENTAL VERIFICATION

The experiment was implemented by X-ray machine GECCO2505 and flat panel detector PAXSCAN2520. The output image was 1920×1536 pixels and 14bit.During the experiment process, 100 samples were chosen randomly from hundreds of representative welding defect samples. After detection and recognition, the welding quality was decided separately by ordinary and rough set based methods. The final result was shown as follows. For ordinary method, there were 74 right and 26 wrong classification results among 100 samples. In the 26 wrong results, there were 24 results migrated from low to high level and 2 on the contrary. For the rough set based method, it shared right results with the ordinary method. While in the 26 wrong results, 18 were reclassified to the right level and 6 remain intact.It was known that the ordinary method has been influenced by the rough characteristic of the recognition process. The correct rate was only 74%. The rough set based method had a higher correct rate up to 94%.Four representative images were chosen from the samples for explanation shown in Fig. 5.



(a) Stoma and slags (b) Bubbles

(c) Two stomas (d) Incomplete penetration

Fig. 5 Four representative samples

Fig. 5(a) is the original image of stoma in Fig. 2. After recognition and classification, it was classified to level III. According to the condition attributes and their values, here existed $c = 2$. For the rough set based method, it was classified to level IV.

Fig. 5(b) is the original image with a group of round defects. The recognition method could only recognize part of the bubbles. It was classified to level III. But for rough set based method, it was classified to level IV.

Fig. 5(c) is the original image with two stomas. The recognition method disrecognized them with bar defects and classified the defect to level III. But for rough set based method, it was classified to level IV.

Fig. 5(d) is the original image with a bar slag and incomplete penetration. The latter was disrecognized as a bar defect and classified to level III. But for rough set based method, it is classified to level IV.

V. Conclusion

From the experimental results, we reached the conclusion that the rough set based method was slightly influenced by error migration of welding defect recognition method. The misclassified quality of welding seams was reclassified to the right level. This method was independent on the welding parameters and suit for the classification of multiple compound defects. It had good robustness on unstable recognition results. The correctness was improved greatly. Applying this method to industrial site, it could help improving productivity and reducing labor costs. This method represents the future development of the intelligent welding.

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