Local interrogations for detection of multiple defects using an active sensor network

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Abstract: With the application of a clock-like sensor network, a local interrogation strategy is established to extend the reconstruction algorithm for the probabilistic inspection of damage (RAPID) into multiple defects identification. In this strategy, the monitoring area is divided into several monitoring subareas, and each subarea is covered by a particular sensor network. Local interrogations are then employed in each subarea using the associated network of sensing paths. Benefit from that, the artifacts arise from the intersection of key sensing paths associated with different defects may be absent completely from some monitoring subarea. With the application of a proper image fusion strategy, the artifacts would be reduced and the damage indications could be preserved. The algorithm is applied to an aluminum plate with two artificial through-thickness holes introduced. The results demonstrated that the RAPID algorithm with the application of local interrogations is capable of identifying multiple defects in plate-like structures.

1. Introduction
Interrogation algorithms using ultrasonic guided waves have attracted considerable attentions in the nondestructive evaluation (NDE) and structural health monitoring (SHM), because of the advantages including fast scanning capabilities, low cost, long-range inspection, and testing inaccessible or complex components [1-2]. Especially, small and conformal sensing devices, e.g. piezoelectric ceramics, have been widely studied for generating and receiving guided waves for structural integrity monitoring [3].

Theoretically, if damage arises, some changes, more or less, always occur in the captured signals. The key process in signal-based identification is to correctly tease out these changes and then establish the linkages between them and damage [4]. Because of the dispersive and the multimode character,

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it’s really hard to find out the changes caused by the defects from the Lamb wave signal. Signal
difference coefficient (SDC) is a tomographic feature derived from the normalized cross covariance of
the signals between the reference and present states. It captures the overall changes of guided wave
signals, which are caused by the occurrence of damage. Making use of SDC as the tomographic
feature, the capability of the reconstruction algorithm for the probabilistic inspection of damage
(RAPID) would not be affected by the complexity of structural geometry or material property, as these
influences are implicitly included in both the reference signals and present signals [3,5-7].

The objective and motivation of this study is to investigate the RAPID algorithm for damage
localization of structures with multiple defects. A clock-like sensor array is used and a local
interrogation strategy is established. Then, its performance in multiple defects identification is
investigated. Specifically, the entire monitoring area is divided into several monitoring subareas. Since
different subareas correspond to distinct sensor networks, a particular artifact may appear at different
locations on individual images, or be absent completely from some images. In contrast, the dominant
response from an actual defect occurs at the same location. Benefit from that, the artifacts would be
reduced and the damage indications could be preserved, with the application of a proper image fusion
strategy.

2. Review of RAPID Algorithm
The physical intuition behind RAPID algorithm is that a defect would cause the most significant signal
changes in the direct wave path, and if the defect is away from the sensing path, the degree of signal
change would decrease [3].

In practice, the severity of the signal changes could be evaluated by the tomographic feature, signal
difference coefficient (SDC), which is defined as a statistical comparison between the signal in the
present state and that in the reference state [8].

\[
SDC = 1 - \frac{\sum_{k=1}^{K}(X_k - \mu_X)(Y_k - \mu_Y)}{\left(\sum_{k=1}^{K}(X_k - \mu_X)^2\right)^{1/2}\left(\sum_{k=1}^{K}(Y_k - \mu_Y)^2\right)^{1/2}}
\]  

(1)

where \(X\) is the reference and \(Y\) is the new set of data recorded with respect to current state, \(\mu\) is the
mean of the respective data set and \(K\) is the length of the data set. If the environmental and
measurement conditions are fixed, these changes are all attributed to the presence of damage.

In the tomographic reconstruction process, besides the severity of signal changes caused by the
defect, its spatial distribution also influences the estimation of probability of a defect occurrence at a
certain point. For a particular transmitter-receiver pair, \(S_{ij}\) (transmitter \(i\) and receiver \(j\)), the spatial
distribution function is non-negative and linearly decreasing [3].

\[
w_{ij}(x, y) = \begin{cases} 
1 + \frac{1}{\beta-1}\left[1-R_{ij}(x, y)\right] & \text{when } R_{ij}(x, y) < \beta \\
0 & \text{when } R_{ij}(x, y) \geq \beta 
\end{cases}
\]  

(2)

where
$$R_{ij}(x, y) = \frac{\sqrt{(x_i - x)^2 + (y_i - y)^2} + \sqrt{(x_j - x)^2 + (y_j - y)^2}}{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}$$  \hspace{1cm} (3)$$

Here, \((x, y)\) is the coordinate of any individual point within the reconstruction region, \((x_i, y_i)\) and \((x_j, y_j)\) are the coordinates of transmitter \(i\) and receiver \(j\), respectively.

Assuming that there are \(N\) array elements in the active sensor network used for damage identification, the estimation of probability of the presence of damage at position \((x, y)\) within the monitoring area can be expressed as [3],

$$P(x, y) = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} P_{ij}(x, y) = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} w_{ij}(x, y) A_{ij}$$  \hspace{1cm} (4)$$

Here, \(P_{ij}(x, y)\) is the defect distribution probability estimation from the transmitter \(i\) and receiver \(j\) sensor pair, \(S_{ij}\). \(A_{ij}\) is the SDC of the sensor pair \(S_{ij}\).

3. Local Interrogation Strategy Using Clock-like Sensor Network

In this section, an appropriate strategy is established, which enables a clock-like sensor array (as shown in figure 1a) to be employed for local interrogations. The scheme consists of three main steps: region partition, data fusion and image stitching, all of which are elaborated as follows.

3.1. Region partition

The monitoring area enclosed by the clock-like sensor network is divided into eight sectors by the straight lines which coincide with sensing paths connecting PZT A0 to other array elements, i.e. Sectors ①-⑧ in figure 1b. In this sensor network, the longest sensing paths pass through three contiguous sectors (e.g. Path 11 and Path 17 in figure 1b). Without loss of information from these sensing paths, the subarea for each local interrogation must contain no less than three adjacent sectors. In this experiment, the subarea to be interrogated consists of four contiguous sectors in the clockwise direction. For instance, the subarea enclosed by the red bold line consists of sectors ①②③④ is the first monitoring region, and the subarea enclosed by the green dashed line, which consists of sectors ②③④⑤, is the second one (figure 1b).

Figure 1. (a) A clock-like sensor array, and (b) Sectors partition and subareas for local interrogations.
There are eight monitoring subareas in total, and each sector is covered by four of them. Figure 2 (a)-(d) give the sensor networks of sensing paths associated with Subarea 1; Subarea 2; Subarea 3 and Subarea 4, all of which comprise Sector ④. It can be seen that there are eight transmitter-receiver pairs the sensing paths of which pass through Sector ④, including Path 17, Path 22, Path 26, Path 21, Path 25, Path 24, Path 4 and Path 5. Among these, each of the longest sensing paths (i.e. Path 17, Path 22 and Path 26) only exists in two subareas; and the shortest ones (i.e. Path 24, Path 4 and Path 5) exist in all the four subareas; while the others (i.e. Path 21 and Path 25) exist in three of them.

![Figure 2. Network of sensing paths for local interrogation of Sector ④.](image)

Once the entire monitoring area is separated into several different monitoring subareas (e.g. Subarea 1, Subarea 2, Subarea 3 and Subarea 4), RAPID algorithm is employed for local interrogations. In each local interrogation, only one monitoring subarea is inspected. Thus in the corresponding reconstructive image, only the probability distribution in this subarea is valid.

### 3.2. Data fusion

In this step, data fusion is employed to combine the four input images (i.e. the imaging results of the four monitoring subareas which comprise the same sector) obtained from different sensor networks into a resulting image, so that a decision or consensus could be obtained in the sector which is covered by these sensor networks. To reduce artifacts and preserve damage indications, an image fusion scheme based on the geometric mean is adopted [9].

\[
\text{mean}_{geo} = \sqrt[4]{a_1 \cdot a_2 \cdot L \cdot a_n}
\]

The equation means that the probability value of any grid of the fused image is the geometric mean of that of the same grid in the four corresponding individual images. For instance, the imaging results of Subarea 1, Subarea 2, Subarea 3 and Subarea 4 are fused to estimated the probability value of any grid in Sector ④.

### 3.3. Image stitching

In each individual image obtained in Step 2, the possibilities of damage occurrence are quantified at all mesh nodes of the entire monitoring area, sharing the same coordinates. However, only a sector is interrogated each time, and thus the probability distribution outside is invalid in the corresponding
image. To present the prediction results in terms of the probability of damage occurrence across the entire monitoring area, the image stitching technique is employed. In practice, several strategies of image stitching are possible [10]. The algorithm implemented here is to take the maximum pixel value, i.e. the pixel value of the fused image is the maximum value of all the corresponding pixels of the individual images.

4. Test Specimens and Procedure

The specimens used in this study are aluminum plates with dimensions of 500×500×2 mm, and the artificial defects are introduced in the form of through-thickness holes with a diameter of 8.5 mm (figure 3). The active clock-like sensor networks are configured by 9 surface-mounted piezoelectric ceramic discs with a diameter of 8 mm and 0.5 mm in thickness. The coordinate systems are employed with the plane of the monitoring area spanned by the horizontal, $x$, and vertical, $y$, axes, where the origin of coordinate is set to be the centre of PZT A0. Two application examples are introduced, where configuration of sensors and distributing of artificial defects are different. In the first case, the PZTs (except PZT A0) are centered on a circular template 252 mm in diameter at equi-angular position, and the coordinates of the centre of actual defects are (-16, 89.2), (59, -44), in the form of $(x, y)$. In the second case, the monitoring area enclosed by the circular array has a diameter of 300 mm, and the coordinates of the centre of actual defects are (-74, 33), (67, 83) respectively.

The PZTs are excited at 150 kHz using a 5-count sinusoid toneburst signal. Lamb wave signals captured in the pristine condition are employed as the reference signals. Then, the two defects are introduced. The present signals are captured after the introduction of the two defects.

![Figure 3](image_url)

**Figure 3.** Configuration of sensors and distributing of artificial defects: (a) the first example, and (b) the second example.

5. Results and Discussions

The whole monitoring area (300mm × 300mm) was meshed into 300×300 uniformly distributed grids to define the probability of the presence of damage. The data length, $L$, and the scaling parameter, $\beta$, can be determined according to [11]. In this paper, $\beta$ takes 1.1. Each sensor network in a subarea provides 14 sensing paths (figure 2). Local interrogations are performed in all subareas using their associated sensor networks. For illustration, the corresponding constructed images of the first application example are displayed in figure 4. In each image, the grids indicated by a small cross are the locations of centre of the two actual defects. It can be seen that the highest probability density value always occurs at the neighborhood of the locations of actual defects.
Figure 4. Probability of the presence of damage estimated using local interrogations: (a) Subarea 1; (b) Subarea 2; (c) Subarea 3; (d) Subarea 4; (e) Subarea 5; (f) Subarea 6; (g) Subarea 7; (h) Subarea 8.

The fused images corresponding to different sectors could be calculated from figure 4 by Equation (5), as shown in figure 5. It is noted that if a defect locates in or close to a sensing path connecting PZT A0 and another PZT element, the probability value would spill over into another sector in the associated fused images (e.g. figure 5d and figure 5e). The reason lies that the affected zone of this kind of sensing paths locates symmetrically in the two adjacent sectors.

Figure 5. Fused images corresponding to different sectors: (a) Sector ①; (b) Sector ②; (c) Sector ③; (d) Sector ④; (e) Sector ⑤; (f) Sector ⑥; (g) Sector ⑦; (h) Sector ⑧.
Figure 6a shows the reconstruction image of the entire monitoring area after the eight images in figure 5 are fused. It can be seen that the confusing information due to the intersection of key sensing paths are alleviated in the image. The reason could be explained as follows. Different subareas correspond to distinct sensor networks (figure 3), and thus the intersection of key sensing paths corresponding to different defects may be absent from one or more associated subareas of a particular sector. As a result, its effects would be mitigated or eliminated in the fusion process. However, if there is an actual defect occurred at the crossover point of some key sensing paths, even the intersection of key sensing paths is eliminated, other sensing paths surrounding it would also be possible to detect it and result in a high probability value for the presence of damage. In addition, the reconstruction result of the second application example is shown in figure 6c. It can be seen that the two defects could be identified simultaneously, and further, the grids with high probability value only locate in the areas around the two defects.

For comparison, the reconstruction results using global interrogation are also shown in figure 6. From figure 6b, it can be seen that the intersection of key sensing paths (i.e. Path 10 and Path 22) brings a false alarm at the neighborhood of the crossover point. The reasons could be elaborated as follows. When multiple defects occur, if key sensing paths corresponding to different defects (e.g. Path 10 and Path 22) intersect with each other, a large spatial distribution weight would arise at the neighborhood of the crossover point. Since the probabilistic distribution maps is reconstructed as a linear summation of the product of SDC value and the spatial distribution weight of every possible sensing path, a high probability value will appear for the presence of damage at these interfered areas, and further, cause confusing information for different instances of damage.

In the constructed images of the second application using global interrogation (i.e. figure 6d), there is a particular sensing path which locates close to more than one defect and thus brings an extremely high SDC feature value. In this case, the damage area consisting of the grids with high probability values for the presence of damage would locate in its affected zone. As a result, the identification of the defects becomes confusing.

![Figure 6](image_url)

**Figure 6.** Reconstruction images of two application defects using local and global interrogation: (a) the first application using local interrogation, (b) the first application using global interrogation; (c) the second application using local interrogation, (d) the second application using global interrogation.

6. Conclusion

In this paper, a clock-like array network and a local interrogation strategy are investigated. In addition, the local interrogation reconstruction results and global interrogation reconstruction results have been
compared. Some conclusions are obtained as follows.

(i) The RAPID algorithm using global interrogations is of a potential risk that the intersection of key sensing paths corresponding to different defects may lead to an incorrect identification of multiple defects.

(ii) With the application of local interrogations via an clock-like sensor network, a particular artifact results from the intersection of key sensing paths may be absent from some images, and its effects would be alleviated or eliminated in the image fusion process.

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References
[1] Valdes S H D and Soutis C 2002 Real-time nondestructive evaluation of fiber composite laminates using low-frequency Lamb waves J. Acoust. Soc. Am. 111 2026-2033.
[2] Alleyne D N and Cawley P 1992 The Interaction of Lamb Waves with Defects IEEE Trans. Ultrason. Ferroelectr. Freq. Control 39 381-397
[3] Zhao X, Gao H, Zhang G, Ayhan B, Yan F, Kwan C and Rose J L 2007 Active health monitoring of an aircraft wing with embedded piezoelectric sensor/actuator network: I. Defect detection, localization and growth monitoring Smart Mater. Struct. 16 1208-1217
[4] Su Z and Ye L 2009 Identification of Damage Using Lamb Waves: From Fundamentals to Applications Springer Press, Berlin Ch4 & Ch5
[5] Wang D, Ye L and Lu Y 2009 A probabilistic diagnostic algorithm for identification of multiple notches using digital damage fingerprints (DDFs) J. Intel. Mat. Syst. Str. 20 1439-1450
[6] Gao H, Shi Y and Rose J L 2005 Guided wave tomography on an aircraft wing with leave in place sensors Rev. Prog. QNDE 24 1788-1794.
[7] Wang D, Ye L, Su Z, Lu Y, Li F and Meng G 2010 Probabilistic damage identification based on correlation analysis using guided wave signals in aluminum plates Struct. Health Monit. 9 133-144
[8] Hay T R, Royer R L, Gao H, Zhao X and Rose J L 2006 A comparison of embedded sensor Lamb wave ultrasonic tomography approaches for material loss detection Smart Mater. Struct. 15 946-951
[9] Su Z, Cheng L, Wang X, Yu L and Zhou C 2009 Predicting delamination of composite laminates using an imaging approach Smart Mater. Struct. 18 074002 (8pp)
[10] Su Z, Wang X, Cheng L, Yu L and Chen Z 2009 On selection of data fusion schemes for structural damage evaluation Struct. Health Monit. 8 223-241
[11] Zeng L, Lin J, Hua J and Shi W 2013 Interference resisting design for guided wave tomography Smart Mater. Struct. 22 055017