Intelligent Evaluation of Crack detection with Laser Ultrasonic technique

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Abstract. In this paper, an intelligent evaluation method is proposed to quantitatively characterize surface-breaking cracks based on laser ultrasonic technique and the quantized particle swarm optimized support vector regression algorithm. Based on the physical model analysis, interactions between laser-generated surface acoustic waves (SAWs) and different cracks is numerically investigated. By selecting crucial features of the transmissions and reflections after interacting with cracks, the crack depth is evaluated with the optimized algorithm. To verify the proposed method, experimental datasets containing twelve different depths were used to size the surface-breaking cracks with incomplete prior knowledge. Evaluation results showed the high accuracy of the proposed evaluations, demonstrating the feasibility of this intelligent method for various applications in industry.

1. Introduction

Surface-breaking crack is a typical defect in metallic parts and structures exposed to a defective manufacturing procedure or subjected to a complex and cyclic loading during their service. Once surface cracks initiate, they typically grow under fatigue loading conditions, thereby threatening structural health, and eventually resulting in catastrophic failure of the structure [1,2]. Therefore, it is important to accurately detect the surface breaking cracks using non-destructive evaluation (NDE) methods.

Currently, a great deal effort on inspection of surface-breaking cracks has been taken to detect the location and depth of the defect [3,4,5]. As an alternative to exclusive ultrasonic approaches, laser ultrasonic inspection method, have been revealed as a powerful remote NDE technique. It is a promising modality with several benefits such as it offers the possibility of inspection with non-contact generation and detection, simultaneously generating multimode and wide bandwidth ultrasonic waves [6,7] even when working on the thermo-elastic regime [8]. The resulting broad excitation frequency bandwidth covers the majority of the ultrasonic bandwidths of interest for available applications involving material characterization, especially under some conditions such as curved geometry, high temperature and limited access applications [9]. Among the multiple generated waves, surface acoustic wave (SAW) is
extremely sensitive to the surface cracks and subsurface cracks, which can identify the location, depth and size information.

Recently several researches have investigated the features of the SAWs generated by laser ultrasonic method [10,11]. Wang et al. [12] researched the interactions between Rayleigh wave and subsurface defects. Also, Ni et al. [13] studied the diffracted and reflected ultrasonic wave modes to reveal the relationship between the waves and cracks depth and orientation by combining a Scanning laser source technique. Jian et al. [14] researched the measurement of surface-breaking cracks using Rayleigh-waves generated by lasers and detected by electromagnetic acoustic transducers. Although these works demonstrated the excellent application feasibility, the quantitative inspection of crack depth in metallic components is a promising field of research in terms of applying suitable signal processing techniques and defect characterization. Another significant work, concerning on the generated ultrasonic analysis methods, is the one proposed by Guan et al. [15], where a temporal characteristic of SAWs was proposed to measure the depth of surface cracks accurately. Zhu et al. [16] adopted time-frequency analysis by wavelet transform as the extracting features method to process signals of the laser ultrasonic from finite element model (FEM). Moreover, Zhang et al. [17] applied the wavelet threshold denoising method to significantly improve the signal to noise ratio (SNR) of laser ultrasound. These research demonstrated that the laser ultrasonic technique combined with effective signal processing could quantitatively characterize defects.

Summarizing the signal analysis above, although these procedures show conducive results over some metallic surfaces, the damage quantization is limited. These traditional evaluation methods described above evaluate crack depth need the complete prior knowledge, which is hard to acquire in practical. Moreover, it also involves rebuilding the mappings between the crack depth and signal parameters, which is expensive and time-consuming. Therefore, the quantitative inspection of crack depth in metallic damage components is still a challenge in terms of applying suitable signal processing techniques to extract ultrasonic features for reliable defect estimations. Inspired by the feature learning ability of support vector regression (SVR) algorithm, in this paper, an intelligent crack depth evaluation method based on optimized SVR algorithm is proposed to optimize the parameters of depth regression. Simultaneously, evaluations of unoptimized results is experimentally processed as comparisons to demonstrate the improvement of the proposed crack evaluation methodology.

In this paper, Section 2 introduces the theory of laser ultrasonic regime and its suitability for metal cracks detection. The proposed intelligent evaluation method based on the optimized quantized particle swarm optimized SVR model is introduced in Section 3. Section 4, the modeling and experiments, includes the specifications of laser ultrasonic inspection models and experiment setup. Based on the simulation analysis, experiments are conducted to demonstrate the advantage of the proposed method in this section. Finally, conclusions are drawn in Section 5.

2. Theory of laser ultrasonic detection for defects
In the solid, multi-mode laser-generated ultrasonic waves include longitudinal wave, shear wave, surface acoustic wave and Lamb wave. SAWs are widely used in the detection of surface-breaking cracks. As the power density of pulsed laser is lower than the ablation threshold, the mechanism of ultrasound generation is thermoelastic. The thermoelastic mechanism involves part of laser energy from a pulsed laser being absorbed by materials, creating a transient temperature field with non-uniform distribution, and the resulting thermal expansion giving rise to ultrasonic wave excitation. The thermoelastic mechanism can be modeled using the thermal conduction and the electrodynamic displacement equations as follows [18]:

\[ \rho C_v \frac{\partial T}{\partial t} - \nabla \cdot (K \nabla T) = Q \] (1)

\[ \mu \nabla^2 u + (\lambda + \mu) \nabla (\nabla \cdot u) - \alpha (3\lambda + 2\mu) \nabla T = \rho \frac{\partial^2 u}{\partial t^2} \] (2)
where  is the thermal conductive coefficient,  is the heat source,  is the temperature field,  is the material density,  is the specific heat;  is the time-dependent displacement,  and  are the Lame constants,  is the linear thermal expansion coefficient.

The boundary conditions of the radiated surface take the form given in:

\[
\mathbf{n}[(\alpha - \alpha(3\lambda + 2\mu))\nabla T - \mathbf{I})] = 0
\]  

(3)

Where  and  represent the unit tensor and stress tensor,  is the unit vector vertical to the surface.

Free boundary conditions are determined for the other surfaces. The initial conditions are described in:

\[
\frac{\partial u(t)}{\partial t} = 0 \quad \text{at} \quad t = 0
\]  

(4)

\[
T(t)\big|_{t=0} = 300K
\]  

(5)

3. The proposed quantitative characterization method

Conventional surface crack depth is evaluated by a set of fitting curves which connect the depth and built indicators, such as the coefficient of reflected SAWs and transmitted SAWs [19], and then evaluation results are processed by matching the unknown depth and indicators. However, if any parameter of the surface-breaking cracks dimension changes, the calibration curves should be experimentally determined again. So, an intelligent evaluation method, SVR [20], is utilized in this evaluation, which is an effective method for solving non-linear regression modeling problems such as small sample size, high dimensionality, nonlinearity, local minima, etc. Moreover, it has better regression performance and generalization capabilities to output continuous variable.

In the process of regression, parameter optimization is necessary to obtain global solutions, among which particle swarm optimization (PSO) is a potent algorithm. The main drawbacks of PSO are obviously, that is easily searching the optimal local values, and global convergence is not guaranteed [21]. To address this problem, in this paper, the quantum-behaved particle swarm optimization (QPSO) algorithm is applied to highly adaptively optimize the best penalty parameter  and kernel function parameter  of SVR, which are then employed to regress the surface-breaking crack depth, and the root mean square error of third-order cross-validation is utilized as the fitness function of QPSO. The gaussian radial basis function (RBF) kernel is selected in the SVR for the non-linear relationship of the crack depth evaluation, resulting from it is easy to implement and capable of non-linearly mapping the training data into infinite dimensional space. The specific principle is as follows.

In an  dimensional decision space, a particle swarm consists of  particles, and each particle represents a solution to a problem. At time , the position vector of the  particle is shown in Eq. (6), the optimal position searched at this time is presented in Eq. (7), and the optimal position searched by the entire particle swarm can be expressed as Eq. (8).

\[
x_i(t) = [x_{i1}(t), x_{i2}(t), ..., x_{in}(t)]
\]  

(6)

\[
p_i(t) = [p_{i1}(t), p_{i2}(t), ..., p_{in}(t)]
\]  

(7)

\[
p_g(t) = [p_{g1}(t), p_{g2}(t), ..., p_{gn}(t)]
\]  

(8)

The average value of the individual optimal positions is introduced as follows:

\[
M_{best}(t) = \frac{1}{m} \sum_{i=1}^{m} p_i(t) = \left[ \frac{1}{m} \sum_{i=1}^{m} p_{i1}(t), \frac{1}{m} \sum_{i=1}^{m} p_{i2}(t), ..., \frac{1}{m} \sum_{i=1}^{m} p_{in}(t) \right]
\]  

(9)

In order to balance the search ability of particles at different positions, the distribution range of each particle is set as:

\[
L_y = 2\alpha \times |M_{best}(t) - x_{yj}(t)|
\]  

(10)

The particle position update is from:
\[ p_{ij}(t+1) = \varphi_j(t) \times p_{ij}(t) + \left[1 - \varphi_j(t)\right] \times G_j(t) \]  
\[ x_{ij}(t+1) = p_{ij}(t) \pm \alpha \times \left[M_{\text{best}}(t) - x_{ij}(t)\right] \times \ln \frac{1}{u_{ij}(t)} \]  

Where, \( \varphi_j(t) \in U(0,1) \), \( u_{ij}(t) \in U(0,1) \), is random number between (0,1). \( \alpha \) is a contraction-expansion factor used to control the convergence speed of the algorithm.

In each iteration, after the particle position is updated, the update formulas of the individual optimal value and the global optimal value are:

\[ p_i(t+1) = \begin{cases} x_i(t+1), f\left(x_i(t+1)\right) < f\left(p_i(t)\right) \\ p_i(t), f\left(x_i(t+1)\right) \geq f\left(p_i(t)\right) \end{cases} \]  
\[ p_g(t+1) = \begin{cases} p_g(t+1), f\left(p_g(t+1)\right) < f\left(p_g(t)\right) \\ p_g(t), f\left(p_g(t+1)\right) \geq f\left(p_g(t)\right) \end{cases} \]  

where \( f(\cdot) \) is the cost (fitness) function defined in the process of regression.

4. Modelling and experiments

To study the interactions between surface-breaking crack depth and the generated SAWs, a model is established with the laser ultrasonic technique by FEM. The simulation is presented in Section 4.1. For the purpose of identifying the precision of the proposed evaluation method, surface-breaking crack depth inspection experiment is carried out, the detailed experiment setup is described in Section 4.2, and experiment results are drawn in Section 4.3.

4.1. Numerical model specifications and Simulations

Based on the laser ultrasonic generation theory described above, FEM models are studied to research the interactions between crack depth and generated laser ultrasonic. In this paper, aluminum plates are adopted, on which rectangular notches with six different depths are approximately the surface-breaking cracks. The material parameters of the aluminum used in the model are displayed in Table 1. Fig. 2 shows a FEM to study the physical process of the laser induced ultrasonic waves. The generation, a gaussian pulsed laser, emits 20 mm at the left side of the crack center. Two detection point, \( P_1 \) and \( P_2 \), separately acquire signals 30 mm at the left side and 20 mm at the right side away from the crack to detect the reflections and transmissions.
Figure 2. The FEM model of laser-generated ultrasonic

Table 1. Acoustic parameters of aluminum

| Parameter                           | Value |
|-------------------------------------|-------|
| Density (kg m$^{-3}$)               | 2700  |
| Young's modulus (Pa)                | 70e9  |
| Poisson's ratio                     | 0.33  |
| Coefficient of thermal expansion (1 K$^{-1}$) | 2.3e-5 |
| Thermal conductivity (W m$^{-1}$ K$^{-3}$) | 238  |
| Specific heat (J kg$^{-1}$ C$^{-1}$) | 900  |

Figure 3. The propagation and distribution of generated laser ultrasonic when (a) laser ultrasonic is far away from the crack, (b) laser ultrasonic comes across the crack.

The propagation and distribution of generated laser ultrasonic can be seen from Fig. 3. As can be seen in Fig. 3(a), laser source generates longitudinal wave (L-wave), shear wave (S-wave), surface acoustic wave (R-wave) etc., and the SAW (R-waves) propagate along the surface with limited penetration depth. When the R-wave propagates closer to the surface crack, such as Fig. 3(b), the detected reflected R-wave (rR-wave) originates from the near-field of the generated laser source by the surface-breaking crack. Simultaneously, a considerable part of the wave energy is reflected away by the crack resulting in significant attenuation of the transmitted wave (tR-wave) energy. To quantitative the interactions, these rR-waves and tR-waves are influenced by the crack depth, which consequently are further investigated in this paper.

According to the simulation analysis, we can see that for the smaller cracks, the energy of the rR-waves increases with the depth increasing, on contrast, the energy of tR-waves decreases. And the dominant frequency spectrum of the rR-waves moves to the low frequency band, and the amplitude of the middle-frequency and low-frequency of the tR-waves decreases. For larger cracks, the amplitude of the rR-waves and tR-waves changes slowly with the depth changing. Comparisons indicate that smaller crack depth has more effect on the reflected SAWs and transmitted SAWs. According to the analyses, the depth has a non-linear relationship with transmitted and reflected waves. However, the conventional fitting curves have bad robustness which may lead to the poor accuracy and low applicability. In order to perform intelligent detection and accurately size metal structure cracks, a laser ultrasound experimental platform is carried out in this study to extract sensitive feature information from reflected waves.
and transmitted wave signals, and the improved regression for an intelligent assessment of surface crack depth is combined.

4.2. Experimental setup
The considered aluminum object to be inspected is 100mm×50mm×6mm, with a mechanically induced crack width of 0.2 mm on the surface, and the depths to be investigated is from 0.1 mm to 1.2 mm (in step of 0.1 mm), totally 12 crack depths. The true depth is tested by Scanning Electron Microscope (SEM).

The schematic diagram of the entire laser-ultrasonic inspection system configuration is shown in Fig. 4. The source of the laser excitation is an Nd: YAG Pulsed laser, Model Dawa-200. As can be seen in the diagram, generation pulsed laser is emitted from the laser source under the thermoelastic mechanism. The Gaussian distribution pulsed laser is focused into a line source through cylindrical lenses, then irradiates the surface of specimen. After interacting with the surface crack on the specimen, the generated laser ultrasonic is detected by a Double-Wave mixing interferometer, which is built up to detect the signals with the superiorities of sensitivity, noncontact and broadband characteristics. Then detection laser is converted into electrical signals by the photodetector and finally collected by a high-speed data acquisition system with the sampling frequency of 200 MHz. In this experiment, L₀, L₁ and L₂ are separately 10 mm, 5 mm and 5 mm.

![Figure 4. The schematic diagram of the experiment setup](image)

The flowchart of proposed methodology for depth evaluation is shown in Fig. 5. As is shown in this figure, resulting from the thermoelastic mechanism, the acquired laser ultrasonic signals are digitally pre-processed with a bandpass filtering, and 20 repeated experiments of each crack depth were performed. And a wavelet transform is computed on the experimental signals in to increase the signal-to-noise ratio. Then signal analyses are carried out according to the 20 time-domain parameters and 16 time-frequency domain components. As aforementioned in Section 4.1, a specific extracting signal features based on principal component analysis (PCA) method are processed to exactly describe the depth information, including the 6 time-domain and 6 time-frequency domain features of transmissions and reflections for each crack depth. Training samples are input into the improved model with optimized SVR parameters of c and g. Finally, the testing datasets are applied to evaluate of crack surface depth.
4.3. Results and discussions

4.3.1. Reflections and transmissions captured of crack depths. An example of the ultrasonic waves (crack depth of 0.6mm) is shown in this section. Fig. 6(a) and Fig. 7(a) display the acquired raw signals with noises, which may submerge the characteristic component caused by crack depth. To eliminate noise, the 9-scale decomposition of sym5 function is performed on the raw experimental signals, the coefficients of which is dealt with by hard thresholding. After reconstruction, the denoised ultrasonic is got in Fig. 6(b) and Fig. 7(b), which demonstrates that the signal-to-noise ratio is greatly increased. From Fig. 6 and Fig. 7, direct SAWs, S-waves (reflected shear waves from the bottom-surface), reflected SAWs were received by detection P1 and direct SAWs, transmitted SAWs were detected by P2. Based on the arrival time of initial SAWs and shear waves in Fig. 6(b), the calculated propagation velocities of SAWs and transverse waves are 2961 m/s and 3185 m/s, which demonstrated the reliability of this experiment.

In the present work, 10 time-domain variables (T1–T10: peak value, mean, RMS, variance, skewness, kurtosis, crest factor, shape factor, impulse factor and margin factor) of transmitted SAWs and reflected SAWs were calculated. The principal component analysis (PCA) was used to reduce the dimensions of time domain characteristics. According to PCA, the first three features SR1, SR2, SR3 of reflected SAWs and ST1, ST2, ST3 of transmitted SAWs were extracted to represent the crack depth. An example of 1.0 mm crack depth with 5 experimental datasets is presented in Table 2, which shows the selected features in time dimension.

Wavelet transform is commonly used in time-frequency analysis with redundant basis functions, and hence can provide an arbitrary time-frequency resolution. In this paper, wavelet packets decomposition...
is applied to analyze the transmitted SAW signals and reflected SAW signals at different crack depths, with DB6 wavelet basis function and 3 layers decomposition. The surface waves corresponding to each crack depth, are further decomposed into $2^3 \times 8$ time-frequency signals. From above simulations, frequency distribution of SAWs is crucially affected by crack depth. After decomposition, the components $R(3,0)$, $R(3,1)$, $R(3,2)$ of reflected SAWs and $T(3,0)$, $T(3,1)$, $T(3,2)$ of transmitted SAWs are further studied, whose energy make up 95% of the signals and are sensitive to different crack depths. An example of 5 experimental datasets of 1.0 mm depth in time-frequency analysis is displayed in Table 3.

| samples | Reflected SAWs | Transmitted SAWs |
|---------|----------------|------------------|
| 1.0-1   | SR1 | 0.354 | 0.283 | 0.122 | 0.299 | 0.226 | 0.095 |
| 1.0-2   | SR1 | -0.369 | 0.238 | 0.158 | 0.289 | 0.198 | 0.115 |
| 1.0-3   | SR1 | -0.373 | 0.271 | 0.082 | 0.332 | 0.235 | 0.112 |
| 1.0-4   | SR1 | -0.35 | 0.324 | 0.119 | 0.309 | 0.216 | 0.103 |
| 1.0-5   | SR1 | -0.366 | 0.296 | 0.143 | 0.291 | 0.223 | 0.096 |

| samples | Reflected SAWs | Transmitted SAWs |
|---------|----------------|------------------|
| 1.0-1   | $R(3,0)$ | 0.639 | 0.511 | 0.423 | 0.286 | 0.218 | 0.299 |
| 1.0-2   | $R(3,1)$ | 0.626 | 0.502 | 0.456 | 0.261 | 0.203 | 0.321 |
| 1.0-3   | $R(3,2)$ | 0.635 | 0.510 | 0.489 | 0.253 | 0.193 | 0.298 |
| 1.0-4   | $T(3,0)$ | 0.636 | 0.509 | 0.402 | 0.265 | 0.204 | 0.314 |
| 1.0-5   | $T(3,1)$ | 0.637 | 0.506 | 0.475 | 0.280 | 0.213 | 0.325 |

### 4.3.2. Evaluation of surface crack depth.

To validate the proposed method, 20 samples of 12 crack depths were conducted with the experiment setup in Section 4.2. 15 samples were randomly chosen to construct the training set, and the remaining 5 samples is employed for testing. The training work is processed by inputting the 12 characteristics of transmitted and reflected ultrasonic waves to the optimized model, in which the particle space dimension is set to 2, the maximum iterations are set as 50, and the number of populations is 20. The global optimizations are searched as the parameters of SVR for the crack depth regression. To determine the performance of the proposed evaluation method, as the H-depth evaluation is processed, the other 11 crack depths features are trained except the H-depth features.

Fig. 8 is the root mean squared error (RMSE) with the iterations in the crack depth training process based on the proposed method. From this figure, we can see that the average fitness and best fitness are gradually decreased by the iterations, revealing that the RMSE of the regressions decrease in the process of iterations. This demonstrated the increasement of evaluation ability after the optimization. The average fitness of all particles is close to the optimal fitness at the 41st iteration, that is, all particles have reached a position approaching to the optimal space. Two crucial parameters of the regression model are obtained from the best global positions. After optimized training, the best parameter $c$ is 9.71 and the best $g$ is 0.54, which is then be used for the testing.

For comparison, the unoptimized SVR model is simultaneously tested for different crack depths. An average of the depth results obtained for all initial particles is determined as the evaluated depth. By the trained model, the average relative error of the test datasets is validated, which is shown in Fig. 9. From this figure, the average relative error of the unoptimized SVR test decreases with the crack depth increasing. However, it is very large when the crack depth is smaller. In Fig. 9, we can see that improved
QPSO-SVR has better evaluation ability for the defect depth prediction, especially when the defect depth is smaller. For example, at the depth of 0.1 mm, the average relative error of SVR is 82%, and improved method 9%. Overall, the proposed optimized model has a more accurate prediction for defect depth detection, especially for smaller depth defects.

Fig. 10 gives the error box plots of the five test datasets based on the SVR and improved SVR, which shows that the maximum absolute error of SVR is more than 0.1 mm, and improved QPSO-SVR within 0.05 mm (almost half of the SVR). From this figure, it displays that for the depth evaluation of 0.3 mm, the absolute error of the proposed method is 0.02 mm, which is 0.1 mm by the unoptimized SVR. Moreover, the median error is less than 0.05 mm for the proposed method, whereas it has a large difference of the unoptimized method. As detailed in Fig. 10(a), the median is nearly 0.09 mm at the tested depth of 0.1 mm and 0.4 mm. Comparing Fig. 10(a) and Fig. 10(b), it can be proved that it is a considerable improvement on the evaluation robustness and fidelity by the proposed method.

![Figure 8. RMSE with the iterations of the training process](image1)

![Figure 9. The average relative errors](image2)

![Figure 10. Absolute error of crack depth evaluation based on: (a) optimized SVR (b) unoptimized SVR](image3)

**Table 4. RMSE of the evaluation for the surface crack depth**

| Method     | RMSE/10^2 |
|------------|-----------|
| Optimized SVR | 0.836 0.978 0.684 0.784 1.076 1.380 1.275 1.377 1.869 1.759 1.385 1.813 |
| SVR        | 3.483 4.725 9.138 4.359 6.099 3.509 4.926 5.041 7.252 4.503 5.301 6.458 |

In order to quantify the evaluation performance, the root mean square error (RMSE) of different crack depth evaluation is calculated. The specific RMSEs are displayed in Table 4. It could be inferred from this table, the RMSE of unoptimized SVR has a large difference in depths prediction, which is between 0.03 and 0.09. Moreover, evaluations for different samples of the same depth have larger difference by unoptimized SVR method, for example, the absolute error of 0.3 mm-depth could be 0.1 mm, which can be seen from Fig. 10. After optimization, the RMSE of regression result is better than the SVR method. It is evident that the difference in RMSE for a series depth prediction is also smaller, which demonstrates the stability of the proposed method.
In summary, the optimized SVR method has high accuracy for the defect depth evaluation, especially enhances the ability for shallower defects and increases the robustness of the evaluation.

5. Conclusion
An innovative intelligent method was proposed for surface-breaking defect characterization. In this paper, numerical simulations showed that defect depths have interactions with the laser ultrasonic SAWs in terms of time-domain and frequency-domain. On this basis, an intelligent evaluation based on the optimized algorithm was proposed to automatically size the surface defect depth. In this method, surface defect depth can be specified by detecting the SAWs after interacting with the surface crack. Laser ultrasonic experiment platform was setup to verify the proposed method. The quantitative evaluation results demonstrated the proposed method could effectively detect the depth of sub-millimetre defects, consequently promoting the potential applications of intelligent evaluation in industry and structural health monitoring.

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