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► **To cite this version:**

Othmane-Latif Ouabi, Pascal Pomarede, Matthieu Geist, Nico Felicien Declercq, Cedric Pradalier. Monte-Carlo Localization on Metal Plates Based on Ultrasonic Guided Waves. International Symposium on Experimental Robotics, Nov 2020, Malte, Malta. hal-03120508

HAL Id: hal-03120508

<https://hal.science/hal-03120508>

Submitted on 25 Jan 2021

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Monte-Carlo Localization on Metal Plates Based on Ultrasonic Guided Waves

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Abstract. In this work⁴, we propose a method based on a particle filter for the localization of an industrial robot on a large metal structure that leverages first-order reflections of acoustic waves on a metal plate edges. In our approach, the acoustic measurements are acquired in a (pseudo) pulse-echo mode using a co-localized emitter/receiver pair of piezoelectric transducers, and we assume a known size of the metal plate. To validate the method, the acquisition of acoustic data is made manually, but it is aimed to be performed by a robotic platform soon. The results demonstrate that with our approach, it is possible to recover the robot localization to a precision of a few millimeters.

Keywords: localization, ultrasonic guided waves, particle filtering

1 Introduction

Maintaining the integrity of marine vessels structure is a significant stake in ensuring safe travels on the sea. When not removed, bio-fouling that forms on the hull can increase fuel consumption, while concealed damages like corrosion patches can lead to catastrophic failures. Hence, in the marine industry, inspection and cleaning of ship hulls are to be carried out regularly.

Current inspection methods of ship hulls are mainly based on visual inspection, and human operators perform cleaning while the ship is in dry docks. These methods are sub-optimal and time-consuming, as the ship can be immobilized for up to 8 days, with significant financial impacts for shipowners [1]. Autonomous robotic inspection and cleaning of large metal structures have not yet been established. In contrast, they have the potential to be faster, safer, more accurate, and less expensive than conventional methods. The mentioned thought is yet to be demonstrated, but it holds tremendous potential and major benefits to shipowners [1].

As localization is one of the critical features necessary for a proper autonomous application, we address this problem for a robot (namely a magnetic

⁴ This work is part of the BugWright2 project. This project is supported by the European Commission under grant agreement 871260 - BugWright2.

crawler) moving on a rectangular metal panel, which represents the essential element of ship hulls. In combination with conventional localization systems (laser theodolite, Ultra-Wide Band (UWB) beacons...), accurate localization on a metal structure may be achieved by using Lamb waves [8]. Lamb waves are Ultrasonic Guided Waves (UGWs) able to propagate in metal plate structures in a direction parallel to the surface. They can be generated in the material and received by using piezoelectric transducers. These waves can potentially travel over large distances, and when encountering the plate boundaries, they are reflected perpendicularly.

In the literature, prior work was addressing the problem of acoustic-based localization for a mobile agent in indoor environments using the acoustic reflections of sound waves in air [3, 6]. Furthermore, studies of Lamb waves mainly focus on the detection and localization of damages by a static network of sensors, consider only the direct transmission of the incident waves (e.g. [2, 5, 10]) and alleviate the effect of the reflections due to the boundaries that can also be received [7]. However, the localization of a mobile unit on a metal structure using Lamb waves is yet to be thoroughly investigated.

In this work, we show that by leveraging the waves' reflections on the boundaries of a rectangular panel and a basic wave propagation model, a particle filter [4], [9] can estimate the robot position despite the complex nature of guided waves [8], the sensing symmetries intrinsic to the plate geometry and the highly reverberating propagation media. The performance of our approach is assessed with real acoustic measurements that are acquired by hand, and results suggest that the position can be recovered with sufficient precision.

2 Technical Approach

Given a rectangular metallic panel of known size $l \times h$, we aim at estimating, for any time step t , the robot state $\mathbf{x}_t = [x_t, y_t, \theta_t]^T$ (2D cartesian coordinates and heading) from acoustic measurements and odometry data $\mathbf{u}_t = [\Delta r_t, \Delta \theta_t]^T$ (translation and rotational movements). The estimation is done in the metal panel frame, *i.e.* the origin is assumed to be the bottom left corner of the plate. The x and y axis are respectively aligned with the edges of size l and h . An illustration of the adopted notations is provided on Fig.1. In our setup, the acoustic waves are generated in the structure by a piezoelectric transducer, and the reflections are received by a second transducer co-localized with the emitter. This aims at approximating sonar-like pulse-echo sensing, though constrained to an acoustic wave guide.

2.1 Echo detection

Detecting the acoustic reflections from the measurements is essential to enable the localization of the mobile agent on the metal plate. To this aim, we rely on a basic wave propagation model [5] to model the signal $\hat{\mathbf{s}}(r) \in \mathbb{R}^N$ sensed after a single orthogonal reflection of the incident wave excited by the emitter,

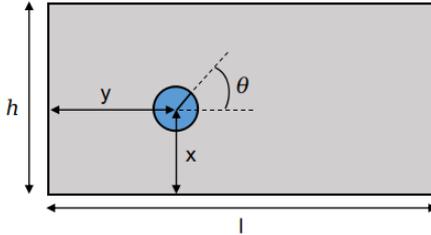


Fig. 1. Illustration representing an agent at the position $\mathbf{x} = [x, y, \theta]^T$ on a metal plate of dimensions $l \times h$.

on the border, at a distance r from the transducer pair. Under the assumptions that the plate is made of a homogeneous and isotropic material, and that the propagation is linear, $\hat{\mathbf{s}}(r)$ can be expressed by:

$$\hat{\mathbf{s}}(r) = \hat{\mathbf{g}}(r) * \mathbf{e}$$

where $\mathbf{e} \in \mathbb{R}^N$ is the discretized excitation signal, $*$ denotes the convolution product and $\hat{\mathbf{g}}(r)$ is the propagation model. From acoustic measurements $\mathbf{s}_t \in \mathbb{R}^N$, the echoes are extracted by computing the correlation signal:

$$\bar{\mathbf{z}}_t[k] = \frac{\hat{\mathbf{s}}(r_k) \cdot \mathbf{s}_t}{\|\hat{\mathbf{s}}(r_k)\|_2 \|\mathbf{s}_t\|_2} \quad (1)$$

for pre-defined ranges r_1, r_2, \dots, r_K . \cdot is the simple dot product. We next determine the envelope $\mathbf{z}_t \in \mathbb{R}^K$ of the resulting correlation signal $\bar{\mathbf{z}}_t \in \mathbb{R}^K$ from the Hilbert transform of the latter. The envelope is assumed to yield the likelihood to observe, within the measurements \mathbf{s}_t , an orthogonal reflection of the incident wave at the distances r_k from the transducer pair with the probabilistic model:

$$p(r_k | \mathbf{s}_t) = \eta \cdot e^{\beta \mathbf{z}_t[k]} \quad (2)$$

where β is a tunable parameter and η a normalization constant. In the next, we leverage the probabilistic model built to extract the echoes from the acoustic measurements in a particle filter to estimate the robot position. This approach is also known under the name of Monte-Carlo Localization (MCL) [9].

2.2 Particle filter

Bayesian filtering is a recursive estimation technique used to infer a probability distribution over unobserved variables from measurements using Bayes rule. Particle filters are approximations of the Bayes filter. They approach the target-probabilistic-distribution with a set of M particles, each of them carrying, at each measurement step, hypothetical values of the hidden variables. The particles are also provided with a weight indicating how their hypothesis on the values of the variables accounts for the measurements. After each time step, the particles are resampled with a probability proportional to their respective weight.

Consequently, particles that carry a hypothesis that is consistent with the measurements will tend to survive, while those who do not, will tend to disappear. For the localization problem, each particle represents a belief on the robot state at any measurement step t : $\mathbf{x}_t^{[m]} = [x_t^{[m]}, y_t^{[m]}, \theta_t^{[m]}]^T$, $m = 1, 2, \dots, M$. Our implementation of the filter using guided waves measurements is then the following:

Initialization: The particle filter is initialized by sampling M particles on the metal plate with a uniform distribution.

Prediction: The motion model is applied to every particle:

$$\mathbf{x}_{t+1}^{[m]} \sim p(\mathbf{x}_{t+1} | \mathbf{x}_t^{[m]}, \mathbf{u}_t).$$

If one limits the prediction to this single step, the particle filter will be likely to fail when there are no particles in the vicinity of the actual position. A simple remedy to this problem consists of disturbing the proposal distribution [9]. Here, we will randomly disturb a particle state by drawing, after the prediction and with a low probability α , a new sample:

$$\mathbf{x}_{t+1}^{[m]} \leftarrow \mathcal{N}(\mathbf{x}_{t+1}^{[m]}, \boldsymbol{\Sigma}),$$

where \mathcal{N} represents the normal distribution and $\boldsymbol{\Sigma}$ is a parameter of the filter.

Update and resampling: We compute, for every particle, the importance weight by determining the likelihood of presence of the four first-order echoes that should be contained within the measurement \mathbf{s}_{t+1} given the particles belief of the position, and using the model in (2):

$$w_{t+1}^{[m]} = p(x_{t+1}^{[m]} | \mathbf{s}_{t+1}) p(y_{t+1}^{[m]} | \mathbf{s}_{t+1}) p(l - x_{t+1}^{[m]} | \mathbf{s}_{t+1}) p(h - y_{t+1}^{[m]} | \mathbf{s}_{t+1}).$$

Finally, we create a new set of particles by drawing the m -th particle with a probability proportional to $w_{t+1}^{[m]}$. This procedure is then repeated for the next measurement step.

3 Results

We acquired acoustic data by placing an emitter/receiver pair of transducers at 108 different positions on a rectangular grid. Each measurement contains $N = 500$ samples collected at a sampling rate of 1.25 MHz. The metal plate used for the experiment has a size of $l \times h = 60 \times 45$ cm and is made of aluminium with a thickness of 6 mm. The experimental setup can be seen on Fig. 2.

To generate Lamb waves in the plate, we use an excitation signal that corresponds to two tone-bursts of a sinusoidal waveform at 100 kHz as shown on Fig. 3.a. The signal is amplified to up to 100 V peak-to-peak before being sent to the emitter. We use coupling gel to ensure good contact between the transducers and the plate surface. We also remove the very first received wave packet from

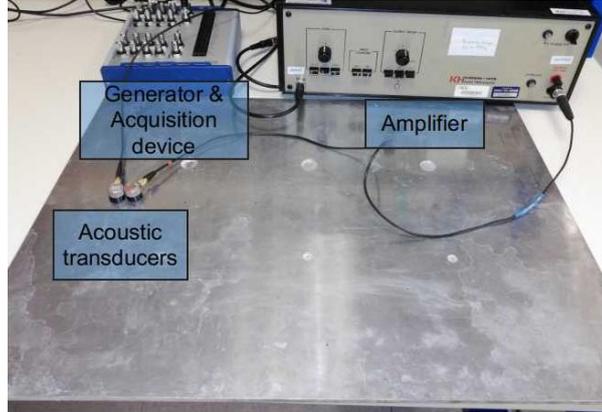


Fig. 2. Picture of the experimental setup. Two acoustic transducers are co-localized to approximate pulse-echo sensing.

the measurements, as it is due to the excitation of the emitter near the receiver. Fig. 3.b depicts a typical acoustic measurement obtained in this configuration and Fig. 3.c shows the envelope of the resulting signal \mathbf{z}_t obtained by correlating the measurement with the propagation model as in (1). It can be observed that the peaks of the correlation signal match with the expected ranges for the first-order reflections.

Next, to test our framework, we simulate a robot following a lawnmower path along the y -axis by presenting the corresponding sequence of measurements to the particle filter along with the theoretic displacement of the transducers used as the odometry data. At the end of the path, the “simulated” robot is taking the same path but backwards. We use, however, the same measurements. This provides us with a total of $T = 2 \times 108 = 216$ measurement steps. The particle filter is then run in this scenario using $M = 500$ particles. We first illustrate the performance of our approach in Fig. 4, which depicts the position of the particles during the measurement steps 2, 12, 108 and 216. During Step 2, the particles are concentrated in the bottom-left part of the plate as, for establishing the uniqueness of the position, the filter shall be initialized with particles only in one quarter of the surface due to the plate symmetry. At this stage, both the position and orientation of the fictional robot is still very uncertain. After only a few measurement steps, the position is well recovered, as shown during Step 12. The state estimation remains correct during the entire trajectory as the particles remain globally in the vicinity of the true position until the very last step.

To quantitatively assess the accuracy of the estimation, we show in Fig. 5 the median of the belief on the position and the ground truth. The results show that the estimation of the y coordinate is accurate as only a few measurement steps were necessary to reach an estimation error lower than 1 cm, and this level of accuracy remains stable for all the rest of the trajectory. It took a few more measurement steps for the filter to converge towards a correct estimation of x .

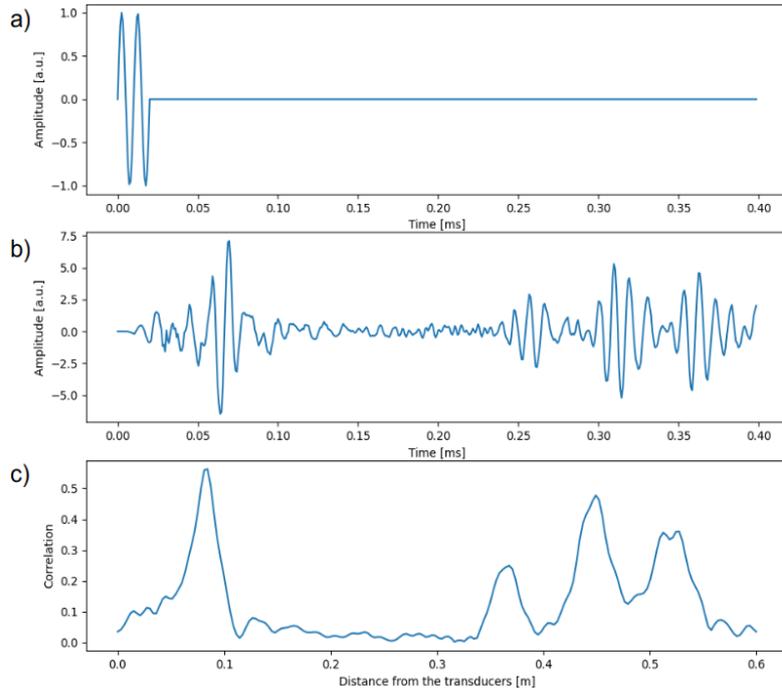


Fig. 3. a) Excitation signal used to generate Lamb waves. b) Acoustic measurement obtained for the transducer position $[x, y] = [0.08, 0.08]$. c) Signal \mathbf{z}_t obtained from the measurement shown in b). The peaks related to the 4 first orders echoes and which should be observable for the ranges $[x, y, l-x, h-y] = [0.08, 0.08, 0.52, 0.37]$, are clearly visible. The peak present at 37 cm is due to a higher-order reflection.

Nevertheless, still, it eventually achieves a comparable level of precision on the estimation. Overall, the results suggest that our approach has the potential for the estimation of 2D coordinates of an industrial robot in the plate frame, and it should be further investigated.

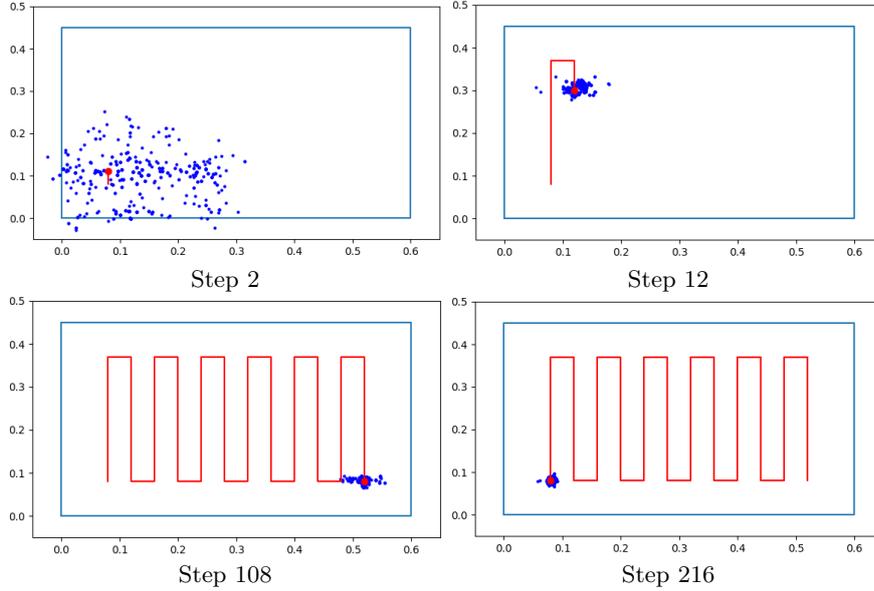


Fig. 4. Position estimated by all the particles (blue dots) during Steps 2, 12, 108 and 216 for a lawn-mower path on the plate. The true outline of the plate and true sensor positions correspond to the blue rectangle and red dot respectively.

4 Experiments completed or scheduled

The experiment that was carried out aimed at demonstrating the applicability of guided waves for the localization of an inspection robot on a metal structure. Although the results showed that acoustic measurements might contain sufficient information for that objective, the presented approach raises some questions:

The first limitation lies in the use of two transducers which are not rigorously at the same position. In contrast, the algorithm assumes co-localization of the emitter/receiver pair—the error due to such an approximation increases when the spatial periodicity of the waves decreases. The reason is that the measured signal will be more sensitive to small displacements. Hence, in our future experiments, we will use specific equipment enabling the use of a single transducer in a pulse-echo mode, as this could also reduce the estimation error.

Besides, further investigations are required to assess the stability of the filter using different scenarios. Indeed, a common issue of particle filters is that, when

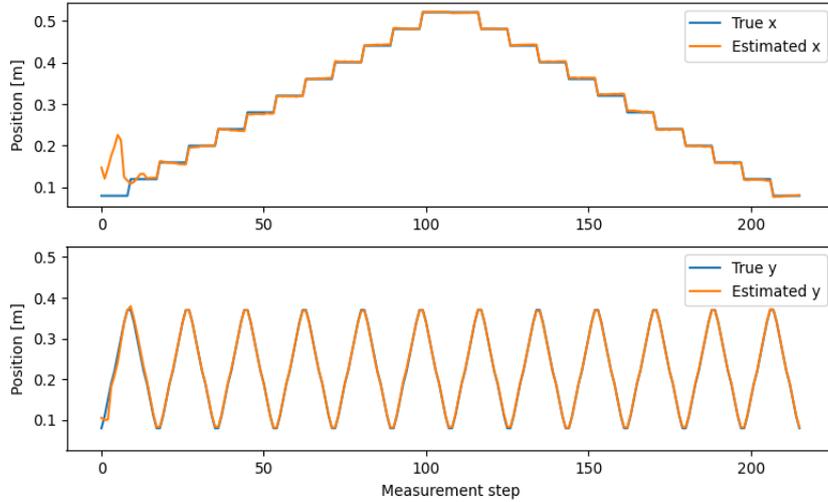


Fig. 5. Results of the robot localization using the particle filter.

the number of particles is not sufficient to cover the whole state space, there might not be any particle that will approach the right position and the estimation could fail. Moreover, our approach only makes use of first-order reflections, whereas high order echoes can also be sensed, as seen in Fig. 3.c. This may also hinder the filter’s convergence.

Finally, using a robot to acquire the acoustic measurements will be implemented as well, with the corresponding odometry readings. Taking into account the speed of the acoustic waves, which can typically be higher than 2000 m/s, the performances of our algorithm could also be assessed with a higher data acquisition rate.

5 Main Experimental Insights

We aim to achieve practical implementation of the filter on the field, but this may bring its challenges. Here, the experiment was done in a laboratory environment, which resulted in the acquisition of clean acoustic measurements with a high signal-to-noise ratio. However, noisy signals are to be expected on a real ship hull in outdoor environments, due, for example, to challenging environmental conditions and more inferior surface quality of the metal plates. Besides, metal plates on ship hulls may be larger than the one use in the experiment, which would also participate in the attenuation of the signals, and not perfectly rectangular. Rough metal plates may cause complex scattering of the waves, which is likely to prevent a proper localization of the robot as well.

Future work shall also focus on the problem of Simultaneous Localization and Mapping. Indeed, accurate knowledge of the shape of the plates may not

always be available. Hence, estimating both the plate geometry and the robot localization from acoustic data is a desirable next step.

Finally, the fact that the acquisition has to be done on an embedded system will be a source of additional difficulties. For instance, the robotic system will have to automatically ensure a good coupling between the transducers and the surface while the device itself might be a source of noise due to the mechanical displacement of the robot and/or the electronics.

References

1. Bugwright2, autonomous robotic inspection and maintenance on ship hulls and storage tanks, description of the innovative action (2019)
2. Alleyne, D.N., Cawley, P.: The interaction of lamb waves with defects. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control* 39(3), 381–397 (1992)
3. Bordoy, J., Schindelbauer, C., Höflinger, F., Reindl, L.M.: Exploiting acoustic echoes for smartphone localization and microphone self-calibration. *IEEE Transactions on Instrumentation and Measurement* 69(4), 1484–1492 (2020)
4. Chen, H., Liu, Z.: Application and Challenges of Signal Processing Techniques for Lamb Waves Structural Integrity Evaluation: Part A-Lamb Waves Signals Emitting and Optimization Techniques (09 2018)
5. Jeong, H., Cho, S., Wei, W.: A baseline-free defect imaging technique in plates using time reversal of lamb waves. *Chinese Physics Letters* 28(6), 064301 (jun 2011), <https://doi.org/10.1088/0256-307x/28/6/064301>
6. Kreković, M., Dokmanić, I., Vetterli, M.: Echoslamb: Simultaneous localization and mapping with acoustic echoes. In: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp. 11–15 (2016)
7. Sedlak, P., Hirose, Y., Enoki, M.: Acoustic emission localization in thin multi-layer plates using first-arrival determination. *Mechanical Systems and Signal Processing* 36(2), 636 – 649 (2013), <http://www.sciencedirect.com/science/article/pii/S0888327012004669>
8. Su, Z., Ye, L.: Identification of Damage Using Lamb Waves: From Fundamentals to Applications, vol. 48 (01 2009)
9. Thrun, S., Burgard, W., Fox, D.: Probabilistic Robotics (Intelligent Robotics and Autonomous Agents). The MIT Press (2005)
10. Zhang, Y., SIDIBE, Y., Maze, G., LEON, F., Druaux, F., Lefebvre, D.: Detection of damages in underwater metal plate using acoustic inverse scattering and image processing methods. *Applied Acoustics* 103, 110–121 (Feb 2016), <https://hal-normandie-univ.archives-ouvertes.fr/hal-02503535>