Defect recognition and strength evaluation of dissimilar diffusion bonding based on support vector machine

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Abstract. A defect recognition method was proposed based on support vector machine to solve the problem of defect recognition and strength evaluation in TiAl and 40Cr diffusion bonding. The ultrasonic C-scan was performed on the diffusion bonding interface using a 10MHz focused transducer. The interface signals were converted into time-scale domain using continuous wavelet transform to extract the amplitude and phase characteristics as the input of the recognition models. Two models were trained to distinguish the kissing bond and the unbonded from the perfectly bonded interface. The bonded ratio obtained from the recognition results was studied to evaluate the shear strength. It was found that the trained models were effective in recognition of the kissing bond and the unbonded. The recognition accuracy of the two defects were 90.25% and 92.75%, respectively. Calculated bonded ratio established a good correlation with the shear strength which increased with the bonded ratio. The kissing bond and the unbonded are automatically recognised from the perfectly bonded interface. The shear strength of dissimilar materials can be evaluated by the bonded ratio.

Introduction

In recent years, considerable interests have been focused on nondestructive testing of diffusion bonding. Interfacial imperfections such as kissing bond and unbonded which are also observed in other solid-state bonding are parallel to the specimen surface and are suitable for ultrasonic testing [1-4]. Applications of this technique include transmission and reflection measurement [5-7], ultrasonic C-scan [8,9] and nonlinear imaging [10-14], guided wave inspection [15,16] and bonding process monitoring [17]. One difficulty of ultrasonic testing of diffusion bond is that the kissing bonds are only a few micrometers in size, which is much smaller than the wavelength of ultrasound. Most of the ultrasonic wave will pass through the defect and the reflection is very weak. The bonding joints appear to be flawless under ultrasonic testing [18]. Another difficulty is that as for the dissimilar diffusion bonding, some ultrasonic energy reflects not only from the imperfect interface but from the perfectly bonded interface due to the effect of impedance mismatch between the materials to be bonded [19]. If the bonding is imperfect and the size of the imperfections is considerably smaller than the wavelength of ultrasound, the interface can be modeled by a set of distributed springs [20,21]. The ultrasonic wave interaction with such an interface can be described using spring boundary condition. The reflection coefficient of normal incidence ultrasonic wave is related to three factors: the acoustic impedances of the materials on either side of the interface, the
ultrasonic frequency, and the normal interfacial stiffness. The interfacial stiffness is correlated to the bonding state. The normal interfacial stiffness varies from infinity when perfectly bonded is achieved, to zero for an unbonded surface. The normal interfacial stiffness must be much less than infinity when kissing bond occurs at the interface. Relationships among the reflection coefficient, the ultrasonic frequency and the bonding state have been studied in our previous work. It is found that the amplitude of the reflection coefficient is almost a constant, and the phase of that is the same for the perfectly bonded interface; for the kissing bond interface, the amplitude increases with the ultrasonic frequency, and the phase is the same at the low frequencies and opposite at the high frequencies; the amplitude doesn’t vary with the frequency, and the phase is opposite for the unbonded interface [22]. Although the kissing bond and the unbonded can be detected by the frequency-dependent amplitude and phase, decision is made artificially which sometimes lead to misjudgment. Recognition of the defects has not been realised automatically. Moreover, present study doesn’t provide information about relationship between the amplitude and phase characteristics and the bond strength. There is no reliable method to evaluate the bond strength.

In this study, a defect recognition method is proposed. The method is based on support vector machine (SVM) to train recognition models to distinguish the kissing bond and the unbonded from the perfectly bonded interface. The bonded ratio obtained from the recognition results are utilised to evaluate the shear strength. The aim of the study is not only to realise automatically defect recognition but to provide a valuable method for bond strength assessment.

1. Experimental

1.1 Diffusion Bonding

The materials used in this study were TiAl intermetallic compound and 40Cr steel. The chemical compositions of TiAl and 40Cr are given in Table 1. The specimens were machined to a rectangular shape of 45 mm × 30 mm, and the thicknesses were 4.2 mm and 14.8 mm for TiAl and 40Cr, respectively. Six specimens were bonded in a vacuum furnace and the bonding parameters are given in Table 2. A TiAl plate without diffusion bonding was prepared as a reference specimen for the characteristics extraction.

**Table 1** Chemical compositions of experimental materials (wt %)

<table>
<thead>
<tr>
<th>Material</th>
<th>Al</th>
<th>Ni</th>
<th>Cr</th>
<th>Nb</th>
<th>Ti</th>
<th>Fe</th>
<th>Si</th>
<th>C</th>
<th>Mn</th>
<th>S</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>TiAl</td>
<td>47.2</td>
<td>1.17</td>
<td>0.56</td>
<td>0.11</td>
<td>51.0</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>40Cr</td>
<td>–</td>
<td>0.18</td>
<td>0.95</td>
<td>–</td>
<td>–</td>
<td>base</td>
<td>0.27</td>
<td>0.40</td>
<td>0.65</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

**Table 2** Diffusion bonding parameters

<table>
<thead>
<tr>
<th>Specimen Number</th>
<th>Temperature (K)</th>
<th>Pressure (MPa)</th>
<th>Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1173</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>2</td>
<td>1223</td>
<td>15</td>
<td>15</td>
</tr>
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<td>3</td>
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<td>15</td>
<td>15</td>
</tr>
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<td>4</td>
<td>1223</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>5</td>
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<td>15</td>
</tr>
<tr>
<td>6</td>
<td>1223</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>
1.2 Ultrasonic C-scan

Ultrasonic C-scan was performed using ULTRAPAC C-scan immersion system. A broadband focused transducer with central frequency at 10 MHz was used. The ultrasonic wave was focused on TiAl and 40Cr diffusion bonding interface and TiAl-air interface. The reflected signals, which were called the interface signal and the reference signal, respectively, were collected with scan resolution of 0.2 mm and sampling frequency of 100 MHz and stored in a computer. The reference signal had 99 % amplitude and opposite phase of the incident wave. Phase inversion was performed on the reference signal.

1.3 Characteristics Extraction

Characteristics extraction was performed using the time-scale characteristics extraction algorithm proposed in our previous study [22]. Here the authors gave a brief introduction. The algorithm procedures were as follows:

1. The continuous wavelet transforms were performed on both the interface signals and the reference signal according to the following equation:

\[
W_j(a, b)_{\text{interface}} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)_{\text{interface}} \overline{\varphi}_{a,b}(t) dt = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)_{\text{interface}} \bar{\varphi}(t-b/a) dt
\]

\[
W_j(a, b)_{\text{reference}} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)_{\text{reference}} \overline{\varphi}_{a,b}(t) dt = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)_{\text{reference}} \bar{\varphi}(t-b/a) dt
\]

where \( W_j(a, b) \) is the continuous wavelet transform of function \( f(t) \), \( a \) and \( b \) are the scale and time parameter, \( f(t) \) is the ultrasonic signal, \( \varphi(t) \) is complex morlet wavelet, which is defined as:

\[
\varphi(t) = \frac{1}{\sqrt{\pi f_b}} e^{\frac{t^2}{2f_b}} e^{2\pi if_c t}
\]

where \( f_b \) and \( f_c \) are the bandwidth parameter and the central frequency of the wavelet. The optimal time-scale resolution was obtained when \( f_c \) was set as 1 Hz and \( f_b \) equaled 0.8. The scale parameter \( a \) was ranged from 17 to 6 according to the sampling frequency \( f_s \) (100 MHz) of the ultrasonic C-scan.

2. The time-scale ratio of the interface signal to the reference signal \( R(a,b) \) was obtained by:

\[
R(a,b) = \frac{W_j(a, b)_{\text{interface}}}{W_j(a, b)_{\text{reference}}}
\]

3. The time-scale amplitude \( |R(a,b)| \) and the time-scale phase \( \Phi(a,b) \) were obtained by:

\[
|R(a,b)| = \sqrt{R_R^2(a,b) + R_I^2(a,b)}
\]

\[
\Phi(a,b) = \angle R(a,b) = \arctan \frac{R_I(a,b)}{R_R(a,b)}
\]

where the subscript \( R \) and \( I \) correspond to the real and the imaginary part of \( R(a,b) \). Concerned only with the same or opposite of the time-scale phase, “+1” was utilised to represent the same phase, and “-1” was utilised to represent the opposite phase.

4. The time-scale amplitude \( |R(a,b_j)| \) of every time parameter \( b_j \) was linear fitted along the scale parameter \( a \) decreasing direction to obtain the fitting curve \( y_j \) according to the following equation:
\[ y_j = A_j \left( R(a,b_j) \right) + K_j \quad j = l, l + 1/f_s, \cdots, m \] 

where \( A_j \) and \( K_j \) are the fitting slope and the fitting constant of the fitting curve \( y_j \), \( l \) and \( m \) are the scope of the time parameter \( b \). The amplitude characteristic \( C_R \) was obtained by:

\[ C_R = \sum_{j=l}^{m} A_j \] 

(8)

(5) The phase characteristic \( C_\Phi \) was calculated by:

\[ C_\Phi = \frac{s}{v - u + s} \cdot \frac{1}{m f_s - l f_s + 1} \sum_{i=u}^{v} \sum_{j=l}^{m} \Phi(a_i, b_j) \quad i = u, u + s, \cdots, v \quad j = l, l + 1/f_s, \cdots, m \] 

(9)

where \( s \) is the step of the scale parameter \( a \) (\( s \) was set as 0.2 considering the computation efficiency), \( u \) and \( v \) represent the scope of the scale parameter \( a \), \( \Phi(a_i, b_j) \) is the time-scale phase of every scale parameter \( a_i \) and every time parameter \( b_j \).

1.4 Metallographic Analysis and Shear Test

The edges of the specimens were trimmed off to eliminate the edge effect caused by the focused transducer in the ultrasonic C-scan. The cross-sections of the specimens were prepared by standard polishing techniques. The specimens were etched in 2% nitric acid. The microstructures of the interfaces were examined by an optical microscope.

The central part of each diffusion bonding specimen was machined to obtain 20 shear test specimens with the dimensions of 4 mm × 9 mm × 19 mm and then subjected to the shear tests in a universal testing machine. The shear strength of TiAl and 40Cr diffusion bonding interface \( \tau_b \) was obtained by:

\[ \tau_b = \frac{F_b}{S} \] 

(10)

where \( F_b \) is the loading of the final failure, \( S \) is the area of the shear test specimen.

2. Defect Recognition

The defect recognition was performed using support vector machine. SVM is a supervised learning model used for pattern classification. The main goal of SVM is to construct an optimal hyperplane as the decision surface in such a way that the margin of separation between the closest data points belonging to two categories is maximised. A modified maximum margin idea that allows for mislabeled examples was suggested. The method introduces non-negative slack variables, \( \xi_i \), which measure the degree of misclassification of the data point. Parameter \( C \) is a user specified positive value that controls the trade-off between maximizing the margin and minimizing the error. It often happens that the data to discriminate are not linearly separable in the space. For this reason, it is proposed that the original finite-dimension space be mapped into a much higher-dimensional space by applying a kernel function [23].

For a binary classification problem, given a set of training data, each marked for belonging to one of two categories, a SVM training algorithm builds a model that assigns new data into one category or the other [24]. A binary decision tree is used for multi-category classification problem. A SVM in each node of the tree is trained using two of the categories. Several SVM models are trained to realise multi-category classification.

Considering the distinction of the defects, the structure of the binary decision tree was constructed as shown in Fig. 1. There are two models in the binary decision tree. The first
model was trained to recognise the unbonded from the kissing bond and the perfectly bonded interface. The unbonded was considered as one category and both the kissing bond and the perfectly bonded interface were considered as the other category. The second model was trained to distinguish the kissing bond from the perfectly bonded interface. The radial basis function kernel was chosen in the recognition as it is commonly used in the SVM classification:

\[ K(x, y) = \exp(-\gamma \|x - y\|^2) \]  

(11)

where \( \gamma \) is kernel parameter.

![Fig. 1 Structure of binary decision tree for the defect recognition](image)

The following procedures were utilised during the training stage:

1. Prepared the training and the testing samples. The samples were selected randomly from the interface signals of the perfectly bonded, the kissing bond and the unbonded. For each kind of the signal, the number of the samples was 1000. Twenty percent of the samples were set aside as the training samples and the remaining eighty percent of the samples were used as the testing samples. The extracted characteristics were used as the input of the model.

2. Determined parameter \( C \) and \( \gamma \) for each model. Grid search method was used to estimate accuracy for all possible combinations of \( C \) and \( \gamma \). Exponentially increasing values were considered initially to find a better possible set of values for \( C \) and \( \gamma \) that yielded better accuracy. Finally, \( C \) and \( \gamma \) values thus obtained were varied slightly to gain the best possible accuracy.

3. Trained the models using the determined \( C \) and \( \gamma \) values. Note that the parameter \( C \) and \( \gamma \) were different for the two models.

Then the testing samples were input to the binary decision tree to evaluate the recognition accuracy. The recognition was performed from the upper node of the tree. A decision was made about the assignment of the input testing sample into one of the two categories represented by transferring the testing sample to the left or to the right sub-tree. If the testing sample was transferred to the left sub-tree, it was recognised as the unbonded. Otherwise, it was input to the model 2 to decide whether it was the kissing bond or not. If the testing sample was correctly recognised, it was fallen on the half-space which it belonged to. Otherwise, it was fallen on the other half-space and recorded as the incorrect sample. The recognition accuracy \( R_A \) for each kind of the defect was calculated by:

\[ R_A = \frac{N'_r}{N_t} \times 100 \% \]  

(12)

where \( N'_r \) is number of the testing samples that had been correctly recognised and \( N_t \) is the total number of the testing samples.
3. Results and Discussion

Figure 2(a) and (b) are the ultrasonic C-scan image and the shear strength of specimen one. The rectangular regions A, B and C were discussed. The average amplitude of the interface signal was approximately 40% in the region B, which was close to that in the region A. However, the shear strength of the region A was 165.7 MPa, whereas that of the region B was 0 MPa. The average amplitude of the interface signal in the region C was up to 99% and the shear strength was 0 MPa. The microstructure of the interface proved that a bonding layer was formed at the interface of the region A. A few micrometer areas in which diffusion process was inhibited could be seen at the interface of the region B. These areas matched the feature of the kissing bond. And the interface was totally unbonded in the region C. It can be seen that there are reflected signals not only from the kissing bond and the unbonded but from the perfectly bonded interface. Moreover, there is no apparent difference between the signals from the perfectly bonded interface and those from the kissing bond. It is difficult to detect the defects from the C-scan image.

![Figure 2](image)

**Fig. 2 Ultrasonic test and shear test results: (a) C-scan image, (b) shear strength.**

Figure 3 shows the relationship between the average amplitude of the interface signal and the shear strength of the diffusion bonding specimens. There was only an approximate tendency that the shear strength decreased with the average amplitude of the interface signal increasing. The average amplitude of the interface signal of four specimens indicated using the symbol “◆” (the others used symbol “◇”) were 36.6%, 38.1%, 47.1% and 50.8%, respectively. The predicted shear strength of the specimens according to the approximate tendency should be between 20 and 50 MPa. In fact, the shear strength of these four specimens were 0 MPa. The shear strength can not be assessed by the average amplitude of the interface signal.

![Figure 3](image)

**Fig. 3 Relationship between average amplitude and shear strength**

Differences were illustrated after the characteristics extraction. Figure 4(a) and (b) are the amplitude and phase characteristics images of specimen one, which were reconstructed...
according to the position of the C-scan image. The amplitude and phase characteristics of the region A were approximately “0.2” and “0.8”. The amplitude characteristic approached to “8” and the phase characteristic was approximately “-0.7” in the region B (containing the kissing bond). The amplitude characteristics in the region C (containing the unbonded) were less than zero due to signal saturation sampling and the phase characteristic was close to “-1”.

Although the kissing bond and the unbonded can be distinguished from the perfectly bonded interface by the amplitude and phase characteristics, the defects cannot be identified automatically, which may lead to misjudgment. In addition, neither the amplitude characteristic nor the phase characteristic can be used to evaluate the shear strength. The shear strength doesn’t have a reliable evaluation method.

The recognition models are shown in Fig. 5. The model 1 separated the unbonded from the kissing bond and the perfectly bonded interface. The model 2 distinguished the kissing bond from the perfectly bonded interface. Symbols “○” and “☆” represented two categories. Note that symbols in the two models have different meanings. The hyperplane separated the space into two half spaces. There was a clear gap between the two categories. The testing sample was then input to the models to decide which category it was belonged to. The recognition accuracy calculated by equation (12) for the kissing bond and the unbonded were 90.25 % and 92.75 %, respectively. The kissing bond and the unbonded are successfully recognised by the models.

The recognition results were reconstructed according to the position of the C-scan images using different colors to indicate the bonding state. The orange, yellow and blue color were utilised to present the unbonded, the kissing bond and the perfectly bonded interface. The rectangular region A, B and C were further discussed. No obvious distinction was observed between the region A and B in the C-scan image, though their shear strength were different. While in the recognition reconstructed image, the bonding state were different. The specimen
was almost perfectly bonded in the region A, and only a few small areas existed kissing bond. The interface contained the kissing bond in the region B. There was the unbonded in the region C. The recognition results were consistent with the destructive test. Comparing the ultrasonic C-scan image with the recognition image, one can see that the recognition method is useful to identify the defects in TiAl and 40Cr diffusion bonding interface. The reconstructed image clearly illustrated the bonding state.

Fig. 6 Reconstructed image of recognition result of specimen one

Analogous recognitions were performed on the other specimens, and the same results were obtained. Figure 7 gives the recognition result of specimen two. Corresponding C-scan image and shear strength are also given in the figure. As can be seen that the average amplitude of the region D was approximately 35%. No obvious illustration indicated whether there was defect or not. However the average shear strength was only 21.4 MPa in the region D. The recognition results showed that there was kissing bond lying in the region D.

Fig. 7 Recognition results of specimen two: (a) C-scan image, (b) shear strength, (c) reconstructed image of recognition.

As it was discussed before, there was no reliable bond strength evaluation method. The bonded ratio obtained from the recognition results was studied to evaluate the shear strength. The interface bonded ratio was calculated by the following equation:

\[
B_r = \frac{S_B}{S} \times 100\%
\]  

(13)

where \(S_B\) is the area of the perfectly bonded region, \(S\) is the area of the shear test specimen. The relationship between the bonded ratio and the shear strength are shown in Fig. 8. Linear
fitting was performed to show the tendency of the two parameters. As can be seen from the figure the shear strength increased with the bonded ratio. There was a good correlation between the bonded ratio and the shear strength. The specimens using symbol “●” were those being discussed in Fig. 3. The bonded ratio of these four specimens calculated by equation (13) was 0 %, 5.2 %, 6.7 % and 8.6 %, respectively. It was predicted by the bonding ratio that the shear strength was low. Actually the shear strength of the four specimens was 0 MPa. Although the shear strength can not be evaluated by the average amplitude of the C-scan image, one can reliably assess the shear strength using the bonded ratio.

![Fitting line](image)

**Fig. 8 Relationship between bonded ratio and shear strength**

4. Conclusions

From the above study, we draw the conclusion that the proposed recognition method solve the problem of defect recognition and strength evaluation in dissimilar diffusion bonding. The trained models are effective in defect recognition and the recognition accuracy of the kissing bond and the unbonded are 90.25 % and 92.75 %, respectively. The bonded ratio obtained from the recognition results establishes a good correlation with the shear strength which increases with the bonded ratio. One achievement of the study is that the kissing bond and the unbonded are automatically recognised from the perfectly bonded interface. Another achievement is that the shear strength of dissimilar diffusion bonding can be evaluated by the bonded ratio. In the future study, the method will be applied to other solid-state welding methods, such as friction stir welding, friction welding and brazing to analyse its universality.

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