

Suppression of geometrical artifacts from acoustic lenses through low-rank approximation

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Abstract

Acoustic lenses have recently been used in non-destructive testing (NDT) for pipeline inspections. They increase the spatial coverage of linear phased array ultrasonic transducers, thereby reducing inspection time. However, the acoustic lens also introduces geometrical artifacts in the acquired signal, degrading image contrast and reducing flaw detection. Usually, artifact suppression methods rely on simulations or additional inspections to generate signals that emulate these artifacts, which are then subtracted from the signals of interest. In this work, we propose a method to reduce geometrical artifacts through a truncated Singular Value Decomposition (SVD). Since, in a mechanical sweep, the geometric artifacts remain constant and flaws are spatially localized, the low-order SVD components represent geometric artifacts, whereas the higher-order components contain information about the flaws. In a circumferential sweep of a pipe with a side-drilled hole, the most significant improvement of the proposed method, compared to the raw signal, occurred when the flaw intensity was minimal, resulting in an increase of approximately 1.92 dB in CNR. Overall, our method effectively enhances the ability to detect flaws by exploiting the spatial behavior of specific types of flaws.

Keywords: Non-destructive testing (NDT), Geometric artifacts, Singular Value Decomposition (SVD), Flaw detection, Pipe inspection.

1 Introduction

In the oil and gas industry, steel pipes are well-established for transporting fluids such as water, oil, and gas. However, these are not the only elements that go through the pipes during the process. Produced water, chemical additives, and even CO_2 are examples of transported components in the process. The elevated acidity and high CO_2 concentration in oil result in low pH values, which is the main cause of thickness loss. These conditions are observed in the Brazilian pre-salt layer. Therefore, periodic inspections of the steel pipelines are necessary to measure remaining thickness and guide decisions on preventive maintenance, to prevent significant natural damage and financial losses [1].

A method combining acoustic lenses with electronic scanning has recently been proposed to expand the inspected area while reducing the need for circumferential mechanical movement. Thus, it is possible to reduce inspection time and, consequently, inspection costs, since expensive infrastructure is required to inspect subsea equipment [2]. However, these acoustic lenses could introduce geometrical artifacts arising from internal reflections at their interfaces, worsening the detectability of flaws. A possible way to compensate for undesired internal echoes from the lens is to obtain an inspection without the specimen, where the expected echoes are from the lens, and then, from the real inspection, subtract this reference signal [3]. These reference signals can be obtained through simulations or

additional experimental inspection, either of which requires more human and computational effort.

Since geometrical artifacts depend mainly on the lens geometry, they theoretically must remain constant through a mechanical sweep. One way to take advantage of this fact is to decompose the original image using Singular Value Decomposition (SVD), which separates the most important patterns from the signal, identifies which components are associated with geometrical artifacts, and filters them out. In particular, the low-order SVD components will represent geometric artifacts, while the high-order components will represent spatially localized flaw information.

This paper presents a method to suppress geometric artifacts by reducing shot-to-shot background variability through robust normalization and applying truncated Singular Value Decomposition (SVD) from inspection acquisitions, thereby avoiding increased inspection time and simulation costs.

2 Methodology

Our geometrical artifact suppression methodology comprises three main steps: data pre-processing, SVD application, and low-rank reconstruction. The acquired data are first re-arranged via an unfolding process, followed by robust normalization to mitigate amplitude variations and outliers. Then, we apply the SVD to it to identify the dominant coherent components, which is followed by a low-rank reconstruction to attenuate weakly correlated variations arising from noise and artifacts. The details of each step are described in this section.

2.1 Data unfolding and robust normalization

During pre-processing, the main goal is to adjust the input data, which consists of several sectorial scans (S-scans), into a single matrix suitable for SVD. One way to achieve this goal is to flatten the images to compose this matrix.

Consider that each inspection is a mechanical sweep, which is composed of multiple consecutive S-scans. Each S-scans is represented by $I \in \mathbb{R}^{N_t \times N_\alpha}$, where N_t represents the number of time samples and N_α the number of steering angles (which is could be interpreted as pipe sectors, since we are using an acoustic lens). If we join multiple S-scans from this mechanical sweep into a single tensor, the result is $\mathbf{Y} = [I_1, I_2, \dots, I_{N_{acq}}]$, thus $\mathbf{Y} \in \mathbb{R}^{N_t \times N_\alpha \times N_{acq}}$, with N_{acq} indicating the number of positions assumed during the mechanical sweep.

Each S-scan is flattened into a 1D vector $\mathbf{s}_i \in \mathbb{R}^{N_t N_\alpha \times 1}$, yielding the unfolding matrix data $Y = [\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_{N_{acq}}]$, where $Y \in \mathbb{R}^{N_t N_\alpha \times N_{acq}}$ and each column of Y represents the unfolded S-scan at the i_{th} position of the mechanical sweep. Thus, each line of Y (i.e., $\mathbf{y}_k \in \mathbb{R}^{1 \times N_{acq}}$) corresponds to a unique pixel position in the S-scan along the mechanical sweep, achieving highly correlated lines that represent stationary structures. To avoid high-amplitude pixels and remove outliers, we adopt the Median Absolute Deviation (MAD) defined as:

$$\text{mad}(\mathbf{y}_k) = \text{median}(|\mathbf{y}_k - \text{median}(\mathbf{y}_k)|), \quad (1)$$

where the median of any row vector $\mathbf{x} \in \mathbb{R}^{1 \times N_{acq}}$ is denoted by $\text{median}(\mathbf{x})$.

To finally obtain the robust normalization of Y , we compute a standardized matrix Y_{std} :

$$Y_{std} = \begin{bmatrix} \frac{\mathbf{y}_1 - \text{median}(\mathbf{y}_1)}{1.4826 \cdot \text{mad}(\mathbf{y}_1)} \\ \vdots \\ \frac{\mathbf{y}_m - \text{median}(\mathbf{y}_m)}{1.4826 \cdot \text{mad}(\mathbf{y}_m)} \end{bmatrix}, \quad (2)$$

where the constant 1.4826 is used in MAD to obtain a statistically consistent estimate of the standard deviation under Gaussian assumptions [4], and $m = N_t \cdot N_\alpha$.

2.2 Singular Value Decomposition

The SVD will serve as the backbone of our artifact-suppression method. This operation will decompose the robust normalized matrix that represents all acquisitions from a mechanical sweep (Y_{std}) into orthogonal spatial and temporal components:

$$Y_{std} = USV^T, \quad (3)$$

where U and V are unitary matrices, S is a diagonal matrix with the singular values of Y_{std} in an decreasing order. In this decomposition, U contains the spatial patterns, S the singular values proportional to the contribution of each singular vector, and V the temporal patterns across the mechanical sweep.

Assuming that the geometrical artifacts remain constant across the acquisitions, they will predominantly be captured by the low-order components due to their high temporal coherence. The signal variability, quantified by the cumulative energy of the singular values, is defined as:

$$e_k = \sum_{j=1}^k S_{jj}^2. \quad (4)$$

We filtered out the low-energy components through a truncated low-rank approximation of the unfolded matrix, given by

$$\tilde{Y} = U\tilde{S}V^T, \quad (5)$$

where

$$\tilde{S} = \begin{cases} S_{ii} & \text{if } e_i \geq \gamma \cdot \|S\|^2 \\ 0 & \text{otherwise} \end{cases}, \quad (6)$$

where γ is a constant proportional to the total matrix energy S and defines the truncation threshold.

This reconstruction preserves the dominant coherent structures of the signal while attenuating weakly correlated variations. Suppressing weakly correlated components produces a stable, homogeneous background, thereby reducing its variance, since geometrical artifacts are preserved in the low-rank reconstruction.

Finally, all the filtered S-scans $\tilde{I}_n$ (where $n = 1, 2, \dots, N_{acq}$) are retrieved by an inverse unfolding process of the corresponding n -th column of $\tilde{Y}$.

3 Experiments and Results

The ultrasound data were acquired using Panther (Eddyfi, Quebec, Canada) acquisition platform, along with a linear phased array ultrasound transducer by Olympus® Model 5L64-A32. The transducer has a central frequency of $f_c = 5$ MHz, 64 elements, and a pitch of

$p = 0.5$ mm. The sampling frequency was $f_s = 125$ MHz. The hardware gain was 35 dB and the software gain was 0 dB; we set the gain to maximize the inner surface and the scatterer amplitude as much as possible. Data from the acquisition system was retrieved using the AUSPEX toolbox for ultrasound signal processing and image reconstruction [5].

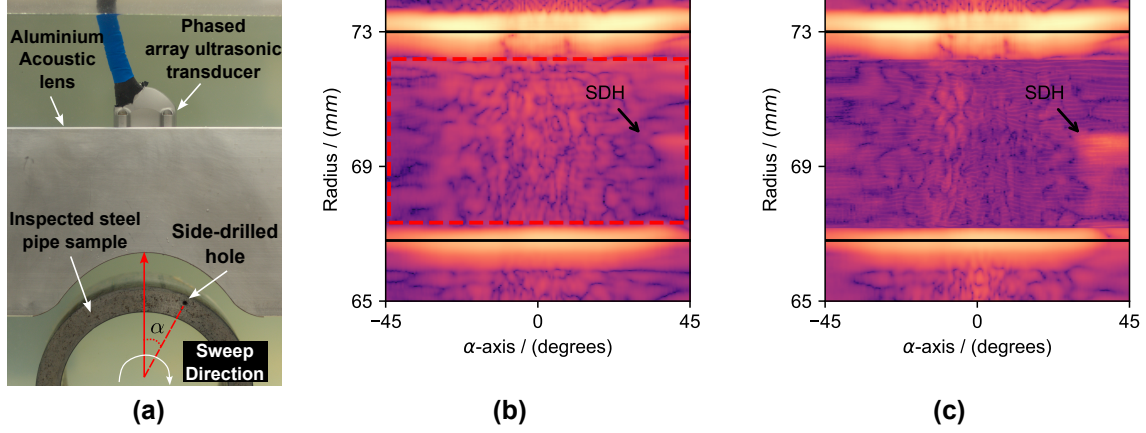


Fig. 1. Experimental setup and its corresponding sectorial scan. (a) Experimental setup with a pipe specimen featuring a side-drilled hole (SDH) and an ultrasound transducer coupled to an acoustic lens; (b) Sectorial-scan image with the area under the acoustic lens projected to cylindrical coordinates, before geometrical artifact suppression. The horizontal black lines represent the inner and the outer surfaces, and the ROI area is limited by red dotted lines; (c) The same sectorial-scan image after geometrical artifact suppression shows an enhanced contrast-to-noise ratio.

To evaluate our method's performance, we conducted a controlled experiment inspecting a pipe sample with a side-drilled hole (Fig. 1a). The side-drilled hole was initially aligned with $\alpha = 0$. Then we rotated the specimen clockwise and acquired 33 shots, with an angular difference of roughly 1° between consecutive shots. Since the acoustic lens projects the pipe into cylindrical coordinates due to its geometry, the side-drilled hole appears as a horizontal moving feature at the S-scan. Fig. 1b shows a particular S-scan where the side-drilled hole was approximately located at 40° . The geometrical artifacts, on the other hand, remain relatively constant throughout the mechanical sweep.

From this experiment, we applied the steps described in Section 2 to process and filter the S-scans. To preserve the amplitude of the outer and inner surfaces, we defined a region of interest (ROI) as the space between them (red rectangle in Fig. 1b) and applied our method only within this region. For visualization purposes, we stitched the ROI back into the original S-scan after geometrical artifact suppression, resulting in Fig. 1c. The ROI and original S-scan were individually normalized to equalize their amplitudes and ensure a clear view.

If we compare the original S-scan (Fig. 1b) with the S-scan after our artifact suppression (Fig. 1c), we can see a clear improvement in contrast and reduced background noise. As previously noted, this S-scan corresponds to a shot in which the flaw is near the boundary of the acoustic lens coverage, which corresponds to the worst-case scenario: when the flaw amplitude is comparable to the background. After applying our method, the flaw becomes clearly distinguishable.

We used the contrast-to-noise ratio (CNR) as a metric to evaluate our method's quantitative performance, which is defined as:

$$\text{CNR} = \frac{|\mu_{flaw} - \mu_{bg}|}{\sqrt{\sigma_{flaw}^2 + \sigma_{bg}^2}}, \quad (7)$$

where μ_{flaw} is the signal of interest (flaw) average pixel brightness and μ_{bg} the background noise average pixel brightness, and finally σ_{flaw} and σ_{bg} their respective standard deviations.

To compute these values, for a given shot, we selected a rectangular mask aligned with the side-drilled hole that did not reach either the inner or the outer surface, then applied a -6 dB filter to this region. From the pixels above the -6 dB threshold we computed μ_{flaw} and σ , then computed μ_{bg} and σ_{bg} from the bellow or equal this threshold.

Quantitative evaluation using the CNR metric shows a significant improvement after filtering. The proposed method achieved an increase of approximately 1.92 dB for the selected shot, compared to the reference-based subtraction method, which is commonly used to suppress structural noise.

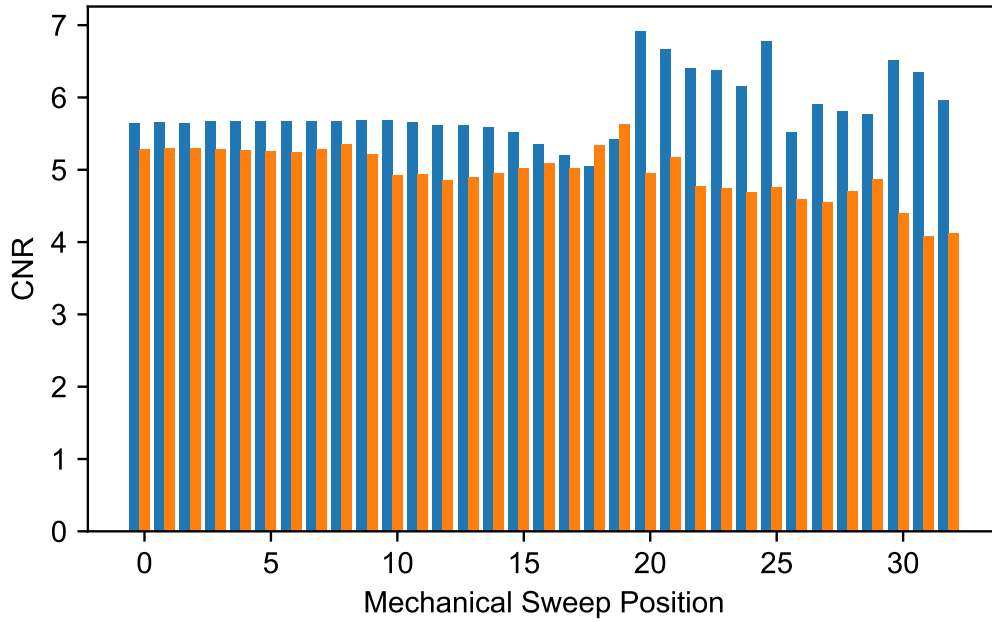


Fig. 2. Comparison between CNR values of images obtained by the reference-based subtraction method (orange bars) and low-rank approximation (blue bars). At position 0, the flaw is in the center of the lens, and in this region the reflectors exhibit high intensity. As the reflector moves away from the center of the lens, the reflectivity decreases, and the influence of the geometrical artifacts becomes more prominent. In these cases (samples on the right), the contribution of the proposed method is more relevant.

The observed improvement in CNR is primarily attributed to the reduction of background variability introduced by the low-rank reconstruction. Although geometric artifacts are retained in the reconstructed data, their shot-to-shot fluctuations are attenuated, resulting in a more homogeneous background and improved flaw detectability.

4 Conclusion

In this work, a low-rank SVD-based approach was proposed to suppress geometric artifacts in ultrasonic inspections using acoustic lenses. The method exploits the temporal coherence of structural components across a mechanical sweep to reduce background variability without requiring reference signals or modeling. The results demonstrate a consistent improvement in contrast-to-noise ratio, particularly in scenarios where the flaw amplitude is comparable to the background. The method enhances the detectability of flaws while preserving the main structural features of the signal.

Acknowledgements

This work was funded by Petrobras/CENPES through the R&D project AUSPEX2 (SIG-ITEC 2022/00436-2); and by the Brazilian National Council for Scientific and Technological

Development (CNPq) through grant number 305075/2025-0. The authors thank UTFPR, CAPES, Fundação Araucária, FINEP, and CNPq for the scholarships and additional funding.

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