Master Thesis

Towards 3D freehand ultrafast multi-perspective imaging of the abdominal aorta

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of the

Biomedical Engineering
Master Track Medical Imaging

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Abstract

In current clinical practice, the decision-making for clinical intervention of abdominal aortic aneurysms (AAAs) is based on the aneurysm diameter, which inadequately describes the rupture risk. Strain imaging and wall stress analysis can provide functional and mechanical information of AAAs to improve rupture risk assessment. Ultrasound imaging is a widely available imaging modality to obtain the geometry and motion estimates for this assessment. However, its performance is limited by low lateral resolution and a limited field of view (FoV). 2D ultrafast multi-perspective bistatic imaging has shown merit to overcome these challenges, but single plane positioning with two transducers is cumbersome for the operator. Moreover, volumetric imaging will be required to fully assess the AAA geometry and strains in all directions. Performing multi-perspective 3D imaging freehand could improve the image quality of abdominal images with clinical feasibility. In this research, a phantom study was performed to assess image quality of freehand 3D ultrafast multi-perspective bistatic imaging. Subsequently, a registration method has been proposed for accurate 3D probe localization. To compound the resulting data, a local fusion technique was implemented to obtain maximum information content in coherently compounded volumes.

A point source phantom was designed to allow for point-based registration for multi-perspective bistatic imaging. Multi-perspective volumes were acquired in an interleaved ultrafast scanning sequence in dual-receive (i.e. bistatic) mode. The image quality was assessed and compared to single-perspective imaging and multi-perspective imaging in single-receive (i.e. monostatic) mode in terms of contrast and resolution. The volume of the 3D speckle size, which is a measure for resolution, was decreased with 61% when comparing multi-perspective monostatic imaging to single-perspective imaging at a depth of 8 cm. Resolution was further improved for multi-perspective bistatic imaging, as it demonstrated a decrease of 71% compared to single-perspective imaging. On top of that, the FoV was extended for the multi-perspective set-up.

The developed point-based registration algorithm is highly dependent on the presence of point sources. Therefore, an automatic volume registration method for the abdominal aorta has been proposed. The relative probe positions were found using feature detection and alignment of multi-perspective monostatic US volumes with an optimization of the reconstruction quality of the trans-probe data. The method was tested on experimental data of a porcine aorta phantom. The registration error, which was quantified in a simulation study, was only in the order of one wavelength, thus accurate probe localization was achieved. Subsequently, the obtained volumes were compounded using a smart fusion algorithm. The weights for fusion were determined locally by means of a principal component analysis on a multi-resolution representation of the volume. This technique yielded an improvement of wall-lumen contrast, and therefore increased the visibility of the porcine aorta.

In conclusion, the feasibility of 3D freehand ultrafast multi-perspective bistatic imaging has been shown. Future research could focus on further developing the presented optimization method to determine all transformation variables, resulting in robust and generic probe localization. Moreover, it is recommended to investigate the applicability of the described methods in the clinic.
Abbreviations and symbols

**Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
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<tbody>
<tr>
<td>1D</td>
<td>One-dimensional</td>
</tr>
<tr>
<td>2D</td>
<td>Two-dimensional</td>
</tr>
<tr>
<td>3D</td>
<td>Three-dimensional</td>
</tr>
<tr>
<td>AAA</td>
<td>Abdominal aortic aneurysm</td>
</tr>
<tr>
<td>B-mode</td>
<td>Brightness mode</td>
</tr>
<tr>
<td>CNR</td>
<td>Contrast to noise ratio</td>
</tr>
<tr>
<td>CR</td>
<td>Contrast ratio</td>
</tr>
<tr>
<td>CT</td>
<td>Computed tomography</td>
</tr>
<tr>
<td>DAS</td>
<td>Delay and sum</td>
</tr>
<tr>
<td>DOF</td>
<td>Degree of freedom</td>
</tr>
<tr>
<td>DR</td>
<td>Dynamic range</td>
</tr>
<tr>
<td>DSC</td>
<td>Dice score</td>
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<tr>
<td>DWT</td>
<td>Discrete wavelet transform</td>
</tr>
<tr>
<td>EVAR</td>
<td>Endovascular aneurysm repair</td>
</tr>
<tr>
<td>FEA</td>
<td>Finite element analysis</td>
</tr>
<tr>
<td>FoV</td>
<td>Field of view</td>
</tr>
<tr>
<td>FWHM</td>
<td>Full width half maximum</td>
</tr>
<tr>
<td>ICP</td>
<td>Iterative closest point</td>
</tr>
<tr>
<td>IQ</td>
<td>In-phase quadrature</td>
</tr>
<tr>
<td>LPCAv</td>
<td>Local principal component averaging</td>
</tr>
<tr>
<td>ME</td>
<td>Mean error</td>
</tr>
<tr>
<td>MRI</td>
<td>Magnetic resonance imaging</td>
</tr>
<tr>
<td>OR</td>
<td>Open repair</td>
</tr>
<tr>
<td>PBS</td>
<td>Physiological buffered saline</td>
</tr>
<tr>
<td>PCA</td>
<td>Principal component analysis</td>
</tr>
<tr>
<td>PWS</td>
<td>Peak wall stress</td>
</tr>
<tr>
<td>RF</td>
<td>Radio frequency</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean squared error</td>
</tr>
<tr>
<td>ROI</td>
<td>Region of interest</td>
</tr>
<tr>
<td>RX</td>
<td>Receive</td>
</tr>
<tr>
<td>SA</td>
<td>Search area</td>
</tr>
<tr>
<td>SiC</td>
<td>Silicon Carbide</td>
</tr>
<tr>
<td>Spl</td>
<td>Multiangle spiral</td>
</tr>
<tr>
<td>SRAC</td>
<td>Sparse random aperture compounding</td>
</tr>
<tr>
<td>ToF</td>
<td>Time of flight</td>
</tr>
<tr>
<td>TX</td>
<td>Transmit</td>
</tr>
<tr>
<td>US</td>
<td>Ultrasound</td>
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</tbody>
</table>

**Symbols**

- $\alpha$: Integration variable Hough transform
- $\lambda$: Wavelength
- $|| x_i ||$: Euclidean distance
- $\mu$: Mean
- $\sigma$: Standard deviation
- $\theta$: Rotation
- $A$: Amplitude
- $a$: Shortest axes ellipsoid
- $a_{ij}$: Rotation matrix parameters
- $b$: Longest axes ellipsoid
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>C</td>
<td>Discrete autocorrelation</td>
</tr>
<tr>
<td>c</td>
<td>Second longest axes ellipsoid</td>
</tr>
<tr>
<td>$C_v$</td>
<td>Covariance matrix</td>
</tr>
<tr>
<td>$D_{eigen}$</td>
<td>Eigenvalues</td>
</tr>
<tr>
<td>$E$</td>
<td>Expected value</td>
</tr>
<tr>
<td>$E_{aorta}$</td>
<td>Registration error aorta</td>
</tr>
<tr>
<td>$E_{elem}$</td>
<td>Registration error element positions</td>
</tr>
<tr>
<td>ecc</td>
<td>Eccentricity</td>
</tr>
<tr>
<td>$N$</td>
<td>Amount of samples</td>
</tr>
<tr>
<td>$P$</td>
<td>Signal power</td>
</tr>
<tr>
<td>$R$</td>
<td>Rotation matrix</td>
</tr>
<tr>
<td>r</td>
<td>Radius</td>
</tr>
<tr>
<td>$S$</td>
<td>Segmentation</td>
</tr>
<tr>
<td>$T$</td>
<td>Transformation matrix</td>
</tr>
<tr>
<td>$t$</td>
<td>Translation</td>
</tr>
<tr>
<td>$V$</td>
<td>Volume</td>
</tr>
<tr>
<td>$V_{eigen}$</td>
<td>Eigenvectors</td>
</tr>
<tr>
<td>$W_i$</td>
<td>Weights for fusion</td>
</tr>
<tr>
<td>$w_i$</td>
<td>Weights for metric calculation</td>
</tr>
<tr>
<td>$X$</td>
<td>Image matrix</td>
</tr>
<tr>
<td>$(a,b)$</td>
<td>Midpoint circle Hough transform</td>
</tr>
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</table>
1 General Introduction

Cardiovascular disease causes 4.3 million deaths in Europe each year, which corresponds to nearly half of all deaths in Europe. The overall costs of cardiovascular disease for the EU economy are estimated to be 192 billion a year [1]. Therefore, the development and implementation of new techniques in the clinic are essential to ensure affordable and high-quality healthcare. Moreover, new technologies can improve diagnosis and patient selection for clinical intervention in a patient-specific manner.

1.1 Abdominal aortic aneurysm

An aortic aneurysm is a local dilatation of the aorta, with a diameter that exceeds 30 mm [2]. An aneurysm can be present in the entire arterial tree. However, the most prevalent site of an aneurysm is in the abdominal aorta (Figure 1.1), known as an abdominal aortic aneurysm (AAA). The size of an AAA is related to patient characteristics, for example gender, body size and age, but it is also dependent on other several risk factors as atherosclerosis, smoking, genetics, etc. [3]. The prevalence of AAAs is between 1.9% and 18.5% for men, and 4 times less for women [4]. This cardiovascular pathology is mostly asymptomatic and therefore, AAAs are often found coincidentally. When a dissection or rupture of the aortic wall occurs, only 1 out of 5 patients survive [5].

To prevent rupture of AAAs, surgery can be performed that places a synthetic graft by open repair (OR) or, most commonly nowadays, by endovascular aneurysm repair (EVAR). EVAR is a minimally invasive clinical intervention in which a stent-graft is placed in the aneurysm using catheters, accessed through the patient’s femoral arteries. Both procedures yield risks and reintervention could be necessary [6]. Therefore, clinical intervention is only performed when the rupture risk of the AAA exceeds the risk of the clinical intervention. To accurately select the patients, who are eligible for surgical intervention, a rupture risk assessment is required.

1.2 Rupture risk assessment

In current clinical practice, the anterior-posterior diameter of the AAA is used as the most relevant parameter in decision making for clinical intervention. Previous studies have shown that there is a negligible rupture risk for AAAs with diameters ranging from 3 - 3.9 cm. Furthermore, there is no long term survival benefit for patients with an AAA diameter that is smaller than 55 and 52 mm for men and women, respectively. Therefore, the clinical guidelines for surgical intervention of AAAs are set to $\geq 55$ mm for male, and $\geq 52$ mm for female patients [2]. However, rupture can still occur for diameters of the AAA that are below the threshold [7]. On the contrary, some AAAs with a diameter that exceeds the limit for surgical intervention remain stable [8]. This suggests that the diameter alone is not sufficient for rupture risk assessment. Hence, a more patient-specific rupture risk estimator is required.
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1.3 Imaging modalities

Computed tomography (CT) is currently the golden standard imaging modality for assessing geometry in the clinic. However, CT involves nephrotoxic contrast agents and ionizing radiation, that is harmful for the patient. On top of that, CT has a poor temporal resolution and is therefore unsuitable for functional imaging. Alternatively, magnetic resonance imaging (MRI) can be used as a modality to image AAAs. From MRI scans, the geometry and the motion of the aneurysm wall can be derived. However, disadvantages of MRI are the relatively high cost, long scanning time and exclusion of patients with metal implants [10]. Ultrasound (US) is an imaging modality that is more widely available, low cost, non-invasive, easily accessible, and portable. Moreover, US provides a high temporal and spatial resolution. Hence, US imaging is favored in the clinic [11]. Previous studies have shown that the PWS can be estimated based on CT data [12]. However, the temporal information in US imaging could be used to improve the PWS estimation, since a patient-specific elasticity can be estimated from wall motion tracking by an inverse FEA [10]. However, mechanical properties of the aortic wall are still estimated globally due to poor reflections of tissue interfaces that lie parallel to the US beam [13]. Hence, to assess geometry and mechanical characterization of an AAA accurately, a 3D US acquisition scheme that can provide volumetric images of decent quality at high frame rates is required.
1.4 3D ultrafast multi-perspective bistatic imaging

In the last years, many advances have been made in 3D US imaging. It has attracted a lot of attention in medical research, as it can provide temporal and spatial information of the scanned volume. 2D matrix array transducers, which transmit an acoustic beam that can steer in both azimuth and elevational direction, enable volumetric imaging [14]. High-frame-rate volumetric imaging with matrix probes was made possible by the development of ultrafast imaging, which led to a paradigm shift in US imaging [15]. In conventional line-by-line US scanning, transducer elements in a sub-aperture are consecutively transmitting and receiving US pulses that form a focused wavefront. The sub-aperture is shifted over the entire array to reconstruct a complete image (see Figure 1.2a). This results in a relatively low frame rate, especially for volumetric imaging, which is unfavorable for strain imaging. Higher frame rates can be achieved with ultrafast imaging, which only requires one unfocused transmit to reconstruct an image. However, this is at the cost of resolution. To overcome this problem, while maintaining a high frame rate, different transmit angles can be coherently compounded (see Figure 1.2b) [16]. However, the translation of high-frame-rate volumetric imaging with matrix arrays into the clinic is still challenging, due to the high cost to drive an US system with a very large amount of channels [17]. Recent studies by Roux et al. and Bernal et al. showed the potential of sparse aperture imaging. Sparse apertures provide a low-channel count alternative for 3D imaging, while the image quality and the high frame rates are preserved [15] [17].

![Figure 1.2: Visualization of difference between conventional line-by-line scanning with focused wavefronts (a) and ultrafast imaging with unfocused wavefronts (b) [18].](image)

In 3D US imaging, the anisotropy of contrast and spatial resolution, and the limited field of view (FoV) still remain a challenge, which cannot be overcome with a single transducer [19]. Moreover, images could lack anatomical information of structures that lie parallel to the US beam [20]. When imaging the abdominal aorta, this will cause that only the aortic wall perpendicular to the US beam will be visible (see Figure 1.3a and 1.3b). With the use of two transducers, multi-perspective monostatic imaging can be performed. In multi-perspective monostatic imaging, the probes alternately transmit and receive. The use of a dual-receive acquisition scheme, allows for bistatic imaging. Bistatic imaging means that one probe transmits a diverging acoustic wave and that both probes receive the backscattered US field. The same process is repeated for the other probe. Monostatic and bistatic imaging will yield two signals, T1R1 and T2R2, and four signals, T1R1, T1R2, T2R2 and T2R1, respectively. T indicates the transmitting probe and R indicates the receiving probe. The different signals in multi-perspective monostatic and bistatic imaging are visualized in Figure 1.3. Previous studies have shown that 2D ultrafast multi-perspective bistatic imaging improves strain estimations [21] and image quality in terms of lateral resolution [19].
1.5 Thesis objective and outline

This thesis continues on previous efforts on ultrafast multi-perspective imaging of the abdominal aorta. It is of great interest to translate this technique from 2D to 3D imaging. In volumetric imaging, the full AAA geometry and strains in all directions can be determined. Moreover, for 2D bistatic imaging it is required that the probes are positioned in exactly the same imaging plane. This positioning is quite challenging and repositioning of the probes with this constraint is cumbersome for the operator. Hence, a 3D freehand approach of imaging the abdominal aorta is favorable. Ideally, this imaging method is totally intrinsic, so without the need for an external hardware device, since it is inconvenient for clinicians to operate with an extra device. On top of that, coherent compounding requires a subwavelength accuracy for the relative probe positions, which is in practice not achieved by manual measurements or tracking devices [22]. Therefore, it is important that the relative probe positions, which are essential to coherently compound backscattered echoes from different transmit and receive locations, are determined accurately based on the data provided by the US system. This thesis presents the first steps towards 3D freehand ultrafast multi-perspective imaging of the abdominal aorta.

Firstly, the effect of including the bistatic signal during 3D freehand multi-perspective imaging is determined quantitatively, since this has only been investigated for 2D imaging. Chapter 2 describes a phantom study that is performed to assess the change in contrast and resolution. In this chapter, a semi-
automatic 3D registration algorithm is proposed to determine the relative probe positions. Moreover, a comparison is made between single-perspective, multi-perspective monostatic and multi-perspective bistatic imaging. In Chapter 3 a translation is made to developing the 3D multi-perspective imaging method for a set-up that better resembles the clinic. In this chapter, a method is described that automatically determines the relative probe positions from volumetric images of a porcine aorta phantom. The described method combines feature detection and alignment of multi-perspective monostatic US volumes with an optimization of the reconstruction quality of the trans-probe data. The relative probe positions are necessary to coherently compound the backscattered echoes, resulting from bistatic imaging. Finally, in Chapter 4, different fusion algorithms that coherently compound the signals from bistatic imaging are developed and compared. The different fusion algorithms are evaluated in terms of wall-lumen contrast and aortic wall tracking performance. Chapter 5 and Chapter 6 are a general limitations and outlook, and conclusion, respectively.
2 Quantitative analysis on image quality of ultrafast multi-perspective volumes

2.1 Introduction

In ultrasound imaging, the limited lateral spatial resolution and the restricted FoV remain a challenge. The imaging performance can be increased with a larger aperture size [23]. However, in clinical practice, the extension of the aperture is limited by the complexity of the system, its high cost and by the low flexibility [19]. Therefore, in this study, the aperture size is increased by using a non-continuous aperture. This is achieved by using two synchronized ultrasound transducers in dual-receive mode (i.e. bistatic imaging). The different probes can be placed freely, enabling 3D freehand acquisition of volumes. Coherently adding up signals from different ultrasound transducers has the potential to greatly improve imaging performance [24]. In order to minimize decorrelation between perspectives, volumes can be acquired in an ultrafast fashion [25].

In this chapter, the effect of adding bistatic data from a 3D freehand multi-perspective US set-up is investigated quantitatively. In order to evaluate image quality on contrast and resolution, a phantom was developed. The phantom consisted of position markers, allowing a point-based registration algorithm to find the relative probe positions. The relative probe positions are necessary to reconstruct all four signals on the same grid and to coherently compound the volumes. Finally, a quantitative image quality assessment was conducted to compare single- and multi-perspective 3D US imaging.

2.2 Methodology

2.2.1 Phantom development

To acquire and reconstruct multi-perspective freehand US images, it is of great interest to accurately determine the relative probe positions. To enable point-based registration of the volumes, a phantom with position markers was designed. Plastic rocailles beads with a diameter of approximately 2 mm functioned as these position markers in the phantom. In order to guarantee a unique solution for the registration algorithm, the position markers were placed on three different non-reflective threads of which one thread is non-orthogonal compared to the other threads. Moreover, in the z-direction a non-equidistant spacing was used. Furthermore, water beads acting as spherical anechoic inclusions were embedded in the phantom in order to evaluate contrast on the volumes. Water beads were placed at three different depths in the phantom. The final phantom design can be seen in Figure 2.1.

Subsequently, gelatin and Silicon Carbide (SiC) were combined to compose a tissue-mimicking material [26]. The gelatin was prepared by heating up water to 65 °C, using a hot plate stirrer. 6 wt. % gelatin (300 bloom, FormX, the Netherlands) was gradually dissolved in the water, after which 1.5 wt. % of Sic was added to the medium. SiC served as an acoustic scatterer, which represents the inhomogeneities of
the speed of sound in tissue (e.g. speckle). When the solution cooled down to approximately 27 °C, it was poured into the phantom container. The gelatin was left overnight to solidify into a gel.

2.2.2 Data acquisition scheme

In this study, a 3D multi-perspective ultrafast ultrasound acquisition scheme was designed. In conventional line-by-line scanning, focused waves are transmitted by the transducer resulting in a good lateral resolution, but a poor framerate. In 3D ultrafast ultrasound imaging, transducer elements are stimulated, transmitting diverging waves. This technique allows for very high framerates compared to conventional ultrasound imaging [18]. Images obtained in the ultrafast imaging mode have inferior quality in terms of resolution and contrast, since focusing is now only possible in receive mode. To increase image quality, while maintaining a high frame rate, different transmit angles are coherently compounded [16].

Two synchronized Verasonics 256-Vantage systems, each equipped with a $32 \times 32$ element matrix array (3 MHz, Vernon), were used to perform bistatic 3D ultrasound acquisitions from two perspectives. To minimize decorrelation of US signals and induce heterogeneity between acquisitions, an interleaved ultrafast scanning sequence was designed [25]. This means that the first probe transmits a diverging acoustic wave and both probes receive the backscattered ultrasound field. Subsequently, the second probe transmits and again both probes receive (see Figure 2.2). This dual-receive mode resulted in four signals, $T1R1$, $T2R2$, $T1R2$ and $T2R1$, that were reconstructed and fused to obtain a volume.

In order to keep high frame rates while using a high-element-count matrix probe (1024 elements) in combination with a relatively low-channel-count ultrasound system (256 channels), the concept of sparse-random-aperture compounding (SRAC) was used (see Figure 2.3a). This technique uses random apertures to introduce more inhomogeneity, which improves image quality and preserves high frame rates. As mentioned, when imaging in the ultrafast mode, it is important to coherently compound multiple angle transmits. Therefore, a multiangle spiral (Spl) scanning method was implemented (see Figure 2.3b). In this method signals from diverging waves from different virtual sources were coherently compounded. The virtual sources were all located at $z = -32\lambda$ ($\lambda \approx 0.43$ mm). In the x-y plane the virtual sources describe a spiral around the z-axis [15]. The x-, y-, and z-orientations relative to the probe are visualized in Figure 2.4. All important scanning parameters are given in Table 2.1.
CHAPTER 2. QUANTITATIVE ANALYSIS

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Figure 2.2: Interleaved dual-receive scanning sequence.

Figure 2.3: Implemented acquisition scheme using sparse-random-aperture compounding (a) and multi-angle spiral scanning (b, adapted from Bernal et al.).

Figure 2.4: Probe orientations.

Table 2.1: Summary of acquisition parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transducer central frequency</td>
<td>3.47 MHz</td>
</tr>
<tr>
<td>Transducer elements</td>
<td>1024</td>
</tr>
<tr>
<td>Transducer pitch</td>
<td>0.3 mm</td>
</tr>
<tr>
<td>Element width</td>
<td>0.275 mm</td>
</tr>
<tr>
<td>Wavelength</td>
<td>0.43 mm</td>
</tr>
<tr>
<td>Speed of sound</td>
<td>1500 m/s</td>
</tr>
<tr>
<td>Frame rate</td>
<td>45 Hz</td>
</tr>
<tr>
<td>Sampling frequency</td>
<td>13.9 MHz</td>
</tr>
<tr>
<td>Number of virtual sources</td>
<td>49</td>
</tr>
</tbody>
</table>
2.2.3 Reconstruction

In conventional line by line US scanners, beam-forming is often applied in the hardware of the system. However, when imaging with diverging waves there is no focusing in transmit and therefore a software beam-forming approach is required. The backscattered RF signals were reconstructed using the delay-and-sum method (DAS). For each reconstruction point in the grid, the time-of-flight (ToF) to every element was determined by summing up the transmit and receive time. The ToF was then converted to a delay and the signals from all elements are summed [27]. This technique is illustrated in Figure 2.5. The result of the reconstruction is in-phase quadrature (IQ) data, which is the same as radio frequency (RF) data with one sideband of the frequency spectrum omitted. This IQ data was envelope detected by taking the magnitude of the signal. The envelope detected signal was log-compressed and finally thresholded to obtain a Brightness mode (B-mode) image with the desired dynamic range.

![Figure 2.5: Illustration of delay-and-sum (DAS) beam-forming, adapted from Hendriks et al. [27]](image)

2.2.4 Registration

In this study, the volumes were acquired freehandly, meaning that the ultrasound transducers were not fixated to a certain plane or orientation. The relative probe positions were determined by aligning the positions of the point sources in the two monostatic volumes. The position markers in combination with a point-based registration algorithm yielded a rigid transformation matrix. This transformation matrix was used to transform the apertures of the probe. All four signals were reconstructed on the same grid and finally compounded.

The first step was to select all position markers that were visible in the reconstructed monostatic volumes. Position markers were detected automatically by finding local intensity maximums in the volumes. Local maximums were detected by searching for maximums in all three directions separately. A position marker was detected when a maximum was found in all three directions. The automatic point detection algorithm did not yield a desirable result when imaging artifacts were present. Therefore, the point selection was corrected manually. This was done by sliding through the volume in the y-direction. If a position marker was present in the slice, it was selected using a point selection tool (see Figure 2.6). After selection of the points in the two monostatic volumes, the obtained 3D point sets were registered using a rigid transformation. The iterative closest point (ICP) algorithm is an effective way of aligning 3D point sets [28]. In this study, the volume reconstructed from the T2R2 signals, i.e. the moving volume, was registered to the volume reconstructed from the T1R1 signals, i.e. the fixed volume. Source points and target points were detected from the moving and fixed volumes, respectively. The ICP algorithm consists
of four steps:

1. Each source point is matched to the closest target point.
2. The transformation matrix $T$ is calculated for which the root mean squared error (RMSE) between the corresponding points is minimized.
3. The source points are transformed using the obtained transformation matrix $T$.
4. Iterate until a suitable stopping criterium is reached.

The RMSE is given by equation 2.1. In which $\|x_i\|$ represents the Euclidean distance between corresponding points.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \|x_i\|} \tag{2.1}$$

![Figure 2.6: Example of point selection on a y-slice in a volume.](image)

The ICP algorithm is usually an efficient method to minimise the RMSE, but it can be prone to finding local minima [29]. In order to make the ICP algorithm more robust, the ICP was performed on the point sets with ten different starting configurations. Besides the original starting configuration, the source points were rotated 90, -90 and 180° around the x-, y- and z-axis. The correct transformation matrix was selected by selecting the minimal RMSE of all starting configurations. The entire workflow is illustrated in Figure 2.7.

Finally, the obtained transformation matrix was applied to the aperture of the second probe. This was done by multiplying the coordinates of this probe with the transformation matrix. If the transformed probe is in receive mode it is important that the normal angle of the probe, which is required for depth dependent apodization, is rotated by means of the rotation matrix. After rotating and translating the aperture, the T1R1, T2R2, T1R2 and T2R1 signals were reconstructed on the same grid and coherently compounded. The signals were compounded by adding up the IQ data in two different ways: a compounded volume excluding (e.g. multi-perspective monostatic imaging) and including (e.g. multi-perspective bistatic imaging) the trans-probe signals (equations 2.2 and 2.3 respectively)

$$V_{\text{monostatic}} = V_{T1R1} + V_{T2R2} \tag{2.2}$$
**2.2.5 Quantitative analysis**

In order to quantitatively determine the effect of adding trans-probe data from a 3D freehand multi-perspective US set-up, the image quality was evaluated for single-perspective, multi-perspective monostatic and multi-perspective bistatic imaging. The image quality was determined by evaluating the contrast and resolution.

Contrast refers to the ability to differentiate between two regions with different intensities. The contrast-to-noise-ratio (CNR) is a measure for contrast (equation 2.4)

\[
CNR = 20 \log_{10} \left( \frac{|\mu_i - \mu_o|}{\sqrt{\sigma_i^2 + \sigma_o^2}} \right) \tag{2.4}
\]

With $\mu_i$ and $\mu_o$ being the expected value of the signal power inside and outside the target area, respectively. It also takes the standard deviation of the signal power inside ($\sigma_i^2$) and outside ($\sigma_o^2$) the target area into account [30]. The CNR was evaluated on the spherical anechoic inclusions that were embedded in the designed phantom. The CNR was calculated on the envelope data, so before any log-compression was applied. Four circular regions of interest (ROIs) of equal size were selected on a x-z slice: one inside the anechoic inclusion and three in the background of the phantom. The same was done for a y-z slice. An example of how the ROIs were selected is shown in Figure 2.8. The CNR was calculated for the five closest slices and for all defined ROIs. This yielded 15 values for both orientations. The values of the CNR were then averaged for the different slices and orientations.

\[
V_{bstatic} = V_{T1R1} + V_{T2R2} + 0.5 \times (V_{T1R2} + V_{T2R1}) \tag{2.3}
\]
Spatial resolution is often expressed in axial and lateral resolution, representing the minimum distance that can be differentiated parallel and perpendicular to the ultrasound beam, respectively [31]. However, when fusing volumes that were acquired with different (non-restricted) relative probe positions, ultrasound signals with different beam orientations are compounded. Therefore, it is hard to express the resolution of the system with the conventional lateral and axial resolution. In this study, a more generic metric, the 3D speckle size, was used to evaluate resolution in all directions. The 3D speckle size was determined using the autocorrelation function. The power spectrum is the Fourier transform of the autocorrelation function in the spatial domain. Both functions do not have a phase component. This implies that the autocorrelation of a speckle pattern will be equal to the autocorrelation of a point source. Thus, the autocorrelation of the speckle quantifies the resolution of the system. The discrete autocorrelation function is given by equation 2.5, with $p(k, l, m)$ the detected amplitude signal of voxel $(k, l, m)$ [32].

$$C(x, y, z) = \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} \sum_{m=0}^{M-1} p(k, l, m) p(k + x, l + y, m + z)$$

(2.5)

The 3D ROIs for speckle analysis were placed at two different depths in the volumes (6 cm and 8 cm). For these depths it was known that the speckle was saturated. Subsequently, the autocorrelation was calculated and the full-width-half-maximum (FWHM) is taken to obtain the 3D speckle size. The speckle size was quantitatively evaluated by calculating the volume and the eccentricity, representing the resolution and the uniformity of the resolution, respectively. The eccentricity of the ellipse containing the longest and shortest axes, the first eccentricity, was calculated. Moreover, the eccentricity of the ellipse containing the middle and shortest axes (e.g. the second eccentricity) was calculated. The calculated eccentricities are visualized in Figure 2.9. The ellipses of the first and second eccentricity are perpendicular and their eccentricities are given by equation 2.7 and 2.6, respectively.

$$ecc_1 = \frac{\sqrt{b^2 - a^2}}{b}$$

(2.6)

$$ecc_2 = \frac{\sqrt{c^2 - a^2}}{c}$$

(2.7)

With $a$, $b$ and $c$ the shortest, longest and second longest axes, respectively.

---

**Figure 2.8:** Selection of the regions of interest (ROIs) in an anechoic inclusion (red) and in the background (green, pink and blue).
Figure 2.9: Illustration of the first and second eccentricity, adapted from commons.wikimedia.org/wiki/File:Ellipsoid-1-tab.svg
2.3 Results

2.3.1 Registration

The automatic point-based registration method described in section 2.2.4 was successful for 12 out of 13 datasets. In one case, the minimum RMSE did not correspond to the correct relative probe positions and the selection of the correct transformation matrix was corrected manually. In this specific case, the number of points in the FoV of one probe was much larger than the number of points in the FoV of the second probe. Therefore, a lot of source points were incorrectly matched to the target points, resulting in a high RMSE even for the correct configuration. The selection of the transformation matrix was corrected manually by visually selecting the configuration where the point sets were correctly aligned. An example of a target, source and registered pointset can be seen in Appendix A.

2.3.2 Data

3D volumes were acquired freehandly with an ultrafast interleaved scanning sequence. The dual receive mode results in four signals: T1R1, T2R2, T1R2 and T2R1. After registration these signals were reconstructed on the same grid. In Figure 2.10 one can see a reconstructed cross-sectional B-mode image of each received signal. It can be observed that the trans-probe signals result in a more noisy image compared to the monostatic signals. Moreover, the intensities of the reflections are smaller.

Figure 2.10: Cross-sectional B-mode image (DR=60) of all four reconstructed signals from a multi-perspective bistatic acquisition of the designed point source phantom. In all images the reflections of the point markers are visible.
2.3.3 Quantitative analysis

The quantitative assessment of contrast and resolution was performed on 13 different datasets. For all datasets, the probes were located and oriented freely in space. The contrast and resolution was determined for single-perspective imaging, multi-perspective monostatic imaging (Equation 2.2) and multi-perspective bistatic imaging (Equation 2.3). In Figure 2.11 one can see the determined CNR on the anechoic inclusions for the y-z plane (2.11a) and x-z plane (2.11b) visualized in a boxplot for the 13 datasets. For both planes no significant increase nor decrease in contrast between the anechoic inclusions and the background is observed when a second probe is added in the acquisition scheme.

![Figure 2.11: Evaluation of contrast-to-noise ratio (CNR) for single-perspective imaging, multi-perspective monostatic imaging and multi-perspective bistatic imaging in the y-z plane (a) and the x-z plane (b) (n=13).](image)

Figure 2.12 shows the cross sections of a 3D speckle size. A speckle size from a single-perspective imaging (2.12a), multi-perspective monostatic imaging (2.12b) and multi-perspective bistatic imaging (2.12c) is visualized. For single-perspective volumes the speckle size is a relatively large flat elliptical volume. For the multi-perspective volumes the speckle size is having a more circular shape in one direction (y-z plane) and the volume is decreased. Including the trans-probe signal in compounding results in a smaller speckle size compared to compounding without the trans-probe signal. Moreover, an experiment was performed to investigate the influence of noise, so the speckle size was also calculated of a volume for which the receive data was averaged over time. This yields similar results as Figure 2.12 (see Appendix B).
Moreover, the effect of bistatic imaging on the speckle size is quantitatively assessed by calculating the volume, first and second eccentricity of the speckle size (Figure 2.13). The volume of the speckle size at a depth of 8 cm was $0.033 \pm 0.009 \text{ mm}^3$ including the trans-probe signals opposed to $0.044 \pm 0.01 \text{ mm}^3$ excluding the bistatic signals. For both single-perspective images the volume was $0.098 \pm 0.02 \text{ mm}^3$ and $0.13 \pm 0.06 \text{ mm}^3$. Thus, a decrease in volume size can be seen. At 6 cm the volume sizes are $0.053 \pm 0.007 \text{ mm}^3$, $0.062 \pm 0.02 \text{ mm}^3$, $0.018 \pm 0.006 \text{ mm}^3$ and $0.015 \pm 0.003 \text{ mm}^3$ for the two single-perspectives, the multi-perspective monostatic and multi-perspective bistatic volumes, respectively.

Moreover, a decrease in the second eccentricity is shown by Figure 2.13c and 2.13f. At the depth of both 6 and 8 cm, the eccentricity of the monostatic and bistatic compounded volumes are decreased by 5 % and 8 %, respectively. However, for the first eccentricity it can be seen in Figure 2.13b and 2.13e that there is no significant change for the different volumes at both depths.

Figure 2.12: Cross sections of a 3D speckle size of single-perspective imaging (a), multi-perspective monostatic imaging (b) and multi-perspective bistatic imaging (c).
Figure 2.13: Evaluation of resolution based on the volume of a 3D speckle size at a depth of 6 cm (a) and 8 cm (b), the first eccentricity of a 3D speckle size at a depth of 6 cm (c) and 8 cm (d) and the second eccentricity at a depth of 6 cm (e) and 8 cm (f) for single-perspective imaging, multi-perspective monostatic imaging and multi-perspective bistatic imaging (n=13).
2.4 Discussion

In this chapter, automatically registered volumes, acquired with multi-perspective bistatic imaging, were coherently compounded, which resulted in an extended FoV. Subsequently, the contrast and resolution was assessed and compared to single-perspective and multi-perspective monostatic imaging. The developed automatic point-based registration algorithm was able to correctly find the relative probe positions, since the position markers were correctly aligned in 92% of the reconstructed volumes. However, in cases where the FoV of target structures was limited, the chances of registration mismatch increased. The speckle size is a measure for the resolution of a system. To quantitatively evaluate the speckle size in 3D, the volume, the first and the second eccentricity were determined. Ultrasound systems have superior resolution in the direction of the US beam (e.g. axial resolution). In 3D imaging, the two directions perpendicular to the US beam, the lateral and elevational direction, have similar and poor resolution that is spatially dependent. Therefore, it is expected that the 3D speckle size is discus shaped. From Figure 2.12a it can be seen that the speckle size has the expected shape for single-perspective imaging. Furthermore, it is expected that the resolution deteriorates when the depth increases. This effect is observed in Figure 2.13a and 2.13d, where the speckle size volume increases for larger depths.

When comparing single-perspective imaging to multi-perspective monostatic imaging, it can be seen in Figure 2.13a and 2.13d that there is a mean decrease in speckle size volume of 68 and 61% at a depth of 6 and 8 cm, respectively. This suggests that adding an extra transducer and coherent compounding improves the resolution. When the bistatic signals are added, this results in a mean volume decrease of 74 and 71% at a depth of 6 and 8 cm, respectively. Hence, the volume of a speckle size is the smallest when both the monostatic and bistatic signals are included in coherent compounding. The presence of noise potentially influences the result of the autocorrelation function and therefore the speckle size. To ensure that the decrease in speckle size volume is caused by an increase of the resolution and not by the increase of noise, an experiment was performed that filters noise out of the received data by taking the time average of multiple transmits. The experiment showed similar results. This indicates that the decrease in volume of the speckle size is caused by an improvement of resolution. The improvement in resolution of a system with a multi-transducer set-up has also been shown in 2D imaging by Peralta et al. [19].

In ultrasound imaging, the resolution is anisotropic. The anisotropy is described by the first and second eccentricity. A uniform distribution of the resolution will result in a spherical shaped speckle size with both eccentricities equal to zero. However, as described previously, the speckle size is actually discus shaped for single-perspective imaging, which will result in eccentricities close to 1. Figure 2.13b and 2.13c show that there is no decrease in the first eccentricity at both depths. On the other hand, Figure 2.13c and 2.13f, show a decrease in the second eccentricity. This can also be seen in Figure 2.12, in which the speckle size is only reduced in one direction. The addition of an extra probe only adds signal in one direction, improving only the elevational or lateral resolution. In order to also reduce the first eccentricities, one can investigate a set-up with more than two transducers. However, this will complicate volume acquisition, which will make the translation to the clinic more challenging.

On top of the resolution, the CNR was also evaluated. Figure 2.11 shows no significant increase nor decrease of image quality in terms of CNR. In a multi-transducer set-up, a trade-off between contrast and resolution is made [33]. Large spacing between the probes results in an extended aperture, and therefore an improvement in resolution is expected. However, Peralta et al. showed that there is an opposing trend for contrast, since contrast will be compromised due to the effect of sidelobes. In 2D imaging the probe surface is typically larger, resulting in smaller gaps for the same distance between the center of the probes. For future research, this effect could be investigated by systematically acquiring or simulating volumes with an increasing spacing or angle between the two probes to affirm that the same effect is present in 3D imaging. Moreover, it could be the case that the CNR estimation is affected by
thermal noise.

For future research, other methods to improve image quality could be considered. For example, different beamforming methods could be investigated. On top of that, image quality might also be further improved, by improving the probe localization, since a subwavelength accuracy cannot be reached by ICP. Moreover, the developed ICP algorithm is highly dependent on the presence of point markers, which are not present in an in-vivo setting. Therefore, a generic optimization of the transformation variables could be considered (see Chapter 3). Finally, in an in-vivo setting the image quality will depend on a complex combination of transducer separation, relative angle between transducers, aperture width and imaging depth [19]. Future research could focus on determining the effect of all these factors on imaging performance.
3 Automatic volume registration of the abdominal aorta

3.1 Introduction

Multi-perspective imaging of the abdominal aorta requires the relative probe positions in a subwavelength accuracy to coherently compound the signals. It is favourable to do this intrinsic, so without the need of an external hardware device, to make imaging the abdominal aorta more convenient and accurate. Moreover, it is known that the use of electromagnetic or optical trackers will not yield this accuracy [22]. Noise and calibration errors in the tracking system are propagated to coherent volume compounding, resulting in degradation of the image quality. Previous research proposed a 2D registration method that finds the relative probe positions by automatic shape detection of the non-transmitting curved array [25][21]. However, this technique does not translate to 3D multi-perspective imaging, since the probe surfaces are not visible in the FoV and other shaped transducers are used. A study of Peralta et al. proposed a method that optimizes the coherence between backscattered echoes coming from the same point scatterer [19]. However, this method is highly dependent on the presence of point sources, which is not the case in an in-vivo setting. Therefore, in this chapter, a 2D registration method is proposed, which is suitable to align volumes that were acquired in the same imaging plane. This method was extended to a 3D method in order to allow for freehand positioning of the probes. The 2D and 3D registration methods are intrinsic methods that can solve three and six degrees of freedom (DOF), respectively. Both methods combine feature alignment of monostatic volumes with an optimization of the image quality of the trans-probe data. Both methods were verified with a simple simulation study. The described registration methods are still dependent on the volume content, in this case the abdominal aorta. Lastly, a method is proposed that is more generic, allowing it to be easily applicable for imaging organs in general.

3.2 Methodology

First, the experimental set-up to acquire volumes of a porcine aorta will be discussed. Secondly, the developed 2D registration method will be explained. Subsequently, the 3D registration method will be discussed. Finally, the verification of the methods will be explained.

3.2.1 Experimental set-up

In this study, 3D multi-perspective images of a porcine aorta phantom including anatomical features were acquired. A porcine aorta and a 3D printed model of the human spine were placed in a gelatin medium (6 wt. %) to mimic the surrounding tissue. The aorta was clamped with a longitudinal prestretch of approximately 1.3, which is in line with the expected stretch in physiology [34]. The geometry of the spine was modeled using CT data of the abdominal part of a human spine. To include acoustic scattering, 1 wt. % silicon carbide was added to the medium. A more elaborated explanation on how to prepare
the medium is given in chapter 2.2.1. In order to mimic the in vivo hemodynamic conditions, the phantom was placed in a mock circulation set-up (figure 3.1) [35]. The basin was filled with a physiological buffered saline solution (PBS), which can be pumped into the lumen. The inflation of the porcine aorta was arranged with an axial piston pump. Unidirectionality of the flow was ensured with two mechanical valves. The distal side of the aorta was connected to a three-element windkessel model, consisting of an inflow resistance, an air chamber to mimic arterial compliance and an outflow resistance.

The used acquisition scheme and reconstruction method are described in chapter 2.2.2 and 2.2.3, respectively. Volumes were acquired with a framerate of 45 Hz. Firstly, it was assured that the probes were positioned in the same x-z plane during acquisition. This was done by placing the probes in probe holders, that were mounted on an arch. The probe holders were shifted over the arch to get a desirable angle between the probes, in which a large part of the aortic wall was imaged. Secondly, volumes were acquired with one probe fixated and the other probe positioned freely in space. So, the probes were not restricted to the same imaging plane and volumes were acquired freehandly.

![Figure 3.1: Schematic representation of the mock circulation set-up (a) and a cross section of the phantom container including approximate probe positions (b).](image)

### 3.2.2 Automatic 2D registration of the abdominal aorta

Volumes that were acquired in the same imaging plane, can be aligned by a 2D transformation. A 2D transformation consists of 3 DOFs: translation in x- and z-direction and a rotation over the y-axis ($t_x$, $t_z$, and $\theta_y$, respectively). In this research, a 2D registration method is proposed that determines the x- and z-translation based on the image content (e.g. a porcine aorta). The porcine aorta was detected with a circular Hough transform. Subsequently, the porcine aortas were aligned, yielding $t_x$ and $t_z$. The final parameter, the y-rotation, cannot directly be determined from the single-perspective volumes. This is due to the axisymmetric shape of the aorta and the mismatch in reflections. Therefore, an optimization approach, that maximizes the trans-probe image quality, is proposed to obtain the y-rotation.

### Aorta center alignment

In computer vision, the Hough transform is often used for object detection. The Hough transform transforms a point in the x-z plane to a point in the parameter space, which is described according to the shape of interest. The general Hough transform can be implemented to detect any kind of shape. However, the complexity of the transform increases with the number of variables that is needed to describe the shape [36]. Therefore, in this research, the aorta was detected with a circular Hough transform, since
it correctly describes the shape of the healthy porcine aorta and it is computationally inexpensive. The parametric representation of a circle is given by Equation 3.1.

\[
\begin{align*}
  x &= a + r \cos(\alpha) \\
  z &= b + r \sin(\alpha)
\end{align*}
\] (3.1)

In which \(x\) and \(z\) are the coordinates of a point in the x-z plane, \(a\) and \(b\) are the center of the circle in x- and z-direction, and \(r\) is the radius. So, the parameters that determine the circle are \(a\), \(b\) and \(r\). Hence, this parameterization yields a 3D parameter space. The integration variable of the transform is \(\alpha\), which ranges from 0 to 360 degrees. Prior to detecting the circles, the edges were detected from the image. This was done by applying Otsu’s automatic thresholding method. The obtained threshold minimized the intra-class variance [37]. The binarized image contained the edges of the aorta and the spine. Detecting the aorta with the circular Hough transform was influenced by the spine, since it was the largest structure in the image with the most edge pixels. Therefore, a mask of the spine was applied to the edge detected image. The mask was composed by closing the original edge detected image and selecting the largest structure, which corresponds to the spine. The composition of the binarized image of the aorta is visualized in Figure 3.2.

\[\text{Figure 3.2: Visualization of the composition of the binarized image of the aorta. The tresholded image, obtained by Otsu’s method, is multiplied with a mask of the spine}\]

In order to detect circles in the image, a circle in the parameter space was drawn for every edge pixel and for radii in the range of 8 mm and 12 mm in steps of 0.25 mm. For the coordinates, which belong to the perimeter of the circle, the value in the accumulator matrix was incremented with one. The accumulator matrix contains the number of circles, which pass through an individual coordinate. Hence, the highest value in the accumulator matrix corresponded to the parameters of the circle present in the image [36]. This method is visualized in Figure 3.3. The centers of the detected aortas in both single-perspective volumes, \((x_1, z_1)\) and \((x_2, z_2)\), were used to calculate the x- and z- translation (\(t_x\) and \(t_z\)). The translations are given by Equation 3.2.

\[
\begin{align*}
  t_x &= x_1 - x_2 \\
  t_z &= z_1 - z_2
\end{align*}
\] (3.2)
CHAPTER 3. AUTOMATIC REGISTRATION

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Figure 3.3: Visualization of the circular Hough transform. All edge pixels are transformed to the parameter space. The coordinate in the parameter space, in which most circles pass, corresponds to the parameters of the circle in the image. Adopted from Pedersen et al. [36]

1D optimization trans-probe image quality

From the aorta detection, the centers of the aorta were derived for both perspectives and aligned. In order to keep the center of the aorta in the same location, it was moved to the origin before a rotation was applied. The total 2D transformation matrix \(T_{2D}\) is described by Equation 3.3, with \(\theta_y\) being the unknown y-rotation.

\[
T_{2D} = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
x_1 & 0 & -z_1 & 1
\end{bmatrix}
\begin{bmatrix}
\cos(\theta_y) & 0 & -\sin(\theta_y) & 0 \\
0 & 1 & 0 & 0 \\
\sin(\theta_y) & 0 & \cos(\theta_y) & 0 \\
x_1 & 0 & z_1 & 1
\end{bmatrix}
\begin{bmatrix}
1 & 0 & 0 & 0 \\
sin(\theta_y) & 0 & \cos(\theta_y) & 0 \\
0 & 0 & 1 & 0 \\
-x_1 & 0 & -z_1 & 1
\end{bmatrix}
\]

(3.3)

Signals from all transducer elements are coherently compounded. For the correct relative probe positions, and thus for the correct transmit delays, the signals will be constructively compounded. Therefore, it is expected that the signal power of the trans-probe signals increases towards the correct probe positions. Hence, the signal power was used as a metric during optimization. Firstly, the T1R2 signals were reconstructed after transforming the apertures with the current transformation matrix. Subsequently, the image metric was calculated for the x-z plane at \(y = 0\) cm. The signal power is given by equation 3.4. With \(P\) being the mean signal power, \(N\) the number of voxels in the volume, \(w_i\) the weight that is applied and \(A_i\) the amplitude of a voxel in the envelope detected volume. Most optimization problems are defined to find a minimum. Therefore, a minus sign was added in the metric calculation.

\[
P = -\frac{\sum_{i=0}^{N} w_i A_i^2}{\sum_{i=0}^{N} w_i}
\]

(3.4)

Where

\[
w_i = \begin{cases} 
1 & |A_i| > 0 \\
0 & |A_i| = 0 
\end{cases}
\]

(3.5)

In order to test convergence of the metric, an exhaustive search was performed. Moreover, also other metrics, the speckle size, L2 norm and correlation coefficient, were tested. The metric was calculated for a predefined range of \(\theta_y\), 0-90 degrees. The spacing in the exhaustive search for rotation was 1 degree for all searches performed in this study. Subsequently, \(\theta_y\) was determined by selecting the global minimum of the search. An exhaustive search is computationally expensive and inefficient. Hence, An optimization approach that takes the gradient into account is favorable. In this way, the minimum will
be found successively and it is not required to do a reconstruction and calculation for all possible probe configurations. The problem to be optimized has a non-linear character, since the signal power and transformation variables are not linearly related. On top of that, the transformation variables can be constrained to a feasible range. Lastly, it is assumed that the problem is convex. The interior-point methods (also referred to as barrier methods) are a class of optimization algorithms that are able to solve this type of problems (e.g. non-linear, convex and constrained). This optimization algorithm can handle large, sparse and small, dense problems. On top of that, it is relatively fast and has low memory usage [38]. The \texttt{fmincon} toolbox of Matlab was used to implement the optimization [39]. A summary of the chosen parameters during optimization is shown in Table 3.1.

![Table 3.1: Summary of the optimization parameter set](image)

### 3.2.3 Automatic 3D registration of the abdominal aorta

The method described in section 3.2.2 was extended, in order to determine a 3D transformation matrix for volumes that were acquired freehandly. A 3D rigid transformation is described by 6 DOFs: translation in \( t_x \), \( t_y \), and \( t_z \)-direction and rotation over the \( x \)-, \( y \)- and \( z \)-axis (\( \theta_x \), \( \theta_y \), and \( \theta_z \), respectively). Instead of an aorta center alignment, an aorta centerline alignment was performed. The centerline was obtained by segmenting the aorta by means of the Star-Kalman method. After alignment of the centerline, two variables, \( t_y \) and \( \theta_y \), are still unknown due to the axisymmetric shape of the aorta. These geometrical parameters were determined with a 2D optimization problem.

**Aorta centerline alignment**

The aorta centerline was derived from a segmentation of the aorta. This segmentation was automatically obtained by the Star-Kalman algorithm. The Star algorithm was used to estimate the lumen-wall border by finding high probability edge positions, using a step edge detection function. An ellipse was fitted through the highest probability edge positions. A temporal Kalman filter, in which the ellipse parameters serve as the observation, was used to stabilize the estimate of the lumen-wall border [40]. The centerline was derived from the segmentation by taking the mean coordinate for every y-slice. Subsequently, a 3D linear line was fitted by least-square fitting. The rotation between the vectors was derived from the directional coefficient of the fitted lines. After rotating the centerline, the middle of the centerline was determined by taking the mean coordinate. The centers were used to calculate the translations in the same way as in equation 3.2. The transformation matrix that aligns the centerlines was described by equation 3.6. With \( a_{ij} \) being the parameters corresponding to the rotation matrix, which resulted from the directional coefficient.

\[
T_{\text{centerline}} = \begin{bmatrix}
a_{11} & a_{12} & a_{13} & 0 \\
a_{21} & a_{22} & a_{23} & 0 \\
a_{31} & a_{32} & a_{33} & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
t_x & 0 & t_z & 1 \\
\end{bmatrix}
\]  

(3.6)
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2D optimization trans-probe image quality

Similarly to the 1D optimization problem (section 3.2.2), the total 3D transformation matrix \( T_{3D} \) is described by equation 3.7. The parameters, \( \theta_y \) and \( t_y \), need to be optimized.

\[
T_{3D} = T_{centerline} \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
-x_1 & -y_1 & -z_1 & 1
\end{bmatrix} \begin{pmatrix}
\cos(\theta_y) & 0 & -\sin(\theta_y) & 0 \\
0 & 1 & 0 & 0 \\
\sin(\theta_y) & 0 & \cos(\theta_y) & 0 \\
0 & t_y & 0 & 1
\end{pmatrix} \begin{bmatrix}
1 & 0 & 0 & 0 \\
x_1 & y_1 & z_1 & 1
\end{bmatrix}
\]  
(3.7)

During the 2D optimization, the same metric was used as for the 1D optimization (see equation 3.4). In contrast to the 1D optimization, the signal power was calculated for a volume instead of a slice, since the probes were not positioned in the same imaging plane. Firstly, the y-coordinate that was located between the two transducer positions of the current probe configuration was determined \( y_{middle} \). Secondly, a volume was reconstructed for \( y = y_{middle} \pm 15 \text{ mm} \). Finally, the metric was calculated for the reconstructed volume. Again, first an exhaustive search was performed, that calculates the metric for all possible predefined probe positions. The spacing in the exhaustive search for translation was 1 mm for all searches performed in this study. Finally, the optimization problem that is described in section 3.2.2 was extended, such that it solves 2 variables.

### 3.2.4 Verification

For the multi-perspective data acquired of the porcine aorta phantom, no ground truth of the relative probe positions was available. Therefore, the performance of the registration algorithms on this data was only evaluated qualitatively. To obtain a quantitative result for the proposed registration methods, a simple simulation study was performed. To mimic the aorta, a cylinder composed out of point scatters was simulated. Speckle was mimicked by randomly distributed point scatters with a random amplitude. Speckle was only added outside of the cylinder. The amplitude of the scatters that constitute the cylinder are one order of magnitude larger than the scatters resembling the speckle. The cylinder is positioned at a depth of 3.5 cm and has a radius of 1 cm. This size is in line with the size of a porcine aorta. In the simulation, the same parameters are used as for the acquisition scheme described in section 2.2.2 (see Table 2.1). However, in the simulation, 25 virtual sources (instead of 49) were used per acquisition to save memory and computation time. The virtual sources were placed in a rectangular grid above the transducer. One probe was transformed using a predefined transformation matrix. The 2D registration method was verified for probe configurations that were constrained to the same imaging plane. Three different relative angles were simulated for this case: \( 20^\circ \), \( 45^\circ \) and \( 70^\circ \). To test the 3D registration method, four different simulations were performed, which mimic the probe configurations that were used to image the porcine aorta phantom. The transformation parameters of these simulations are shown in Table 3.2. An example of the simulation set-up is visualized in Figure 3.4.

#### Table 3.2: Transformation parameters that were set in the simulations to test the 3D registration method.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>( t_x \text{ [mm]} )</th>
<th>( t_y \text{ [mm]} )</th>
<th>( t_z \text{ [mm]} )</th>
<th>( \theta_x \text{ [°]} )</th>
<th>( \theta_y \text{ [°]} )</th>
<th>( \theta_z \text{ [°]} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation 1</td>
<td>30</td>
<td>10</td>
<td>25</td>
<td>0</td>
<td>70</td>
<td>0</td>
</tr>
<tr>
<td>Simulation 2</td>
<td>20</td>
<td>10</td>
<td>15</td>
<td>0</td>
<td>50</td>
<td>-20</td>
</tr>
<tr>
<td>Simulation 3</td>
<td>20</td>
<td>15</td>
<td>15</td>
<td>0</td>
<td>50</td>
<td>-40</td>
</tr>
<tr>
<td>Simulation 4</td>
<td>20</td>
<td>15</td>
<td>15</td>
<td>-30</td>
<td>50</td>
<td>-10</td>
</tr>
</tbody>
</table>
Figure 3.4: Visual representation of a simulation of a multi-perspective bistatic acquisition. In the simulation, a cylinder embedded in speckle was imaged with two transducers.

The error of the registration methods was determined by calculating the maximum distance between the elements from the estimated probe positions to the elements of the actual probe position \( E_{\text{elem}} \). The maximum distance is taken, since it corresponds to the maximum error in pathlength that could occur during reconstruction of the trans-probe data. The error is given by Equation 3.8. With \((x_{\text{elemPos}}^{1}, y_{\text{elemPos}}^{1}, z_{\text{elemPos}}^{1})\) being the coordinates of the transformed probe.

\[
E_{\text{elem}} = \max \left[ \sqrt{(x_{\text{elemPos}}^{1} - x_{\text{elemPos}}^{2})^2 + (y_{\text{elemPos}}^{1} - y_{\text{elemPos}}^{2})^2 + (z_{\text{elemPos}}^{1} - z_{\text{elemPos}}^{2})^2} \right] \quad (3.8)
\]

On top of that, the estimated mismatch of the top of the aorta in the monostatic images \( E_{\text{aorta}} \) was determined to quantify the effect of the mismatch on the target structure. This was done by determining the relative transformation matrix between the exact and estimated probe positions \( T_{\text{relative}} \). This transformation matrix was obtained by Equation 3.9.

\[
T_{\text{relative}} = T_{\text{exact}}^{-1} T_{\text{estimated}} \quad (3.9)
\]

With \( T_{\text{exact}} \) and \( T_{\text{estimated}} \) the transformation matrix, which was used to obtain the exact and estimated element positions of the transformed probe, respectively. Subsequently, \( T_{\text{relative}} \) was applied to the pixel position of the top of the aorta. Finally, the distance was calculated between the original and transformed top of the aorta to obtain an estimate of the mismatch of the aorta in the monostatic images.
3.2.5 Generic automatic 3D registration

The proposed 2D and 3D registration algorithms are dependent on the volume content. The optimization process in these methods, could potentially be extended in order to solve all DOFs. In this study, the feasibility of a 6D optimization problem for finding the relative probe positions was investigated. To get insights in a 6D optimization problem, an exhaustive search was performed. All variables were varied around the parameter set that was obtained from the 3D registration algorithm. Only 7 values per variable were computed to save computational cost. To describe a rotation in 3D, an Euler angle sequence was used. An Euler angle sequence is a sequence of three rotations around basis vectors. The choice of the axes in the sequence is constrained by the fact that successive axes cannot be the same. A distinction can be made between symmetric and asymmetric sequence that are referred to as Euler angles and Tait-Bryan angles, respectively [41]. In this research, a 3D rotation is defined by an asymmetric set of axes, namely a rotation around the x-, y- and z-axis (see Equation 3.10).

\[
R = R_x R_y R_z = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & \cos(\theta_x) & -\sin(\theta_x) & 0 \\
0 & \sin(\theta_x) & \cos(\theta_x) & 0 \\
0 & 0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
\cos(\theta_y) & 0 & -\sin(\theta_y) & 0 \\
0 & 1 & 0 & 0 \\
\sin(\theta_y) & 0 & \cos(\theta_y) & 0 \\
0 & 0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
\cos(\theta_z) & -\sin(\theta_z) & 0 & 0 \\
\sin(\theta_z) & \cos(\theta_z) & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

(3.10)

The rotation matrices were multiplied with a transformation matrix that described the translations. The definition of the transformation matrix is given by Equation 3.11.

\[
T_{\text{generic}} = R 
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
t_x & t_y & t_z & 1
\end{bmatrix}
\]

(3.11)

In the exhaustive search, the signal power was used as a metric (see section 3.2.2). The metric was evaluated on a volume that was reconstructed as described in section 3.2.3.
3.3 Results

3.3.1 2D registration

The first step in the 2D registration method was to detect the center of the aorta. The circular Hough transform was performed for radii ranging from 9 mm to 12 mm, since the exact radius of the aorta was unknown. Subsequently, the aorta center and radius were determined by finding the parameter set that provided most votes. The detected aortas for both single-perspective volumes are visualized in Figure 3.5. It is observed that the circles, which resulted from the circular Hough transform, correspond to the location of the inner wall of the aorta in the image for both single-perspective volumes.

The metric for the exhaustive search and the optimization was validated by comparing it to three other possible metrics. The correlation coefficient between the reconstructed trans-probe volumes was calculated. Besides, the speckle size (as described in section 2.2.5) was calculated for the reconstructed trans-probe volume. Finally, the L2 norm between the two reconstructed trans-probe volumes. The convergence plot for the 1D exhaustive search is plotted in Figure 3.6. The signal power and correlation coefficient have a global minimum around the expected angle. In contrast to the calculation of the signal power, the calculation of the correlation coefficient requires that both trans-probe volumes are reconstructed, which increases the computational expense of this metric. The same experiment was performed on simulation data (see Appendix C), which also shows that the signal power is a suitable metric.

From the aorta centers in Figure 3.5, the translations were determined. To determine \( \theta_y \), an exhaustive search and an optimization were performed (Figure 3.7a and 3.7b, respectively). Figure 3.7a shows good convergence for the signal power. For small angles (0 to -25°), and thus for relative probe positions close to each other, some local minima can be found. In the exhaustive search, the angle which corresponds to the maximum signal power (1.2095 \( \cdot 10^8 \)) is 70 degrees. The angle which resulted from the optimization is 69.3 degrees. For this angle the signal power is 1.2097 \( \cdot 10^8 \). The computational time of the exhaustive search is 2 minutes, whereas the computational time for the optimization is only 20 seconds. This makes the optimization approach six times faster compared to the exhaustive search.
Figure 3.6: 1D convergence plot of the implemented metrics: signal power, correlation coefficient, L2 norm and speckle size. The signal power and the correlation coefficient show a global minimum around the expected angle.

Figure 3.7: The rotation around the y-axis ($\theta_y$) was obtained by finding the maximum signal power. This was done by either an exhaustive search (a) or by optimization (b).
The relative probe positions, which originated from a manual registration and the automatic 2D registration, were used to reconstruct all signals and to coherently compound the volumes. Figure 3.8b shows the middle x-z slice of these volumes. The manual registration resulted in an angle of approximately 68°. In Figure 3.8b it can indeed be seen that the angle is larger for the automatic registration. In both volumes, the reflection of the aortic wall between the transducers becomes visible, which originates from the side scatter in the trans-probe data. In both cases the circumference of the aortic wall is clearly visible. Near-field clutter, which originates from the trans-probe volumes due to mismatches in path-length between the transducers, is reduced in the resulting volumes of the automatic registration. The signal power of the entire trans-probe volumes are $1.5 \cdot 10^7$ and $1.9 \cdot 10^7$ in the case of manual registration for T1R2 and T2R1, respectively. For the automatic registration, the signal power of the volumes is higher, namely $1.9 \cdot 10^7$ and $2.0 \cdot 10^7$ for T1R2 and T2R1, respectively.

Figure 3.8: B-mode images (DR=60) of the middle x-z slice of a coherently compounded volume, in which the relative probe positions were determined manually (a) and automatically with a 2D registration method (b). In both images the aortic wall and spine are visible, while near-field clutter is reduced for the automatic registration.
3.3.2 3D registration

The 3D registration method is an extension of the 2D registration method, in which a centerline is detected and aligned. The centerline was obtained by a 3D segmentation of the aorta. The segmentations obtained by the Star-Kalman method for both perspectives are visualized in Figure 3.9. The segmentations were initialized at $y = 0$ m. In this case, the segmentations were of sufficient quality for $-0.02 < y < 0.02$. For the other x-z slices, the segmentation algorithm yielded an unrealistic result, which is caused by the low image quality in this region. In these slices the aortic wall is not clearly visible anymore. Therefore, only the correct part of the segmentation was taken into account to calculate the centerline. This part of the segmentation was selected manually. The calculated centerline can also be seen in Figure 3.9.

![Figure 3.9: Segmentation of the aorta obtained from the Star-Kalman method (left). From this segmentation a centerline of the aorta was derived, which is visualized on the middle x-z slice (right). The segmentation and centerline are shown for both single-perspective volume (a and b).](image)
After the centerline alignment of both perspectives, an exhaustive search was performed to determine $t_y$ and $\theta_y$. For all possible probe configurations of a predefined range of $t_y$ and $\theta_y$, the signal power was calculated. This is visualized in a surface plot in Figure 3.10a, which shows good convergence for the provided search area. It can be seen that there is a clear global minimum for the negative signal power. The parameters that correspond to this minimum are a rotation over the y-axis of 69° and a y-translation of -15 mm. This probe configuration resulted in a signal power of $2.6 \cdot 10^7$. The computational time for the exhaustive search is 70 minutes. In addition to the exhaustive search, an optimization was performed. The parameters estimated by the optimization were: a rotation of the y-axis of 69° and a y-translation of -15.2 mm, with a corresponding signal power of $2.6 \cdot 10^7$. So, the differences between the estimated parameters by the optimization and the exhaustive search are very small. The computational time of the optimization was 2 minutes, which is 35 times faster than the exhaustive search.

The estimated parameters were used to reconstruct and coherently compound all volumes. This data was acquired freehandly, so not in the same imaging plane. Therefore, the result of the fused volume is visualized in a 3D transparency plot (see Figure 3.11a and 3.11b). Furthermore, a front view of this plot can be seen in Figure 3.11c and 3.11d. When comparing the single-perspective volume to the coherently compounded volume, the visibility of the circumference of the aorta increases. The reflections of the aortic wall match well, and there is no discontinuity. This is an indication for correct registration. In the volumes, an artefact of the phantom can be observed at the left side of the top of the aorta. This artefact is caused by a crack in the gelatin medium of the phantom. However, the correct alignment of this specific artefact in all volumes also provides an indication for correct registration. Additional results are shown in Appendix D.
Figure 3.11: A 3D and 2D view of a single perspective volume (a and c) and of a coherently compounded volume, in which the relative probe positions were determined automatically with a 3D registration method (b and d). In the transparency plot the aortic wall, spine and gelatin rupture can be observed.
3.3.3 Verification

2D registration

Simulations were performed for three different angles between the two probes. For every set-up, the probe positions of the second probe were estimated with the 2D registration method. In Figure 3.12, the three different simulation set-ups are shown with the simulated cylinder (black), speckle distribution (orange) and the two probes (yellow and purple). Moreover, the estimated probe positions are also plotted (blue). It can be seen that the actual probe positions and the estimated probe position coincide. The difference between the probe positions is also quantified by the maximum distance between the element positions (e.g. $E_{\text{elem}}$). Moreover, the estimated mismatch of the top of the aorta in monostatic images (e.g. $E_{\text{aorta}}$) was calculated. The results for the exhaustive search and the optimization are listed in Table 3.3. In all cases, the errors between the transducer element positions are below 1 mm. At 20°, the estimated mismatch of the top of the aorta is approximately three times larger as at 45° and 70°. For 45° and 70°, the estimated mismatch of the top of the aorta is in the same order as one wavelength ($\lambda \approx 0.43$ mm).

![Simulation of a multi-perspective set-up, imaging a cylinder in a medium with speckle. The position of the second probe was estimated by a 2D registration method (blue) and compared to the actual position of the probe (purple) for different angles.](image)

Table 3.3: Registration error ($E_{\text{elem}}$ and $E_{\text{aorta}}$) of a 2D registration method using an exhaustive search and optimization for different angles ($\lambda \approx 0.43$ mm).

<table>
<thead>
<tr>
<th>Angle</th>
<th>Exhaustive search</th>
<th>Optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$E_{\text{elem}}$ [mm]</td>
<td>$E_{\text{aorta}}$ [mm]</td>
</tr>
<tr>
<td>20°</td>
<td>0.72</td>
<td>1.20</td>
</tr>
<tr>
<td>45°</td>
<td>0.61</td>
<td>0.45</td>
</tr>
<tr>
<td>70°</td>
<td>0.16</td>
<td>0.42</td>
</tr>
</tbody>
</table>
3D registration

Table 3.4 shows the error measures for the simulations that were performed to test the proposed 3D registration method. All error measures are below 0.5 mm and in the order of approximately one wavelength. The reported error is an error that originates from the combination of feature alignment and optimization. An experiment was performed, which tests the performance of the two computations separately. First, the centerlines were aligned and the ground truth for the optimization was applied, resulting in registration errors of 0.86 and 0.27 mm ($E_{elem}$ and $E_{aorta}$, respectively). Secondly, the ground truth of the feature alignment was used and the remaining parameters were estimated with the optimization. This resulted in an $E_{elem}$ of 0.26 mm and an $E_{aorta}$ of 0.26 mm.

Table 3.4: Registration error ($E_{elem}$ and $E_{aorta}$) of a 3D registration method using an exhaustive search and optimization for different probe configurations ($\lambda \approx 0.43$ mm).

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Exhaustive search</th>
<th>Optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$E_{elem}$ [mm]</td>
<td>$E_{aorta}$ [mm]</td>
</tr>
<tr>
<td>Simulation 1</td>
<td>0.32 0.30</td>
<td>0.42 0.32</td>
</tr>
<tr>
<td>Simulation 2</td>
<td>0.48 0.15</td>
<td>0.31 0.18</td>
</tr>
<tr>
<td>Simulation 3</td>
<td>0.48 0.20</td>
<td>0.32 0.35</td>
</tr>
<tr>
<td>Simulation 4</td>
<td>0.37 0.30</td>
<td>0.46 0.29</td>
</tr>
</tbody>
</table>

3.3.4 Generic 3D registration

An exhaustive search was performed, with transformation variables centered around the expected values of the transformation variables that were obtained with the 3D registration method. The result of the exhaustive search was a 6D matrix. To get insights in the exhaustive search, surface plots were made of all possible combinations of variables (see Appendix E). It appeared that all surface plots could be divided in two categories: peak (Figure 3.13a) or valley profiles (Figure 3.13b). The valley profiles do not show a clear minimum at the expected values. Moreover, the global minimum ($-2.7 \cdot 10^7$) in the search did not correspond to the expected variables. The optimization metric that was found at the expected transformation variables was equal to $-2.6 \cdot 10^7$. This resulted in a maximum distance from the estimated probe positions to the expected probe positions of 1.8 cm.

Figure 3.13: Example of the surface plots that resulted from the 6D exhaustive search with a peak-shaped profile where a combination of variables converges into a single solution (a) and a valley-shaped profile where the exhaustive search does not converge well (b)
3.4 Discussion

In this chapter, a registration method for volumes of the abdominal aorta has been proposed. Firstly, a 2D registration method was developed for acquisitions with an arch that ensures precisely known alignment of the probes in the same imaging plane. Secondly, this method was extended to 3D in order to allow for freehand positioning of the probes. Both methods combine feature detection and alignment of multi-perspective monostatic ultrasound volumes with an optimization of the reconstruction quality of the trans-probe volumes. From Figure 3.8 and 3.11 it can be seen that both methods successfully align the aorta. However, no ground truth of the relative probe positions in the experimental set-up was provided. To still gain quantitative insight in the accuracy of the presented registration methods, a simple simulation study was performed. The error of the registration was quantified by the maximum distance between the estimated and exact element positions of the second transducer and by the estimated mismatch of the target structure, i.e. the top of the aorta, in the monostatic images. It was observed that the error measures for the 3D method are lower compared to the 2D method. This could be explained by differences in the feature alignment. In the 2D method, the center alignment was performed for only one slice in the volume. For the centerline alignment, a center was determined for every slice and a least-square fit was performed, so the individual errors of a single slice will have less effect on the estimated transformation parameters. Prior to the fitting, the part of the segmentation of sufficient quality was selected manually. This could be improved by automating this process, for example by cutting the segmentation where the diameter decreases. The average expected mismatch of the top of the aorta in the monostatic volumes was 0.41 mm. This is very small and it is hard to observe this effect in the volume. All the reported errors originate from a combination of feature alignment and optimization. An experiment was performed to evaluate the performance of these computational steps separately. From this experiment, it appeared that $E_{elem}$ is more than three times larger for the feature alignment as for the optimization. This indicates that a larger part of the accumulative error originates from the feature alignment. The accuracy of the feature alignment is limited by the voxel spacing. In this research, the voxel spacing was equal to $\lambda$ ($\lambda \approx 0.43$ mm), explaining why the resulting errors are in the same range. To correctly coherently compound volumes, the registration error must be approximately $\frac{1}{8} \lambda$. However, the error of the element positions represent the maximum difference in pathlength during reconstruction. Therefore, the error during reconstruction of the trans-probe signals is in most cases actually smaller than the reported error, since the pathlength will be approximately the same. On top of that, the interference patterns that could occur due to coherent compounding were not observed in the compounded volumes. It can also be argued that the effect of the presence of aberrations on the error in pathlength could be more severe than the reported error of the registration methods. In conclusion, the probe localization was accurate enough to result in high-quality compounded volumes.

In this study, a simplistic simulation was performed. The simulations could get more realistic by simulating fully developed speckle. In this study, the speckle was not fully developed in order to limit computational expense. In the simulation, the spine was not included. The simulations could be further improved by also placing the virtual sources in a spiral grid and using sparse apertures to mimic the experimental acquisition scheme more closely. Furthermore, more statistics is needed in future research, since in this research, only one experiment per probe configuration was performed.

The additional metrics for optimization that were implemented in this study, the speckle size, correlation coefficient and the L2 norm did have a non-convex character or the global minimum did not correspond to the correct transformation variables. Therefore, the signal power was implemented in this study. For the 1D and 2D optimization, the metric converges well in the defined search area. However, for variables corresponding to a small distance between the probes some local minima and flat surfaces were observed, especially in the 1D exhaustive search (see Figure 3.7). This indicates that it is of great importance to set an initial guess close enough to the global minimum. A rough estimate based on the acquisition or a coarse exhaustive search can provide this initial guess. The optimization has substantially less computa-
tion time compared to the exhaustive search. The computation time for the exhaustive search increases exponentially with the number of variables to optimize. Therefore, optimization is preferred over exhaustive search, especially for large number of variables. However, in some cases the exhaustive search outperforms the optimization in terms of registration error. This can partly be explained by the simulation settings and by the fact that the performance of the exhaustive search is highly dependent on the spacing that is used. In the simulation, the transformation variables are set to round numbers, which are present in the exhaustive search. In a real acquisition this is not always the case, which will increase the error for the exhaustive search. It can also be explained by the fact that in this study the interior-point optimization algorithm was used. This algorithm was chosen, since it is known for its computational speed and low memory usage. However, it is less accurate compared to other algorithms [39]. For further research it is recommended to also investigate other optimization algorithms to see if the registration can be improved. To maintain the high speed and low memory usage during optimization, a two-step optimization approach is recommended. Firstly, an estimation can be obtained with the interior-point algorithm. Secondly, this result can be used as an input for a more accurate algorithm.

The 1D and 2D optimization showed great potential for solving transformation variables. If this method could be extended to all 6 transformation variables, this will result in a very generic registration method. This would mean that not only volumes of the abdominal aorta could be registered, but also any other tissue that is scanned. As mentioned, when solving 6 variables, an optimization approach is required, since a 6D exhaustive search will result in a very high computation time. Therefore, it is important to get insights in the global behaviour of the metric in 6D. To obtain these insights a small exhaustive search was performed, which resulted in peak and valley profiles (see Figure 3.13b). The peak profiles are expected, since it represents a convex problem with a minimum found at the expected values. The valley profiles can be caused by ambiguity between variables. As an example, a rotation around the y-axis could also be approximated with an x- and z- translation. This will result in local minima and flat surfaces, so a non-convex problem needs to be solved. A non-convex problem cannot directly be solved with the proposed optimization method and a global optimization strategy is required. In the last decades, many global optimization methods have been developed (multistart, clustering methods, branch-and-bound methods, etc.). For further research it is recommended to implement a global optimization method, since the global minimum can be found, despite the complexity of the search [42]. Alternatively, reparameterization of the 6 DOF could be investigated to avoid valley profiles.

Another challenge in 6D optimization is that the global minimum of the exhaustive search did not correspond to the expected parameters. The variation of all DOFs results in many probe configurations that differ a lot, resulting in completely different volume compositions. The ratio between the amount of voxels that do belong and do not belong to a large object in the volume, drastically affects the signal power as optimization metric. A higher ratio will lead to a lower optimization metric, since the mean of the signal power was calculated and the mean does not correct for this effect. Especially, the estimation of the translation in z-direction was affected by this. Therefore, the global minimum did not correspond to the correct transformation parameters. This problem might be overcome with a smart region selection for metric evaluation, for example by only evaluating on speckle. The smart region selection will increase computational cost in every iteration of the optimization. Moreover, a local definition of the reconstruction grid for the transformed probe could also improve metric calculation, since the ratio between the amount of voxels that do belong and do not belong to a large object in the volume remains roughly the same. The grid must be updated for every probe configuration. Alternatively, new metrics could be investigated, since the mean signal power might not suffice in a multi-variable optimization.

This research has shown the feasibility of a method in which feature detection and alignment of monostatic volumes is combined with the optimization of the reconstruction quality of trans-probe data for 2D and 3D registration. To the best of our knowledge there is no existing method, which does not depend on point sources, that localizes probes based on trans-probe data. The method was able to determine relative
probe positions for transducers that were placed freely in space. For future research, it is recommended to investigate if the described methods could also be used to reconstruct a volume of an acquisition, in which one probe is fixated and the other probe is moved freehandly. The start configuration of the two probes could be estimated with the 2D or 3D registration method, depending on whether the volumes were acquired in the same imaging plane. Subsequently, the successive relative probe position could be determined by an optimization, which is initialized with the optimum transformation variables of the previous frame. Volumes are acquired in an ultrafast fashion, resulting in a very short time between transmits. This knowledge can be used to set definite constraints in the optimization and define a small search area.
4 Smart coherent volume compounding of the abdominal aorta

4.1 Introduction

In Chapter 2, a multi-perspective bistatic acquisition for volumetric imaging has been proposed. Chapter 3 proposes an accurate method for probe localization. Finally, it is essential that the resulting volumes from the different perspectives are compounded in an optimal manner. In previous studies, masks for weighted compounding of 2D multi-perspective images of the abdominal aorta were designed [25]. These masks were composed using the angle between the midpoint of the aorta with respect to the transducer origin. This technique cannot be directly translated to 3D, due to a more complex angular dependence between the transducer and aorta. Therefore, an image fusion technique that automatically determines the weights for compounding is required. Image fusion techniques combine several images to obtain a fused image that contains maximum information content without producing non-existent details. Image fusion techniques can be classified into two groups: spatial domain fusion methods, for example principal component analysis (PCA) fusion, and transform domain methods, for example discrete wavelet transform (DWT). Spatial domain techniques directly deal with the pixels and transform domain techniques first transfer to a different representation [43]. PCA fusion preserves a better resolution, but it can produce spectral and spatial distortion. DWT fusion provides spectral details and included information at various resolutions [44]. To combine the best of both worlds, previous studies have developed algorithms that combine DWT and PCA to fuse medical images [44][45]. In this chapter, fusion algorithms were proposed, which also combine DWT with PCA, to coherently compound multi-perspective volumes of a porcine aorta phantom. The fused images are evaluated in terms of contrast and displacement tracking performance and compared to conventional compounding.

4.2 Methodology

In this study, registered volumes from two perspectives in the same imaging plane of a porcine aorta phantom were coherently compounded. The experimental set-up described in section 3.2.1 was used. To obtain a coherently compounded volume, three different fusion algorithms were developed. The fusion algorithms are using a PCA in combination with a DWT. The compounded data resulting from the implemented algorithms was evaluated on wall-lumen contrast and displacement tracking performance. Moreover, the developed algorithms were compared to conventional compounding (Equation 2.2 and 2.3) and single-perspective volumes.

4.2.1 Principal component analysis

PCA is a mathematical procedure that is often used in image fusion. It transforms a number of correlated variables into uncorrelated principal components, yielding a compact description of the data. The first principal component is always in the direction of the largest variance in the data. All succeeding principal
components lie in the subspace perpendicular to the first principal component, capturing as much of the remaining variance. In order to perform PCA image fusion, all data must to be stored in column vectors with an empirical mean of zero. In this study, the data consisted of intensities in the reconstructed volumes. The covariance matrix $C_v$, which is a measure of the joint variability between variables, is calculated by means of the expected value (equation 4.1).

$$C_v = E\{XX^T\}$$

(4.1)

In this equation, $X$ represents a matrix containing all column vectors of the images (pixels x number of images). The eigenvectors $V_{eigen}$ and corresponding eigenvalues $D_{eigen}$ of covariance matrix $C_v$ were calculated and stored by decreasing eigenvalue. Finally, the weights of the $i-th$ image for the fusion rule are calculated by equation 4.2 [46].

$$W_i = \frac{V_{eigen}(i,1)}{\sum_{j=1} V_{eigen}(j,1)}$$

(4.2)

PCA fusion of images does not give importance to local covariance and local mean. Thus, local variations are suppressed by the global variation, which is unfavourable. Therefore a new technique, local principal component averaging fusion (LPCAv), is introduced by Vijayarajan et al. Source images are split into small segments and a PCA is performed for every block to calculate the weights for the fusion rule [47].

4.2.2 Discrete wavelet transform

In Fourier domain analysis, the signal is decomposed into sines and cosines, resulting in a good resolution in the Fourier domain. However, no information about the time domain is provided. The wavelet theory extends this by also providing good resolution in the time domain. In wavelet theory the signal is projected on a set of wavelet functions. This mathematical tool is often used in image processing to provide a multi-resolution representation of an image, which is referred as DWT. The wavelet theory processes 1D signals. In order to apply this technique to 2D data (e.g. an image), the horizontal and vertical directions (rows and columns, respectively) are filtered separately [46]. From the wavelets, a high-pass and a low-pass filter were derived. These filters were applied separately to the rows and columns in two stages to obtain a 2D multi-resolution representation of the image. In the first stage, the filters were applied to the rows of the image and the columns were downsampled by a factor 2. Subsequently, the columns were convolved with the filters and the rows were downsampled with a factor 2 [46]. This process is visualized Figure 4.1. The LL-component of the image decomposition contains the average image and is also called the approximate coefficients. The other three components (LH, HL and HH) are the detailed coefficients and they represent the vertical, horizontal and diagonal edges of the image. The image decomposition can be repeated for the desired number of levels, but in this research the decomposition level was equal to 1.
4.2.3 Proposed algorithms

For bistatic imaging, it is of great interest that an algorithm can take multiple images as input. The two bistatic signals (T2R1 and T1R2) have overlapping reflections and contain roughly the same information. So, these images were averaged, resulting in three datasets as input for the image fusion algorithm. Moreover, it is important to coherently compound the volumes to maintain the phase information, which increases image resolution (see Chapter 2). Accordingly, the fusion rule was applied to the IQ data. In this study, two types of a discrete wavelet transform based principal component fusion are proposed. Both algorithms were compared to conventional compounding (equation 2.2 and 2.3) and to a PCA fusion without DWT.

Figure 4.2: Block schematic representation of a discrete wavelet (DWT) based principal component (PCA) fusion acting on envelope detected data (DWTPCAenv) that coherently compounds three datasets from a multi-perspective bistatic acquisition (IM1,IM2,IM3).
The first proposed algorithm is a discrete wavelet based principal component fusion that acts on the envelope data (DWTPCAenv). The schematic overview can be seen in figure 4.2. The algorithm is based on the proposed algorithm by Vijayarajan et al. [45]. First, a DWT of the envelope detected images was performed (see section 4.2.2). Secondly, a PCA was performed on the resulting multi-resolution representation (see section 4.2.1). An important difference with the proposed algorithm from Vijayarajan et al. is that in this case a local PCA was performed. The images were divided in rectangular blocks (7x7 mm) to maintain local variance and information in the fused image. Finally, the obtained complementary weights from the detailed and approximate coefficients were averaged in order to obtain one weight for each block. The fused image was obtained by summing the IQ data, which was multiplied with the corresponding weights.

Figure 4.3: Block schematic representation of a discrete wavelet (DWT) based principal component (PCA) fusion acting on in-phase quadrature (IQ) data (DWTPCAiq) that coherently compounds three datasets from a multi-perspective bistatic acquisition (IM1,IM2,IM3).

The second proposed algorithm, DWTPCAiq, is similar to DWTPCAenv, but it acts on the IQ data instead of on the envelope detected data. First, a DWT was performed followed by a local PCA. In DWTPCAiq, the weights were directly applied to the multi-resolution representation of the IQ data, which was not possible for DWTPCAenv, since it will result in incoherent compounding. Therefore, the obtained weights by DWTPCAenv were averaged to obtain a single weight for each of the three IQ signals. So, averaging of the weights obtained from the detailed and approximate coefficients is not necessary in DWTPCAiq. Finally, the inverse of the DWT was applied to obtain the fused image. The block schematic overview of PCA fusion without a DWT is shown in Appendix F.
4.2.4 Evaluation

Contrast

To determine to what extent the image fusion algorithms can enhance the visibility of the aortic wall, the image quality was determined by quantifying the contrast between the aortic wall and the lumen. The contrast ratio and the contrast-to-noise ratio, given by equation 4.3 and 4.4, were estimated in the envelope detected images.

\[
CR = 20 \log_{10} \left( \frac{\mu_w}{\mu_l} \right)
\]

(4.3)

\[
CNR = 20 \log_{10} \left( \frac{|\mu_w - \mu_l|}{\sqrt{\sigma_w^2 + \sigma_l^2}} \right)
\]

(4.4)

With \( \mu_w \) and \( \mu_l \) being the mean intensities of the aortic wall and lumen respectively. \( \sigma_w \) and \( \sigma_l \) denote the standard deviation of the intensities in the wall and lumen. The aortic wall was segmented by manually selecting points on the lumen-wall border. Subsequently, the aortic wall was segmented by assuming a uniform wall thickness.

Displacement tracking

The different fusion methods were also compared with regards to their tracking performance. A 2D coarse-to-fine displacement estimation algorithm was used to track the pixels in and around the mesh of the aortic wall during one pressure pulse [48] in the middle x-z slice of the volume. This method uses a normalized cross correlation based block matching algorithm to find the displacement of an image kernel within a search area (SA). First, image kernels of 2.6 x 4 mm (axial x lateral) were defined in a SA of 3.1 x 4.2 mm to find the coarse displacements on the envelope detected signals. Then, an image kernel of 0.8x2.4 mm was defined in an SA of 1.1 x 2.6 mm to estimate the fine displacements on the radiofrequency (RF) signals.

The precision of the motion tracking was quantified by the Mean Error (ME) of the estimated points in the aortic wall at begin systole and at end diastole (bs and ed respectively) [25]. In equation 4.5, \( n \) represents the number of estimated points with positions \((x_i, y_i)\) in meters. With a low mean drift error, the points on the aortic wall will have the same position after inflation.

\[
ME = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(x_i, bs - x_i, ed)^2 + (y_i, bs - y_i, ed)^2}
\]

(4.5)

The accuracy of the motion tracking was quantified by determining the Dice score (DSC) of the mesh at end systole [21]. For this purpose, the aortic wall was manually segmented at end systole. This segmentation is compared to the tracked segmentation. The DSC is calculated with equation 4.6 with \( S_1 \) and \( S_2 \), representing the automatic and manual segmentation of the aortic wall in the end systolic phase, respectively.

\[
DSC = \frac{2 | S_1 \cap S_2 |}{| S_1 | + | S_2 |}
\]

(4.6)
4.3 Results

4.3.1 Comparison weighting masks aortic wall

This study proposes PCA for automatic determination of weights for fusion. A previous study proposed a technique, composing weighting masks using the angle between the midpoint of the aorta and the transducer [25]. The resulting masks for both techniques are shown in Figure 4.4. Both methods provide high and low weights for tissue interfaces perpendicular and parallel to the wave propagation, respectively. However, PCA weight determination performs fully automatic and no knowledge about the location of the target structure or the probe is used, which results in a more generic method. On top of that, PCA weight determination also determines weights for the trans-probe data.

![Figure 4.4: Masks for weighted compounding of the aortic wall. De Hoop et al. proposed a technique using the angle between the midpoint of the aorta and the origin of the transducer to compose a mask for monostatic images (a). This study proposes a technique that automatically determines weights using principal component analysis (PCA) for monostatic and bistatic images (b). The bottom row shows a B-mode of the aortic wall (DR=40).](image)
4.3.2 Fused volumes

In this study, different fusion techniques were compared. On top of that, a comparison was made to single-perspective US imaging. A B-mode image (DR=60) of a single-perspective volume can be seen in Figure 4.5a. Only top and bottom reflections of the aorta and the spine are visible, since only these structures are perpendicular to the US beam. The most simple way to fuse volumes from the multi-perspective US set-up is by coherently adding up the monostatic signals (see Figure 4.5b). This monostatic fusion results in an extra reflection of the aortic wall, where the aortic wall is perpendicular to the direction of the US beam of the second probe. The circumference of the aortic wall becomes more clear when the bistatic signals are included in the fusion process, due to the presence of side-scatter. The volume resulting from this fusion approach can be seen in Figure 4.5c. Furthermore, three algorithms that fuse the volume locally were implemented. The volumes that are fused using DWTPCAiq and DWTPCAenv are shown in Figure 4.5d and 4.5e, respectively. In both volumes, the bistatic reflection of the aortic wall is brighter compared to bistatic fusion. Finally, the bistatic reflection of the aortic wall is also clearly visible after fusion using PCA (Figure 4.5f). However, this fusion method gives spatial distortion in the volume.

Figure 4.5: B-mode images (DR=60) of the single-perspective volume (a) and the fused volumes using the conventional monostatic (b) and bistatic (c) fusion, the two proposed discrete wavelet based principal component fusion methods (DWTPCAiq (d) and DWTPCAenv (e)) and local principal component analysis (PCA) fusion (f). In the images a cross section of an aorta and spine can be seen.
4.3.3 Contrast

The images in Figure 4.6 show a cross-sectional view of the porcine aorta. In this view, a high contrast between aortic wall and lumen is desired. From this view, a segmentation of the aortic wall and lumen was obtained to determine the CR and CNR. From Figure 4.6 it can be seen that including the bistatic signal gives a brighter reflection over a larger segment of the aortic wall. Moreover, for the local fusion methods (DWTPCAlq, DWTPCAlenv and PCA) the brightness of the bistatic reflection is enhanced. Again, a spatial distortion can be seen for the local PCA fusion. Table 4.1 shows the CNR and CR between the aortic wall and lumen for the different images. The CR increases by 1 dB when a multi-perspective set-up is used. The CR increases further with 2-3 dB, when a local fusion approach is used. The maximum CR (23.5 dB) is obtained after a local PCA fusion. A similar trend for the CNR can be observed. The CR increases with approximately 3 and 4 dB from single- to multi-perspective when excluding and including the bistatic signal respectively. The largest increase in CNR (5.5 dB) compared to single-perspective is seen for the proposed DWTPCAlq fusion method.

![Figure 4.6: B-mode images of the midslice (XZ-plane) of volumes acquired from the porcine aorta phantom for different fusion algorithms.](image)

Table 4.1: Contrast-to-noise ratio (CNR) and contrast ratio (CR) between the aortic wall and lumen for the implemented fusion algorithms.

<table>
<thead>
<tr>
<th></th>
<th>CR [dB]</th>
<th>CNR [dB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single perspective</td>
<td>19.5</td>
<td>-8.1</td>
</tr>
<tr>
<td>Monostatic fusion</td>
<td>20.6</td>
<td>-5.2</td>
</tr>
<tr>
<td>Bistatic fusion</td>
<td>20.6</td>
<td>-4.2</td>
</tr>
<tr>
<td>PCA fusion</td>
<td>23.5</td>
<td>-4.1</td>
</tr>
<tr>
<td>DWTPCAlq fusion</td>
<td>22.2</td>
<td>-2.6</td>
</tr>
<tr>
<td>DWTPCAlenv fusion</td>
<td>23.2</td>
<td>-3.8</td>
</tr>
</tbody>
</table>

4.3.4 Displacement tracking

The effect of the different fusion methods on the displacement tracking performance was also evaluated. The precision was determined by the ME of the tracking drift and the accuracy by the DSC of the tracked and manually segmented mesh in systole. The results are summarized in table 4.2.

Table 4.2: Mean error (ME) of the estimated positions of the aortic wall and Dice score (DSC) of the automatic and manual segmentation of the aortic wall in systole for the implemented fusion algorithms

<table>
<thead>
<tr>
<th></th>
<th>ME [mm]</th>
<th>DSC [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single perspective</td>
<td>0.93</td>
<td>0.74</td>
</tr>
<tr>
<td>Monostatic fusion</td>
<td>0.87</td>
<td>0.84</td>
</tr>
<tr>
<td>Bistatic fusion</td>
<td>0.59</td>
<td>0.87</td>
</tr>
<tr>
<td>PCA fusion</td>
<td>0.83</td>
<td>0.85</td>
</tr>
<tr>
<td>DWTPCAlq fusion</td>
<td>0.81</td>
<td>0.85</td>
</tr>
<tr>
<td>DWTPCAlenv fusion</td>
<td>0.71</td>
<td>0.86</td>
</tr>
</tbody>
</table>
The ME of the tracking drift is 0.93 mm for a single-perspective volume and can be reduced by fusing the multi-perspective volumes (see Table 4.2). The largest reduction, approximately 37%, is seen for bistatic fusion. This result is supported by Figure 4.7. This figure shows the manual segmentation of the aortic wall (black dotted line), the automatically tracked wall in systole (red dotted line) and the automatically tracked wall in diastole (blue dotted line). Ideally, the estimated points in diastole correspond to the initial segmentation. The difference between the blue and black dotted line represents the error propagation of the motion tracking after one pressure pulse. For the single-perspective case it can be seen in figure 4.7 that there is a large deviation between the segmentation and the mesh after one pressure pulse. This deviation is largest in the regions where the aortic wall is parallel with the US beam. The error propagation is smallest for the bistatic fusion method (see Figure 4.7). The ME of the displacement tracking for the local fusion methods (DWTPCAiq, DWTPCAenv and PCA) is smaller compared to a single-perspective volume. However, it is larger than conventional bistatic fusion (see Table 4.2 and Figure 4.7).

**Figure 4.7:** Segmentation and estimated points of the aortic wall during displacement tracking in end systole and end diastole for the implemented fusion algorithms.

In order to investigate the accuracy of the motion tracking, the DSC of the tracked mesh was determined, which is listed in Table 4.2. Moreover, the tracked segmentations are visualized in Appendix G. The DSC is larger for multi-perspective imaging compared to single-perspective imaging. However, the differences in DSC between the different fusion methods are very small ($\approx 0.01$). This is also in agreement with the estimated points in systolic phase, visualized in Figure 4.7, where the differences between the tracked points are very small.
4.4 Discussion

In this chapter, multiple fusion techniques have been proposed for coherent volume compounding of signals obtained from bistatic imaging. The different fusion techniques were compared to each other in terms of contrast and displacement tracking performance. Moreover, a comparison was made to single-perspective imaging. The different fusion methods can be divided in two different categories: global and local fusion techniques. The global fusion techniques coherently add up signals and use one weight per signal. Hence, the same weight is used for every pixel in an image. Monostatic and bistatic fusion are both global fusion techniques. On the other hand, local techniques, DWTPCAenv, DWTPCAiq and PCA fusion, were implemented. These methods weigh the different signals locally in coherent compounding. The weights were determined automatically, without using the knowledge of image composition and probe locations, which makes the method generic. This resulted in similar weighting masks for the aortic wall compared to a study by de Hoop et al. To evaluate the performance of the fusion algorithms, the contrast between the aortic wall and lumen was determined. The local fusion techniques yield a higher wall-lumen CR and CNR, compared to the global techniques. In ultrasound imaging, the interfaces that lie perpendicular to the direction of the beam propagation will reflect well, whereas other interfaces will reflect to a smaller extent. In other words, the information content of an ultrasound image is highly dependent of the angle of insonification on the tissue surface, and therefore differs locally. Thus, to capture maximum information content and increase contrast, a local fusion technique is required.

Therefore, an improvement in CR and CNR can be seen for local fusion techniques compared to the global fusion techniques and the single-perspective volume. The CR for DWTPCAiq, DWTPCAenv and PCA fusion are 22.2, 23.2 and 23.5 dB, respectively. PCA fusion increases CR most with 4 dB compared to single-perspective imaging. However, when looking at the CNR an opposing trend is observed. The CNR of DWTPCAiq, DWTPCAenv and PCA are -2.6, -3.8 and -4.1 dB, respectively. The volume fused using DWTPCAiq has the highest increase of CNR, 5.5 dB, compared to single-perspective imaging. Figure 4.6 shows the local fusion techniques on the bottom row. It can be seen that the contrast between the aortic wall and lumen for the side regions of the aorta is better preserved in DWTPCAiq compared to DWTPCAenv and PCA fusion. DWTPCAenv and PCA fusion strongly enhance the reflections of the aorta, but the intensity difference between the aortic wall and lumen in the side regions is reduced. This effect gives a high standard deviation of the intensities in the aortic wall, resulting in a lower CNR. Hence, DWTPCAenv and PCA fusion are capable of locally enhancing the reflection of the aortic wall. However, the visibility of the side regions decreases. Moreover, it was expected that PCA fusion would result in spatial distortion [43], which can also be seen in Figure 4.6. The structures in the image look coarser compared to the fusion techniques that include a DWT. Moreover, PCA fusion reduces the grating lobe artifact above the aorta, that is originating from a large reflection of the top of the aorta. This potentially has a positive influence on the displacement tracking, because previous research has shown that this artefact affected the block matching algorithm [21].

The precision and accuracy of the motion tracking was quantified by the DSC and the ME, respectively. The precision and accuracy of motion tracking are both higher for multi-perspective imaging compared to single-perspective imaging. The DSC increases by approximately 0.1 when comparing single-perspective to multi-perspective. However, the differences between the different fusion techniques are really small (≈ 0.01). On the other hand, the accuracy of motion tracking is different for the different fusion algorithms. Minimal ME is achieved with bistatic fusion, despite lower contrast for the global fusion techniques compared to the local techniques. Hence, high lumen-wall contrast does not guarantee more accurate displacement tracking. The relatively low accuracy for the local fusion techniques might be explained by the local changes between and within frames that are induced by the fusion algorithms. Finding the location of an image kernel in a search area of the successive frame could be more complicated due to local the differences that are present in a signal.
The local fusion methods that were developed in this study show an improvement of image quality in terms of wall-lumen contrast. However, this did not have a direct beneficial effect on the displacement tracking performance. Further research is recommended to investigate the cause, and to determine if the block matching algorithm can be adjusted to deal with local differences. On top of that, the tracked displacements in this research are very small, which makes comparing tracking performance on this specific data challenging. Moreover, the methods are only tested on one dataset. Thus, no evidence on contrast and tracking performance improvement can be provided. Therefore, it is highly recommended to perform a statistical analysis on multiple datasets acquired from phantom studies or simulations in which the deformation can be regulated. The developed algorithms fuse a volume by determining the weights slice by slice. This could be extended to a fully 3D fusion method by using a 3D wavelet composition. The current implementation of the algorithm fuses three volumes. However, ideally an entire sweep of the AAA is reconstructed and fused, as described in section 3.4. This will yield more than three datasets. The proposed fusion method can be adapted to handle more input variables by exploiting a multi-dimensional PCA, in which the number of dimensions is equal to the number of volumes to fuse.
5 General limitations and outlook

This thesis presented the first steps towards 3D freehand ultrafast multi-perspective imaging of the abdominal aorta. Firstly, the effect of adding volumetric trans-probe data in coherent compounding was investigated on a point source phantom. Bistatic imaging resulted in an increased resolution and FoV. The increase in image quality was very promising, and therefore this imaging method was used in a clinically more relevant set-up. Thus, a registration method for volumes of the abdominal aorta was developed. This allows for freehand bistatic imaging of an ex-vivo aorta phantom without the use of an external tracking device or probe holder to know the exact relative positions of the transducer. The registration method, that combines feature detection and alignment with an optimization of the trans-probe signal power, successfully determined the relative probe positions of the multi-perspective set-up. Finally, a smart compounding method was developed that maximizes the information content of multiple perspectives, which results in an improved wall-lumen contrast in the compounded volumes.

The implemented registration method is capable of estimating the relative probe positions accurately, even when the transducers are not constraint to the same imaging plane. The implemented method, estimates the relative probe positions on static data. It is recommended to elaborate the method, in order to determine the relative probe positions for dynamic data, in which one probe is moved freehandly. In this way, an entire sweep of the AAA can be reconstructed. The initial transformation variables, can be determined with the proposed registration method. The relative probe positions of subsequent frames can be determined by a constrained optimization, with the initial parameters set to the transformation variables of the previous frame. However, the motion of the aorta and the probe will complicate coherent compounding of a sweep. If an object moves significantly between transmits, which will be the case for the aorta when acquiring multiple frames, coherent compounding will result in motion artifacts [49]. Therefore, temporal registration must be performed. In this way, multiple heartbeats can be combined into one and the motion of the aorta can still be captured. Alternatively, a motion correction algorithm must be implemented to allow for coherent compounding between frames [50]. Currently, the registration method is developed for a healthy aorta. In the case of an AAA, the method must be adopted due to the more complex shape, which will make the initial feature alignment more convenient. The centerline is currently estimated by a linear least-square fitting. In the case of an AAA, this will not suffice and a polynomial fit is required. From polynomial fits, the transformation variables cannot directly be determined and a different approach is needed. For example, a point-based registration method, like ICP, could be useful to align the centerlines. Alternatively, previous research has shown that applying the ICP algorithm directly to a point set, composed of the obtained segmentation is also feasible [51]. However, to still obtain the required subwavelength accuracy, the obtained parameters can be updated using the proposed optimization strategy, initialized at the optimal transformation variables resulting from a point-based registration.

The smart compounding method that combines a DWT multi-resolution representation with a local PCA showed an increase in wall-lumen contrast. This leads to an increased visibility of the aorta in the volumes, which will beneficially affect automatic detection and segmentation algorithms. This is advantageous for rupture risk assessment, since a more complete geometry of the AAA can be acquired using 3D segmentation techniques. No improvements were seen in the precision of 2D displacement

50
tracking between regular and weighted summation. The effect of smart fusion algorithms on motion tracking should be studied in more detail in phantoms or simulations where the order of magnitude of the displacements is larger. Currently, three different volumes were fused. However, when a freehand sweep of the aorta is performed, more volumes need to be fused. Even for a large amount of volumes to fuse, the developed algorithm is still useful, since this will only increase the dimensionality of the PCA.

The developed 3D registration algorithm allows for acquisitions that are not constrained to the same imaging plane, which will make clinical application more feasible, since it reduces operational difficulty. However, further in-vivo studies must be performed to investigate the feasibility of dual-transducer acquisition in the clinic. In this study, only ex-vivo experiments were performed. The presence of anisotropic speed of sound in an inhomogeneous media, will complicate coherent volume compounding [52]. This will especially be a problem for larger imaging depths in obese patients. Previous studies have shown feasibility of local speed-of-sound adaptive beamforming by estimating a local speed-of-sound distribution. This distribution can be extracted from apparent tissue motion between beamformed single plane wave images [53]. This technique and other phase aberration correction techniques may be investigated. Moreover, the depth of an AAA will be deeper in patients compared to the experimental set-up and simulations, in which attenuation will degrade visibility of the aorta.
6 Conclusion

This study continued on previous efforts on ultrafast multi-perspective imaging of the abdominal aorta and contributed to translating this technique to 3D freehand imaging. 3D freehand ultrafast multi-perspective imaging was performed on a self-designed and custom-made point source phantom to execute a quantitative analysis on image quality. The analysis demonstrated an improvement of image quality in terms of resolution for 3D multi-perspective bistatic imaging with respect to multi-perspective monostatic and single-perspective imaging. Moreover, this technique was applied to a porcine aorta phantom, which requires an accurate registration method to find the relative probe positions. A 3D registration method was developed that combines feature detection and alignment of monostatic volumes with an optimization of the reconstruction quality of the trans-probe data. The method resulted in an accurate alignment of the porcine aorta and the registration error was quantified in the order of only one wavelength in a simulation study and this allowed for coherent compounding of the volumes. To obtain maximum information content in the coherently compounded volume, smart volume compounding was performed. An algorithm that locally determines weights for fusion in a multi-resolution representation provided an increase of 5.5 dB in lumen-wall CNR, increasing the visibility of the aortic wall circumference. Future research should investigate the applicability of the described methods in an in-vivo setting, since this gives rise to new challenges, for example phase aberrations and complicated feature alignment due to complex shaped AAAs.
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Marieke
October 6, 2021
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A Iterative closest point registration

Figure A.1: Illustration of the registration of a fixed (a) and a moving point cloud (b) using iterative closest point (ICP). The moving point cloud is transformed using the parameters found by the ICP algorithm to obtain a registered point cloud (c).
B Speckle size analysis for time averaged receive data

Figure B.1: 3D speckle size of single-perspective imaging (a), multi-perspective monostatic imaging (b) and multi-perspective bistatic imaging (c) for which the receive data is time averaged.
C Validation metric on simulation data

Figure C.1: 1D convergence plot of the implemented metrics: signal power, correlation coefficient, L2 norm and speckle size on simulation data.
D Additional results 3D registration

Figure D.1: A 3D and 2D view of a single perspective volume (a and c) and of a coherently compounded volume, in which the relative probe positions were determined automatically with a 3D registration method (b and d) of a second dataset. In the transparency plot the aortic wall, spine and gelatin rupture can be observed.
E Exhaustive search surface plot for all degrees of freedom

(a) 
(b) 
(c) 
(d) 
(e) 
(f) 
(g) 
(h) 
(i)
Figure E.1: Surface plots of an exhaustive search to determine the relative probe positions. For all degrees of freedom (x-, y- and z-rotation and x-, y- and z-translation) the optimization metric (e.g. - Volume Power) is calculated for every configuration. A surface plot of all possible combinations can be seen in α-ο
F  Local principal component fusion

Figure F.1: Block schematic representation of a local principal component (PCA) fusion that coherently compounds three datasets from a multi-perspective bistatic acquisition (IM1, IM2, IM3).
Tracked segmentation of the aortic wall in systolic phase

Figure G.1: Tracked segmentation of the aortic wall in systolic phase as a result of motion tracking for the implemented fusion algorithms.