MOBILE ROBOT-BASED ULTRASONIC MECHANICAL STRUCTURE DETECTION ON A SHIP HULL

A Dissertation
Presented to
The Academic Faculty

By

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In Partial Fulfillment
of the Requirements for the Degree
Master of Science in the
George W.Woodruff School of Mechanical Engineering

Georgia Institute of Technology

May 2022

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MOBILE ROBOT-BASED ULTRASONIC MECHANICAL STRUCTURE
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Date approved: April 28, 2020
Perhaps one did not want to be loved so much as to be understood.

George Orwell
For those who are not remembered.
ACKNOWLEDGMENTS

I would like to thank the members of my thesis committee for their help in preparation of this work – professors Nico Declercq and Cedric Pradalier, without whom I would not have the chance to even start this thesis, and without whose ideas and fully support this thesis would never had been completed. And professor Luis without whose wise advice this theses would be faded into so much less.

Many thanks are due to my friends at Georgia Tech, Othmane, Antoine and many more, for their warm support both in professional and personal life of mine. Also to my parents, for they have always been there for me through thick and thin. And a special thanks for my girlfriend, for helping me through the plain and bitter of daily life.

The author gratefully acknowledges the support from the ultrasonic laboratory of Georgia Tech Lorraine and for this work offered by BugWright2 project. This project has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement No.871260.
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SUMMARY

Defects detection on mechanical structures are of great importance in modern industry. Here we propose a novel method to achieve mobile robot-based ultrasonic mechanical structure inspection on a ship hull. Such a method could be applied to mobile crawlers to achieve both self-localization of the robot and the inspection of the mechanical structure and the defects existing within the ship hull.

The overall objective of this project is to be able to develop a robust signal processing method for information extraction and evaluation to achieve inner mechanical structure detection and visual reproduction. Such a method could be further developed with better precision and robustness to inspect mechanical defects which are considered minor reflectors compared to the detection object in question here.

At the time of the writing, the experimental data acquired for validation purposes is obtained from both in-lab experiments on metal plates and on-site experiments performed on a simulated ship hull environment provided by CETIM(Centre Technique des industries mécaniques). The general dataset for development is obtained from finite element simulation performed on the ElmerFEM platform.

The following content discusses the generation of a simulation database, its practicality, advantage and limit. In addition, it also validates the similarity between simulation signals and ultrasonic signals in a real environment by comparison of real-situation derived mathematical model and simulated model.

It also discussed several viable signals processing methods such as machine learning method and correlation method to achieve reflector inspection and corroborate the results with experimental data to examine its robustness and practicality. During the process, we have developed a novel method based on acoustic theory which separates individual reflection wavelets by curve fitting. Such a method could be of better use in acoustic and ultrasonic inspection with further development in both precision and identification logic.
Finally, it also validated its applicability to mobile inspection robots by introducing both localization error and probability methods. Such measures could fully exploit the precision and massiveness of the simulation ultrasonic signal dataset.
CHAPTER 1
INTRODUCTION AND BACKGROUND

1.1 Introduction

Structural health monitoring (SHM) is essential for modern industrial development, particularly in maintaining the integrity of massive mechanical structures such as storage tanks or shells of transportation vessels. In such context, the inspection of marine transportation vessels presents an even more challenging problem due to its highly corrosive working environment and the uncertainty of their working schedule, preventing regular, long-term inspection. How to tackle this problem to achieve fast, light, preliminary health inspections have become a fundamental challenge in SHM. Current inspection methods of ship hulls are mainly based on visual inspection or human operators performing point-to-point ultrasonic inspection while the ship is in dry docks. These methods are sub-optimal and time-consuming, as the ship can be immobilized for 5 to 8 days, with significant financial impacts for shipowners[1]. Therefore, it is crucial to achieve a fast, light, preliminary health monitoring system that could utilize short time gaps of idol ships in docks to detect hidden defects, preferably achieved by a mobile multi-robot system that could take advantage of its automation and multi-thread working logic. Here we utilize a mobile robotic unit to perform an automated ultrasonic inspection on the ship hull, which could improve the precision and efficiency of inspection and provide a promising prospect for no-parking inspection, as shown in fig.1.1.

However, the main focus of current SHM systems still lies in defects detection, which detects minimal abnormalities in ultrasonic reflections generated and perceived on simple mechanical structures such as metal storage tanks or long-distance transportation pipelines. Nevertheless, in the specific context of transportation vessels, which contain many more
complex mechanical structures such as stiffeners, weld lines and plate edges (Fig.1.2) that could generate in the inspection process stronger ultrasonic echos than those by defects, the major obstacle of defects detection becomes the identification, localization and elimination of the influence of such mechanical structures.

The objective of this thesis is precisely the exact identification and localization of the mechanical structures on the ship’s hull. In this context, the main focus lies in the inspection of stiffeners. Before the main content of the thesis, here we introduce first the development of the relevant technology linked to SHM system and mechanical structure detection in the field of acoustics physics.

1.2 Background and Development

The SHM technology has been developing rapidly in the past decades. It is still one of the most promising and beneficial research areas in material science, acoustical physics and signal processing.

In the year 2005, R. Fenn and J.C. Watson[2] developed a method of using magnetic sensors to perform edge detection of subcutaneous stiffeners in an unknown environment based on thickness change and the magnetic nature of the material. Since then, many more efforts and devotions have been spent on mechanical structure detection based on
different mechanical theories such as laser detection and thermal conduction. Among all the theories, acoustic waves were one of the most promising areas due to their efficiency, robustness and relatively low costs.

Since most inspection objects are in the form of metal plates consisting of simple geometrical structures, the acoustic waves utilized are mainly Lamb waves. These are elastic waves whose particle motion lies in the plane that contains the direction of wave propagation and the plane normal (the direction perpendicular to the metal plate). A Lamb wave usually consists of two wave modes, symmetrical and anti-symmetric, as shown in fig.1.3. These two modes derive into different wavelets corresponding to different wave numbers[3]. The energy distribution between different modes and wavenumbers is tightly linked to the metal plate’s thickness and structure, which could only either be calculated in mathematical functions derived from theoretical models or simulated by modern FEM software.

Scientists have started focusing on abnormality detection on simple metal plates with
the potential of acoustic waves discovered, which could be applied to both stiffeners and
to achieve guided wave-based nondestructive testing for stiffeners, as shown in fig.1.4. It
was developed by H.Sun et al[5] into a multi-emitter-receiver circle and by J.Qiu et al[6]
and J.Hall et al[7] into a transducer matrix for higher information density and efficiency.
However, even though such methods explored the possibility of using guided waves to de-
tect stiffeners, the complexity of the set-up and the limited detection range still constrained
its application prospect.

To tackle the problem of limited detection range and complex set-up, using pure guided
waves echos as an information source for structure detection is developed[8]. This method
combined the emitter and receiver transducer into one uniform transducer and analysed the
acoustic signals acquired from long distance in-plate propagation, as shown in fig.1.5.

With the problems of detection range and set-up complexity solved, the existing signal
acquisition methods appear to be the bottleneck of the advancement of inspections. In
2021, a novel method was developed for mobile robot SLAM (Simultaneous localization
and mapping) on a metal plate based on ultrasonic signals[9], which was further developed
to adopt to polygon geometries[10]. With the corroboration of the previous work, we could,
1.3 Advantages and Challenges

In this thesis, the mobile robot unit utilizes ultrasonic echoes combined with its dynamic command to generate localization information on the metal plate. By associating the localization information with the acquired ultrasonic signals, we could produce a denser coordinate-echo map with high precision and better efficiency than the existing manual
methods. Then with proper signal processing methods, which were also developed in this thesis, we could automatically yield good structure detection results.

However, utilizing ultrasonic signals for structure detection and combining such a method with a mobile robot could present considerable challenges. First of all, for ultrasonic signals, due to their mechanical nature, each defect or mechanical structure, considered commonly as reflectors in this context, could generate reflection wavelets of different wave modes, which travel in metal plates with different phases velocities, confusing with other wavelets when overlapping occurs. Moreover, the inner signal noise caused by either structural abnormality or measurement error of sensors could seriously compromise the final result, leading to high uncertainty in the reconstruction process. To tackle this problem, we need to develop a robust signal processing method that could take advantage of a dataset with a relatively massive number of signals to eliminate random and systematic errors.

1.4 Methodology

There are three main aspects in this thesis: acquiring simulation echos through FEM (Finite Element Method) simulations, signal processing including experimental data validation and robotic application. Here we shall discuss the methods we have utilized and the background of such methods.

1.4.1 FEM simulation

On the FEM side, we used the software ElmerFEM to construct a mechanical model simulating metal plates available at the laboratory. The parameters and simulation model is chosen based on theoretical derivation combined with experimental validation.

In ultrasonic signals, the echo we receive consists mainly of two sequences of modes, asymmetric modes and symmetric modes. Each mode possesses its own wave energy and phase velocity. The thickness of the metal plate influences the speed and wavelength of each mode. To make the ultrasonic signal close to reality, we need to be able to simulate
different modes with their own features close to experimental measurements. To simulate the model with a precision high enough to differentiate different modes in acoustic echos, we need to construct a 3D structured model including a thickness dimension. Nevertheless, considering the computational cost of a full 3D simulation, especially with a small mesh size to simulate acoustic signals in different modes, I decided to use a cross-section 2D simulation method as a substitute. We could produce 3D echos with 2D simulations under simple setups, validated with theoretical models and experimental data by post-simulation processing. Also, during experimental validation, we found out the wave energy of reflected echos concentrates on the first arriving wavelets, the majority of which are in A0 mode. So in the aspect of precision, we only need to differentiate between the first arriving and second arriving wavelets in the signals to obtain most of the information we need.

1.4.2 Signal processing

We tried three methods to reproduce the localization map for edges and stiffener, each with a different theoretical orientation and produced a decent result on the signal processing side. The first method is the wavelet extraction method. Based on the Morlet wavelet assumption, we consider the acoustic signals composed of discrete Gaussian-shaped wavelets. By separating these wavelets, we could identify the possible representation of echos from different objects.

The second method is the machine learning method. By constructing a simple neural network trained on a simulation dataset and validated on an experimental dataset, we could extract essential information from the discrete data points in the signal sequence and reproduce the reflection source and its position and orientation.

The last method uses a mathematical model to generate theoretical signals of reflections from different distances. And then use this series of signals to produce a correlation map by convoluting the different theoretical signals with the raw signal. This way, under proper normalization, we could obtain a probability distribution of reflection distance.
1.4.3 Mobile robot mapping

In the last part, to construct a suitable simulated robotic environment and test our developed signal processing methods, we need to separate our effort into two branches: generate a close-to-reality signal database for processing and optimize the signal processing method to adopt to the noisy environment. We consider adding both signal noise and localization error to simulate the robot environment in the data generation part. In the signal processing part, we developed a multi-window tracking method for a more robust ultrasonic detection process, which could, on some level, eliminate the influence of local maxima in the beam map caused by signal noise and localization error.
2.1 Introduction

The finite element method (FEM) is a popular method for numerically solving differential equations arising in engineering and mathematical modeling. By splitting the object into small calculation elements of relatively insignificant size and applying real physical properties, we could calculate the static and dynamical response of the object under given initial conditions. This method could be applied in magnetic field analysis, thermal field analysis and what is applied here mechanical structure analysis.

![Finite element method mesh](image_url)

Figure 2.1: Finite element method mesh.

The application of FEM in the field of acoustic detection and elastic wave propagation study dates back a long time. In 1996, D.Datta et al[11] already developed a preliminary method to identify defects in composite materials using FEM with coarse meshing. C. Ong et al[12] also developed acoustic FEM simulation in order to study the surface acoustic
wave propagation pattern in the periodic piezoelectric structures. In 2010, B. Ghose et al. [13] simulated two-dimensional ultrasonic wave propagation in isotropic solid media, which shows the applicability of FEM in the field of acoustics in a more refined level by comparing the wave response under different excitation signals.

However, due to the high computational cost, most of the studies still focus on 2D FEM simulation, which would be impractical when we encounter problems of anisotropic nature, which make the model unable to be simplified into a 2D problem. R.Vayron et al[14] developed a 3D simulation based on a simple, isotropic problem on a small scale with a decent outcome. However, such a method could not be applied to problems of a more extensive scale like the ship hull and stiffener in question. So it remains a problem how to achieve 3D analysis with minimum computational costs and high accuracy.

Many prior studies have produced acceptable results for the construction of the FEM model for metal plates and stiffeners. R.Marks et al. [15] assumed the stiffener to be adhesively bonded on the metal plate and have produced Lamb wave interaction with the stiffener in acoustic signals. X.Bian et al[16] take the assumption of rigidly bonded stiffener and validate the practicality in an experiment. S.Schaal et al[17] further explored the model and defined the stiffener model as step thickness discontinuity. D.Greve et al[18] also adopted rigid-bond assumption in their study of defects detection. It is generally well-accepted to use discontinuous thickness to simulate real-life stiffeners. And this rigid-bond assumption could produce relevant inspection results.

Once we have constructed a valid FEM model, it is of great importance that we also establish a method to evaluate the accuracy of the simulation. A generally accepted method is by comparing the dispersion curves of simulated signals and theoretical models. S. Soro-han et al[May2006] have established the numerical method for dispersion curve extraction corroborated with the FEM model. A. Pahlevanpour et al[19] also implemented full FEM simulation for dispersion curve extraction. Both of their methods have shown the practicality of the dispersion curve comparison.
In the FEM simulation section of the thesis, what we are mainly trying to achieve is to build a 2D cross-section simulation model of the metal plate that is close to physical reality and could provide enough information for us to validate our signal processing method and then translate the 2D signal into a 3D signal by mathematical model derivation. Here we try to approach such an objective by comparing parameter convergence, 2D-3D signals conversion and adding random noises.

2.2 Parameter convergence

In this part, we focus on determining the specific parameters for FEM simulation, including element mesh size and excitation frequency, on obtaining a precision convergence while keeping the computational cost reasonable. To keep the simulation consistent with the metal plates we have in case of a need for experimental validation, we build our simulation models based on our plates, which are one 1.7mX1mX6mm steel plate and one 60cmX45cmX6mm Aluminium plate plus an attachable 1mX4cmX7mm steel stiffener.

2.2.1 Element size

To determine the appropriate element mesh size for simulation, we first build a physical simulation model. Here we choose a 2D rectangle model of size 450mmX6mm to simulate a cross-section of the experimental metal plate. The simulation set-up is shown in fig.2.2. In the simulation, we set the material to be Aluminium and set the excitation points on the plate surface at 10 cm, 20 cm, 30 cm, and 40 cm (positions 1,2,3,4) from the edge separately. Set the sampling frequency at 1.25MHz and the excitation frequency to be at 100KHz. Then we do an element size sweep at 0.4, 0.6, 0.8, 1,1.5,2 mm separately to find the convergence point for the simulated reflection echos. The results are shown in fig.2.3.

We could deduce that 1 mm is a comfortable choice for element size in this simulation. The convergence threshold could achieve good robustness in the accuracy of the simulation while maintaining the computational cost at a relatively low level. The slope in the
Figure 2.2: Simulation set up for element size convergence

The excitation frequency in real experimental set-up has a wide range. Nevertheless, the conflict in the simulation is that if the frequency is too low, it could omit necessary reflection signals in the initial excitation wavelets. Moreover, with the frequency increasing, a contemporary upgrade in the sampling frequency becomes necessary to acquire essential oscillation information and ensure the accuracy of the simulation. However, increasing the sampling frequency to a large scale could cause substantial computational costs. It would
also be unnecessary since the accurate sampling frequency of the experimental set-up is limited to a particular scale. So it is essential to find a suitable excitation frequency within a reasonable range.

To find the threshold frequency, we need to do a frequency sweep for simulation to find the convergence point where we could obtain necessary information from the signals without using excessive computational power. Here we build our simulation model based on an experimental aluminium board. We use a 2D model of size 60cmX6mm with and without a stiffener of size 4cmX7mm placed at X=40cm on the side as opposed to excitation points, which are on the bottom surface of the plate. The specific set-up is shown in fig.2.4.

Figure 2.3: Echo signal convergence based on different element size.
The specific simulation set-ups are:

- Time step size: \(2\times10^{-7}\)s
- Output step size: 4
- Sampling frequency: 1.25MHz
- Time span: \(1000\times8\times10^{-7}\)s = \(8\times10^{-4}\)s
- Plate material: Aluminium
- Stiffener material: Steel
- Frequency sweep range: 10 divisions from 10KHz to 100KHz
- Excitation position: \(X = 15\)cm
- Excitation signal: 2 periods of sinusoidal signal

The simulation results are shown in fig.2.5. We could gather from the results that the frequency threshold for convergence appears at 100KHz. We evaluate the convergence based on the envelope method we use. When we reach 100 kHz, the figure shows a negative value in the enveloped signal, which indicates that the signal is smooth enough to eliminate
noisy spikes, which sustains positive values. Also, given that the first arrival wavelets start appearing after frequency 30KHz, 100KHz shows a reasonably decent performance prospect.

We also show the signals with excitation frequency set at 100KHz with different distances from the setup stiffener in fig.2.6. We could derive from the comparison that the

Figure 2.5: Echo signal convergence based on different excitation frequency.
Figure 2.6: Echo signals based on different distances from stiffener.
stiffener reflection is relatively low energy compared to the edge reflection echos. So in
order to detect stiffeners, we should either eliminate the influence of the stiffener by sub-
tracting the related echo entirely or use a more precise processing method to recognize the
minor energy turbulence underneath the edge reflection echos.

2.2.3 Dispersion curve

To further evaluate the validity of our simulation model, we utilize a classical method to
construct a dispersion curve of the model and compare it with a mathematical model we
obtained. By comparison, we should be able to determine whether our simulation set in
general is converging to experience.

The dispersion curves are a set of curves that represent the propagation of wave modes
that are found in a specific geometry. The dispersion curves could be presented in dif-
ferent domains: frequency vs wave number; wavelength vs frequency; phase velocity vs
frequency; and group velocity vs frequency. Here we use the wave number vs frequency
version. We use the theoretical model to simulate the dispersion curves of S0 and A0 modes
waves propagating in a 6mm thick Aluminium plate since they are the two groups of echos
we usually detect as first arrivals in acoustic detection with the highest energy. The theo-
retical model is based on the Rayleigh-Lamb theory. We set up formalism for a solid plate
having an infinite extent in the x and y directions and thickness d in the z-direction. Sinu-
soidal solutions to the wave equation were postulated, having z-displacement in sinusoidal
form.

We set up a cross-section 2D Aluminium plate simulation of size 6mmX60cm. We used
an emitter-receiver mode to collect the acoustic signal propagated at different distances to
obtain the simulation dispersion curve. Then we line up the signals in distance order and
perform a 2D fast Fourier transform to obtain the dispersion curve. The result is shown in
fig.2.7. The bright line in the image represents the simulation-generated dispersion curve.
The blue and red lines are the theoretical dispersion curves of S0 and A0 modes separately.
From the result, we could derive that the simulation set-up is sufficiently representative of
the theoretical model, introducing high credibility into the simulation signals. Furthermore,
the wave energy centralizes in A0 mode, which could be helpful in the further study if we
could associate the signal with specific phase velocity.
Figure 2.7: Dispersion curve for simulation-mathematical model comparison.
2.3 2D-3D conversion

Once we have obtained the 2D cross-section simulation echoes, it remains a problem to translate this signal into a 3D signal. We need to simulate three main phenomena in an actual acoustic signal: dispersion, reflection, and attenuation. The dispersion and reflection could be sufficiently simulated in the cross-section simulation. To translate this signal into a 3D signal, we only need to add the attenuation factor. Here we propose a mathematical model for attenuation with its assumptions and derivations.

1. Assumption

   • No damping considered.
   • The radius of the transducer known.
   • The travelling speed (phase velocity) of the ultrasonic wave in the material is known.

2. Mathematical derivation

   Assume the energy of the initial wavelet is \( E \). The travelling speed of the wave is \( V \). At time \( t \), the energy line density of the wavefront could be expressed as:

   \[
   \rho_{\text{wavefront}} = \frac{E}{2\pi V t}
   \]  

   (2.1)

   If we assume the energy density of the wavelet is proportional to its displacement square (spring assumption \( E = \frac{ky^2}{2} \)), then we could further derive the equation into \( E = Cy^2 \) with \( C \) being a energy constant. Assume the diameter of the transducer is \( D \). Then at time \( t \) the reflection signal we receive would cover approximately the length of \( D \). So we have:

   \[
   E_t = D \frac{E}{2\pi V t}
   \]  

   (2.2)
The amplitude of the reflection wavelet could be expressed:

$$y_t = y \sqrt{\frac{D}{2\pi V t}}$$  \hspace{1cm} (2.3)

Where $y$ stands for the displacement in the original 2D signal.

*Coefficients acquired*

To validate the conversion method, we use the simulation signals combined with experimental coefficients to obtain close to reality 3D signals.

- **Traveling speed**: In stead of using the mathematical model to calculate the phase velocity of a specific mode, here we take the no stiffener simulation signals and take the first edge detection time point, subtract that with the excitation signal center (presumably one period of excitation out of two), then we have the traveling time $t$ with reference to the first edge reflection which also possess the highest energy. Divide the known reflection distance over half the traveling time would be the approximate traveling speed. Here we take the average over signals of 0.15 0.24m range. The result is approximately 2.35km/s

- **Radius of transducer**: assuming 1.7cm

*Results demonstration*

To demonstrate the results of 2D-3D conversion with a denser and more specific database, we performed another set of simulations consisting of two parts: long edge simulation (simplified as the x-axis) and short edge (y-axis). The simulation is also based on the Aluminium experimental plate mentioned before. In the x-axis cross-section, we perform the same simulation as in the excitation frequency section, only with the excitation position placed at a sequence of 1 cm apart from $X=10$cm to $x=40$cm and with the excitation frequency fixed at 100KHz. In the y
axis cross-section, we perform only no stiffener simulation with a cross-section size of 45cmX6mm. The excitation positions are ranged from X=5cm to X=35cm, 1cm apart with excitation frequency fixed at 100KHz.

We show the results of 2d-3D conversion in fig.2.8. In order to show the amplitude change more clearly, here we exhibit the enveloped simulation signal instead of the original oscillation signal. Due to the specific geometry feature of our problem, which is a rectangular ship hull metal plate with stiffeners welded perpendicular to the plate edges, we could simplify the 3D model into the combination of two 2D cross-section models overlaid together. Hence the presented figures with two 2D simulation signals from the long cross-section and the short combined with attenuation could produce a functional 3D signal. From the figures, we could derive the significance of the excitation signal remains, which is also a major residual issue in experimental setups. The rest of the signal provides a reasonable amount of close to reality ultrasonic information for further signal processing.

2.4 Signal visualization and validation

1. Reflection map

With the simulation signal at hand, the next step would be to use the data to reproduce the localization information concerning edge reflection and stiffener reflection. One way to achieve that is to construct a reflection map. A reflection map is a form of probability map which utilizes the probability distribution of reflection at each designated coordinate in the map translated from all the individual acquisitions overlaid together to represent the probability of a reflection source at the coordinate.

We iterate over N acquisitions for each coordinate \((x_i, y_i)\) on the reflection map to acquire accumulated probability density. Assume probability contributed by acquisi-
Figure 2.8: 2D,3D signals comparison. 2D is considered raw signal and 3D the attenuated signal in the graph. X and Y coordinates are imaginary coordinates taken from the simulation board. X could be interpreted as distance from the short edge and Y from the long edge.

Position j at coordinate \((x_j, y_j)\) is of form:

\[
P_{(x_i,y_i),j} = \frac{f(x_j, y_j, T_{i,j})}{\text{Max}(f(x_j, y_j, t))}
\]  

(2.4)

\[
T_{i,j} = \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{V_{\text{mode}}}
\]

(2.5)

In the formula, we use \(f_j(x_i, j_i, t)\) to represent the enveloped signal function, for we
need an absolute value without oscillation to produce proper probability distribution. $T_{i,j}$ represents the estimated arrival time of the reflection signal. $V_{\text{mode}}$ represents the phase velocity with the highest energy. Here we use the method mentioned above to calculate it. Because of the existence of a standard excitation signal, the division could produce a generally applicable normalization for the acquisition signals.

Therefore after accumulation we get a reflection map with a reflection source probability distribution:

$$P(x_i, y_i) = \sum_{j=1}^{N} \frac{f(x_j, y_j, T_{i,j})}{\text{Max}(f(x_j, y_j, t))}$$

(2.6)

Now we use the simulation signals acquired from the 2D-3D conversion section to reproduce the reflection maps of the experimental metal plate. The results are shown in fig.2.9. From the reflection maps, we could infer that the 3D signals we produced contain enough information to localize edges and stiffeners in the simulation with high precision and high resolution.

(a) Reflection map of plate with stiffener.  (b) Reflection map of pure plate.

Figure 2.9: Reflection map based on 3D simulation signals derived from 2D cross section simulations.

2. Beam map

Another way to visualize the localization information in the signal data set is to construct a beam map. A beam map is a polar coordinate probability map.
of each pixel in the map equals the probability of the reflection source existing on the specific beam corresponding to the pixel coordinate. For a pixel at coordinate \((\theta_i, r_i)\), the probability \(P(\theta_i, r_i)\) contributed by acquisition \(j\) would be:

\[
P(\theta_i, r_i) = \frac{f(x_j, y_j, \tau_{i,j})}{\text{Max}(f(x_j, y_j, t))}
\]  

(2.7)

\[
\tau_{i,j} = \frac{|(x_j, y_j) \cdot (\cos \theta_i, \sin \theta_i) - r_i|}{V_{mode}}
\]  

(2.8)

After accumulation, we could have the probability distribution:

\[
P(\theta_i, r_i) = \sum_{j=1}^{N} \frac{f(x_j, y_j, \tau_{i,j})}{\text{Max}(f(x_j, y_j, t))}
\]  

(2.9)

The results are displayed in fig.2.10. The beam map provides localization information in a more objective and easy to process way. Such map could also be utilized for further data processing while reflection map, being the more intuitive visualization method, is more suitable for results demonstration.

### 2.5 Signal-noise ratio

Another aspect of simulating real environment using simulation signals is to add environment noise. In this part, we introduce white Gaussian noise to simulate random environmental noise and use a reflection map to evaluate the validity and robustness of the simulation model under different levels of noise.

We show the results of noise addition in fig.2.11. Here we calculate the signal to noise ratio (STN) based on the ratio between signal energy and the energy of the excitation signal. In the reflection map, the stiffener starts to be undetectable when the noise energy is greater than -125 dBW, with a maximum amplitude of 1.5e-6. Signal amplitude is 1e-5. Therefore the robustness of the model could support a signal-noise ratio up to 10% 15%, which is
an acceptably robust model. For the edge reflection, due to the high energy density of the echos, it remains detectable under a high signal-noise ratio up to 35% in fig.10.1, with a noise of energy level 115 dBW.

Figure 2.10: Beam map produced from 3D simulation signals derived from 2D cross section simulations.
Figure 2.11: Reflection map with random white Gaussian noise. For different energy level of noise we express them into different STN(signal-to-noise) ratio.

2.6 Summary

We have developed a mature FEM model for ultrasonic signal generation combined with a post-processing method by the end of this part. Such a model with specific parameters adopted to this thesis’s specific experimental environmental set and validated by dispersion curve comparison could exhibit satisfying accuracy and consistency. We can generate an extensive ultrasonic signal database with precise correlated localization information for further signal processing with this set-up.
CHAPTER 3
SIGNAL PROCESSING

3.1 Introduction

With simulation acoustic signals and experimental signals, we need to proceed with signal processing to identify, localize and sometimes remove wavelets to acquire the necessary information for specific reflection sources. For example, when we need to identify the stiffener reflection, we have to remove the edge reflection since it is the reflection with much higher energy than the stiffener reflection under whose influence the stiffener reflection would become undetectable. We devised three methods to identify and localize individual wavelets corresponding to specific reflection sources.

For demonstration and adjustment purposes, we utilize a different signal dataset from a different metal plate for clearer signals with a bigger surface area to perform experimental acquisitions in more positions. The metal plate is of size 1.7m×1m×6mm, with and without a stiffener of size 1m×4cm×7mm placed at X=0.85cm on the side opposed to excitation points, which is on the bottom surface of the plate. The specific set-up is shown in fig.3.1. The specific simulation setups are:

- Time step size: 2e-7s
- Output step size: 4
- Sampling frequency: 1.25MHz
- Time span: 1000X8e-7s = 8e-4s
- Plate material: Steel
- Stiffener material: Steel
Figure 3.1: Experimental set up 1 for signal processing. The simulation set up is of the same

- Excitation frequency: 100KHz
- Excitation position for experiment set up: From (10,10)cm to (80,50)cm, 10cm apart
- Excitation position for simulation set up: From (10,10)cm to (85,50)cm, 1cm apart
- Excitation signal: 2 periods of sinusoidal signal

3.2 Wavelet extraction method

The first method is the wavelet extraction method. Information extraction from acoustic signals could be split into two directions, frequency spectrum and wavelet identification. It is well recognized that using Fourier analysis could determine the essential features of the wave packets[20], so the traditional wavelet extraction tends to examine the frequency domain of the reflection wavelet[21][22]. However, such a method performs poorly on distance detection. On the other hand, enveloped wavelet signals could be used for both
feature recognition and distance detection[23][24]. Therefore in this section, we attempt to develop a signal processing method to extract reflection distance based on enveloped signal and pattern recognition method.

According to Morlet’s wavelet assumption[25], acoustic wavelets generally possess the envelope shape of a Gaussian distribution. Based on Morlet’s theory, we could extract individual wavelets with Gaussian function curve fitting[26] and identify, localize and remove each wavelet according to energy level[27]. Here we introduce the derivation of the method. The demonstration data are from one set of experimental data acquired from a 60cmX45cmX6mm Aluminium plate, similar to the simulation set-up we utilized before. Here we list the steps to be taken to realize this method.

3.2.1 Amplitude alignment

To extract the wavelets, we first need to take a signal envelope with minimum information loss. We implemented two methods to compare their validity.

Relative distance

In this method, we filter out the crest and trough of the signal and then take each climax point, use the sum of relative amplitude changes between itself and its neighbour climaxes multiplied by a parameter indicating the influence of the time gap to represent the absolute amplitude of the climax point. This alignment could, on some level, erase the random mean shift observed in previous signal processing. We derive the relative distance according to the following formula:

\[
y_{2,\text{relative}} = \frac{y_2 - y_1}{2(x_3 - x_1)}(x_3 - x_2) + \frac{y_2 - y_3}{2(x_3 - x_1)}(x_2 - x_1)
\]  

(3.1)

This envelope method could avoid negative value in the envelope process but could cause higher information loss than the normal practised method.
Peak envelope

In the second method, we use the MATLAB built-in peak envelope algorithm, which uses high order splines to fit all the local minima and local maxima separately and uses the difference function between two splines as the envelope function. This envelope method could solve the mean shift we encountered before with minimum information loss but could cause negative value during processing. We maintain this method while setting all the negative values to 0.

3.2.2 Wavelet identification

This step is to find highly probable wavelets. By setting thresholds, we could filter out the noise and get an approximate wavelet centre’s location. We could separate the localization process into individual small-window localization, cutting down computational costs. For a scaled signal, we define two thresholds to filter out the improbable wavelets. Absolute value and relative value. For one local maximum, we take the value of two near local minima and define the relative value as:

$$A_{relative} = \frac{\text{Max}((\text{Locmax} - \text{Locmin}_1), (\text{Locmax} - \text{Locmin}_2))}{\text{Min}(\text{Locmin}_1, \text{Locmin}_2)}$$ (3.2)

Relative value should be related to the belief of existence of a wavelet at the given position. It shows the energy of the wavelet and could also be used to determine separate merged wavelets. Now we set preliminary thresholds as follows: Absolute value over 0.1, Relative value over 0.3 And we implement identification according to the following logic:

- Find the crest with the highest maximum value in the signals that could be determined as a wavelet. If there is none, jump out of the loop.
- Jump into the next step to localize the wavelet.
• Calculate a simulation for the wavelet and subtract this simulation signal from the real signal and create a new signal sequence that contains the rest of the wavelets.

• Restart the loop with the new signal.

3.2.3 Wavelet localization

This step includes the localization of the signal and simulating the signal. Assuming the envelope of the wavelet is similar to the form of a Gaussian distribution (Morlet wavelet). We could convolute the signal with a sequence of filter Gaussian function $y = a^2 e^{-ax^2}$ with different value of $a$. The highest value should appear at the center position of the wavelet. The simulation signal could be calculated:

$$y_{simulation} = y_{max} \cdot e^{-a(x-x_{center})^2}$$

(3.3)

or if we use a standard Gaussian’s function:

$$y = \sqrt{\frac{1}{\sigma}} e^{-\frac{x^2}{2\sigma^2}}$$

(3.4)

$$y_{simulation} = y_{max} \cdot e^{-\frac{x^2}{2\sigma^2}}$$

(3.5)

Note that for $y$, we could multiply it by any constant, and it would be equally sufficient. So the expression with $a$ and $\sigma$ does not match.

During the extraction process, The overlapping signals could cause a substantial mean shift. So we change the mean-shift method into a simple near-neighbour search. Take a tolerance window and determine the center of the wavelet width in that window. This way, we could balance errors caused by excitation frequency (unable to sample the exact climax) and overlapping signals. The size of the tolerance window should be linked to signal frequency, which affects the resolution of the wavelets. The final results of wavelets extraction
are shown in fig.3.2. From the figures, we could see that the wavelet extraction could sufficiently extract wavelet information from the envelope signals. Nevertheless, the disadvantage remains that during the two signal processing steps (envelope and wavelet extraction), the information loss could be significant compared to signal processing methods that operate on raw signals directly. Another disadvantage is that, as shown in fig.3.2(a), one dispersed wavelet could be identified as several small wavelets due to the limitation of the Gaussian variance.

### 3.3 Machine learning method

This part explores a machine learning method to detect experimental reflector prediction with a neural network trained in the simulation dataset and validated in the experiment dataset. We build this neural network to identify the two different edge reflections from the enveloped ultrasonic signals. Here we use the enveloped signals to erase the possible influence induced by amplitude mean shift, which could not be ideally removed by the signal processing method. The metal plate from which we gathered the reflection signals has a long edge in the x-direction and a short edge in the y-direction. Different edge lengths could generate two sets of different echos that vary in arriving time. So theoretically, it is possible to separate them in the signal dataset.

**Dataset setup**

- 3D enveloped simulation signals
- X axis length: 1.7m
- X data positions: 76 points equally spread from X=10cm to 85cm
- Y axis length: 1m
- Y data positions: 41 points equally spread from Y=10cm to 50cm
- number of samples: 76X41 = 3116
Figure 3.2: Wavelet extraction method performed on simulation 3D ultrasonic signals.

- number of features: 2001 (time steps in the signal)

Network structure
• input size: 2001

• output size: 2 (coordinates of X and Y in cm. Origin point at plate corner)

• first layer: Linear 2001:1000

• second layer: ReLU

• third layer: Linear 1000:150

• fourth layer: Sigmoid

• fifth layer: Linear 150:2

Training process

• learning rate = 0.001

• loss function: MSELoss

• optimizer: SGD

• epoch: 1000

Training loss and predictions

We present here the result of training and predictions in the simulation data in fig.3.3 and the predictions in experimental data in fig.3.4. From the results we could gather that the predictions on experimental data have many outliers. To quantify the outliers we plot the whole data according to its prediction error in fig.3.5. From fig.3.5 we could derive that the prediction model performs well on the simulation dataset but could still generate a relatively significant error on the experimental dataset. In the prospect of future work, we could further develop this method with a different neural network model (convolutional neural network) and use a more diverse dataset for training (adding a different level of noise for best performance). All in all, the method possesses promising potential.
3.4 Correlation method

In this method, we use a theoretical mathematical model to generate a series of simulated signals of reflection wavelets corresponding to different reflection distance[28]. Moreover, by convoluting the simulated signal with raw signal and under proper normalization, we could construct a correlation map expressing the probability of a reflection source at a given distance.
As for many damage detection strategies based on Lamb wave propagation, this model is based on an approach that uses a burst excitation signal \( e \) generated by a piezoceramic transducer \( m \) in a plate structure and a signal \( u \) measured by another piezoceramic transducer \( n \)[29]. After generation by the emitter \( m \), the burst propagates into the structure and is possibly reflected at a target point \((x_j, y_j)\) back to the receiver \( n \). To simplify the theoretical echo function, here we assume far-field conditions. And the cylindrical propagation of a given Lamb wave mode into the plate structure can be simplified to the propagation function \( p(x_j, y_j, \omega) \) used to relate the stress excitation signal at emitter \( m \) to a strain measured at the receiver \( n \)[30]:

\[
P_{mn}^{mode}(x_j, y_j, \omega) = A \frac{2c_p^{mode}(\omega)}{\pi \omega} \frac{1}{r_m(x_j, y_j)} \frac{1}{r_n(x_j, y_j)} e^{-i\left(\frac{r_m(x_j, y_j) + r_n(x_j, y_j)\omega}{c_p^{mode}(\omega)} - \frac{\pi}{2}\right)}
\]

where \( C_p \) is the phase velocity for given mode at frequency \( \omega \), \( A \) is the reflection coefficient, assumed in this model to be 1 (perfect omnidirectional reflector) and \( r_m \) and \( r_n \) are the
Figure 3.5: Coordinate predictions on different datasets. The absolute value represents the error between prediction and correct coordinates in the absolute distance. The relative value is the division of absolute value over distance from the acquisition points to the origin.

distance respectively from the emitter to the target point and from the receiver to the target point given by:

$$r_{m,n}(x_i, y_j) = \sqrt{(x_j - x_{m,n})^2 + (y_j - y_{m,n})^2}$$  \hspace{1cm} (3.7)

The model we have is in Fourier space. To obtain a specific amplitude-time function of the signal, we only need to convolute the inverse Fourier transform of the propagation function with the excitation function. Here we show the signals generated by the theoretical model in fig.3.6.
3.5 Edge echo elimination

The machine learning method is suitable for predicting individual reflectors, but the precision at this stage is not enough for further processing. So we could only use the wavelet extraction method and correlation method to identify, localize, and eliminate edges from the signal to further detect the stiffener’s existence. In this validation step, we use a dataset that contains acoustic signals acquired from an on-site stiffened plate. Experiment set up shown below:

- Plate thickness: 8mm
- Plate material: steel
- Phase velocity(A0): 2.1868km/s
- Excitation signal frequency: 20 divisions from 20KHz to 250KHz. Here we take 104.74e3hz signal for analysis.
- Sampling frequency: 1.25e6hz
- Set up visualization in fig.17
Here we introduce the two previous signal processing methods to eliminate the edge reflection wavelet from the full signal.

3.5.1 Wavelet extraction method

With the wavelet extraction method, we could assign each extracted wavelet to represent a specific reflection source. Because echos have an unmistakable energy hierarchy, which is \textit{Excitation} > \textit{edgereflection} > \textit{stiffenerreflection}, we could eliminate wavelets according to their energy order. Due to dispersion and high energy levels, excitation wavelets could sometimes be identified as several wavelets. In fig.3.8, we perform wavelet extraction in signals from several positions. To eliminate the influence of the excitation signal, we use a Sigmoid function to convolute with the original enveloped signal function. In the full-scale implementation shown in fig.3.9, we eliminate wavelets of energy orders 1 to 3.
Figure 3.8: Wavelet extraction method with excitation signal removed with Sigmoid function. For comparison. From fig.3.9, we could derive from the reflection map that the stiffener reflection arrears are very clear when removing the first and second-order wavelets. Furthermore, the stiffener echo also disappears when we remove any more than that. In the beam map, we could visualize the information further. When we remove the first-order
Figure 3.9: Reflection maps and beam maps of wavelet extraction method with excitation signal removed with Sigmoid function.

reflection, the prediction for the stiffener position is very accurate and dense. When we remove the wavelets further, the information becomes vague and dispersed. Moreover, after
the third order, the prediction disappears.

3.5.2 Correlation method

We eliminate the highest correlated theoretical signal from the raw signal with the correlation method. However, because of small phase shifts in raw signals, we could have a huge match error in signals which could cause high energy residual in edge reflection elimination, influencing further processing. We introduce a simple warping technique to ensure phase match in the signal.

Small window warping

within a selected window of the baseline signal, shift the other sequence within a limited range of phases to find a good match. Then we keep the central point of the shifted signal in the window as the aligned point corresponding to the baseline phase. This way, we could align the signal and control the accumulated shift not to exceed a limitation we defined:

Warping window size: one period should generally suffice. In this case, 11 signal points, with the sixth the central point. Phase shift maxima $\leq$ half a period on each side (more than one period in total could lead to multiple solutions). We could achieve decent performance with only 1 point shift in this specific case, which gives us a phase shift maxima of 3 data points.

Here we present the results of stiffener prediction in fig.3.10. To eliminate the dead zone between edge and stiffener where the echoes from edge and stiffener overlap, we skip the middle row of signal points. To maintain the far-field assumption, we also eliminate the signal points near the edge and the stiffener. The utilized points are shown in the figure. In fig.3.10(a), we performed the correlation method on unprocessed raw signal and received
(a) Raw signal with highest energy prediction at frequency 104KHz.

(b) Processed signal with highest energy prediction at frequency 104KHz.

Figure 3.10: Stiffener prediction in processed experimental signals.

A Beam map where only edge detection with high precision is visible. This emphasizes the importance of edge reflection echo elimination. So in (b), we performed edge elimination with signal warping at the same excitation frequency. In fig.3.11, we present the same elimination method performed at a different excitation frequency. From fig.3.10(b) and
fig.3.11, we could derive that the correlation method could produce reliable predictions on stiffeners at different frequencies with a different errors. Whether the error is produced randomly or closely related to excitation frequency is studied.

![Processed signal with highest energy prediction at frequency 116KHz.](image)

Figure 3.11: Processed signal with highest energy prediction at frequency 116KHz.

### 3.6 Conclusion and discussion

In this section, we have developed three signal processing methods to achieve individual reflection recognition.

We explored the curve fitting theory in the pattern recognition service for the wavelet extraction method. Combined with traveling speed calculated, both in theory and in experiments, this method can separate different wavelets and perform preliminary echo elimination. At this stage, we still determine the 'identity' of the wavelets by their energy. Nevertheless, with further development in the precision of curve-fitting and association with velocity calculation, this method should be able to associate each wavelet with reflection abnormalities at specific distances, provided we could differentiate them into different modes according to their signal frequency.
For the machine learning part, with the simulation data set, the neural network extracted sufficient information for strong reflection prediction. Such a method has shown promising potential in ultrasonic signal detection but can not yield a comforting, practical result at this stage because of two reasons. The first one is that experimental data acquired from on-site experiments can not provide sufficient information density because of the complexity of the acquisition. In contrast, simulation data acquired from FEM cannot represent reality data fully. The second reason is the relatively simple structure of the neural network, preventing it from extracting deeper, more complex information from the signal sequence.

For the correlation part, we have advanced the precision of the traditional correlation method[31] with signal warping. This method could yield reflection prediction with the best precision. Therefore we choose this method for further development which will be explained in the next chapter.
CHAPTER 4
MOBILE ROBOT MAPPING

4.1 Introduction

Now that we have developed a valid, reliable method for ultrasonic signal processing, we need to integrate this method into a mobile robot system for structural mapping. During such a process, we have two problems to be resolved.

The first problem is that we rely on estimating the stiffener on finding the highest value in the beam map during the development of our signal processing method, which was practical in the simple experimental set-up shown in chapter 3. Nevertheless, when we apply the method with echo elimination to complex situations like the simulation set-up, we developed in chapter 3.1 with four plate edges generating four sets of strong edge reflection echos. It would be tough to identify and eliminate all the influence from all four edges. So it is of vital importance to develop a randomized tracking method to localize sub-optimal local maxima in the beam map. Here we deploy the mean-shift window tracking method[32] commonly used in image processing.

The second problem lies in error control. When simulating a robotic environment and the signal noise, we also have to consider the localization error associated with the robotic trajectory. Combined with the window tracking method, we could analyze the robustness of the whole signal processing procedure and quantify the performance according to its noise level.

4.2 Window tracking

In this section, we try to develop a multi-window mean-shift tracking algorithm to localize sub-optimal local maxima in the beam map.
In the previous simulation set-up shown in fig.3.1, we have generated a signal database consisting of 3116 acquisition positions associated with corresponding coordinates. This data set is based on a metal plate with 4 edges and 1 stiffener, which contradicts the stiffener estimation method we developed in chapter 3. We eliminate the highest echo corresponding to the edge reflection and find the highest value in the beam map. We show in fig.4.1 the echo estimation and beam map derived from the simulation dataset.

Figure 4.1: Set up and beam map estimation for simulation signals.

With multiple edges, it is very improbable that we could eliminate all the edge echoes in the signal, especially with overlapping wavelets. So it becomes important that we should be able to detect sub-optimal local maxima in the beam map. Here we introduce the multi-window mean-shift tracking algorithm for

Here we set the window number to 10 for preliminary tracking in raw signals. The result is shown in fig.4.2. We could tell from the result that even with a window trapped in local noise maxima, we can still track down several edges and stiffeners with changing
**Algorithm 1** Algorithm for multi-window tracking

**Require:** Window number $N$

for $n = 1 : N$ do

Generate random window center coordinates $(x_n, y_n)$

Initialize target window center coordinates $(x_t, y_t)$

while $(x_n, y_n) \neq (x_t, y_t)$ do

$(x_n, y_n) = (x_t, y_t)$

update $(x_t, y_t)$ to its weighted center in the window

end while

Record target window center $(x_t, y_t)$

end for

precision in each process. This result could be promising in the aspect of probabilistic analysis.

![First window tracking](image-url)
4.3 Noise addition

This section focuses on the overall robustness of our window tracking method and its sensitivity to different noise sources. In the signal-noise ratio part in Chapter 2, we have introduced noise into the original ultrasonic signal. So in this section, we focus on how to add localization noise into the processing process and evaluate the robustness.

4.3.1 Localization error

Here we add noise in robotic localization coordinates to simulate the real inspection environment. The signals provided here are at the resolution of 1cm apart. According to previous literature[9], the localization estimation error generated by Ultrasonic SLAM could be reduced to lower than 1cm in an emitter-receiver setup. It could be further reduced in the pulse-echo setup simulated here.

In this setup, we generate the localization noise in Gaussian white noise. The results are shown in fig.4.3. The noise level is expressed as the squared average of the absolute value.

We could derive from the figures that the window tracking method stays robust under a certain level of localization noise but can not achieve high precision. The prediction possesses a certain level of randomness because localization noise smooths the local maxima peak. Furthermore, we take in the echo elimination introduced before to eliminate the high order echoes to accentuate the stiffener echo and compare the outcomes in fig.4.4.

The figures clearly show an accentuation of energy in the stiffener estimation area, which was noted by the black square, indicating that the echo elimination could be of practical use in multi-window tracking.
(a) Window tracking with localization error at 1mm.

(b) Window tracking with localization error at 4mm.

(c) Window tracking with localization error at 7mm.

(d) Window tracking with localization error at 10mm.

Figure 4.3: 10 window tracking under different localization noise level

4.3.2 Overall noise

With the noise model for localization model established, we could introduce the signal noise into the process to test the overall robustness of the method. The results are shown in fig.4.5.

In the figure, the stiffener is still detectable under low noise levels while accompanied by some random estimations due to the local maxima generated by signal Gaussian noise.
4.4 Results and discussion

We have produced a mean-shift multi-window tracking method that could track down sub-optimal local maxima, which could be utilized in stiffener detection as it could be very challenging to eliminate all the stronger echos. When operated on a colossal database, which corresponds to multiple acquisitions in a real environment, this method could produce a probability map indicating more precise estimations based on points clusters. Here we show in fig 4.6 one probability map generated on 150 acquisitions with a localization error of 5mm and the signal ratio of 1%. We could see that several clusters are forming on
(a) Window tracking with signal noise level at 1%.

(b) Window tracking with signal noise level at 4%.

(c) Window tracking with signal noise level at 7%.

(d) Window tracking with signal noise level at 10%.

Figure 4.5: 10 window tracking under localization error of 5mm.

the map, while the stiffener is one of the vague clusters.
Figure 4.6: Probability map generated by window tracking.
CHAPTER 5
CONCLUSION

While still at the early stage of its area, this thesis explores the possibility of collaboration between mobile robot SLAM and ultrasonic inspection on ship hulls. Some approaches provided promising results even within a limited experimental and simulation data set, while some provided a new perspective on the issue. Until now, we have advanced our knowledge on several aspects:

- FEM simulation could effectively recreate the ultrasonic signals generated by Lamb waves propagating in metal plates. We could simulate defects and structural reflections in the metal plates with high resolution and precision with appropriate element size. However, the signal noise model we created here could only account for random noise. For systematic errors, continued development is needed.

- For ultrasonic signal processing, wave extraction and machine learning methods have yielded promising theoretical and practical results. Nevertheless, these two methods still require further refinement for mature integration into inspection systems.

- Correlation method as a relatively mature method could be sufficiently integrated into further development of robotic mapping. However, there is still space for further refinement for specific reflector identification and echo elimination.

- For the robotic mapping part, the traditional mean-shift window tracking method, while proven to be sufficient for the time being, could still be trapped in local maxima and produce excessive noise in the estimation. So the improvement in efficiency and precision with outlier removal should be considered one of the primary objectives for this method.
In future studies, a more significant and more objective data set should be created and tested based on FEM and random error generation and systematic error generation. The machine learning method should be explored for a more complex structure. For example, CNN could be implemented for its superior performance in pattern recognition. The correlation method could be advanced to produce a more complex logical structure for consistent wavelet recognition based on continuous signals of high resolution.
Appendices
APPENDIX A
EXPERIMENTAL EQUIPMENT

Two sets of piezoelectric transducers are used for ultrasonic signal acquisition. Many other instruments were used.
APPENDIX B

DATA PROCESSING

Data was processed before being added to this document.
REFERENCES


