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Citation for published version (APA):

Pourtaherian, A., Scholten, H. J., Kusters, C. J., Zinger, S., Mihajlovic, N., Kolen, A. F., Zou, F., Ng, G. C., Korsten, H., & de With, P. H. N. (2017). Medical instrument detection in 3-dimensional ultrasound data volumes. *IEEE Transactions on Medical Imaging*, 36(8), 1664-1675. [7894219]. <https://doi.org/10.1109/TMI.2017.2692302>

DOI:

[10.1109/TMI.2017.2692302](https://doi.org/10.1109/TMI.2017.2692302)

Document status and date:

Published: 01/08/2017

Document Version:

Accepted manuscript including changes made at the peer-review stage

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

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Medical Instrument Detection in 3-Dimensional Ultrasound Data Volumes

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Abstract—Ultrasound-guided medical interventions are broadly applied in diagnostics and therapy, e.g. regional anesthesia or ablation. A guided intervention using 2D ultrasound is challenging due to the poor instrument visibility, limited field of view and the multi-fold coordination of the medical instrument and ultrasound plane. Recent 3D ultrasound transducers can improve the quality of the image-guided intervention if an automated detection of the needle is used. In this paper, we present a novel method for detecting medical instruments in 3D ultrasound data that is solely based on image processing techniques and validated on various *ex-vivo* and *in-vivo* datasets. In the proposed procedure, the physician is placing the 3D transducer at the desired position and the image processing will automatically detect the best instrument view, so that the physician can entirely focus on the intervention. Our method is based on classification of instrument voxels using volumetric structure directions and robust approximation of the primary tool axis. A novel normalization method is proposed for the shape and intensity consistency of instruments to improve the detection. Moreover, a novel 3D Gabor wavelet transformation is introduced and optimally designed for revealing the instrument voxels in the volume, while remaining generic to several medical instruments and transducer types. Experiments on diverse datasets including *in-vivo* data from patients show that for a given transducer and instrument type, high detection accuracies are achieved with position errors smaller than the instrument diameter in the 0.5 to 1.5 millimeter range on average.

Index Terms—medical instrument detection, 3D ultrasound, interventional guidance, Gabor transformation, line filtering.

I. INTRODUCTION

ADVANCES in modern imaging modalities like magnetic resonance imaging, computed tomography and ultrasound (US) evolved image-guided surgical techniques into established procedures within minimally-invasive interventions. Such interventions include biopsies, radio-frequency ablations, regional anesthesia, as well as all therapies that require the percutaneous advancing of a needle or a catheter to a target

inside the patient's body. Ultrasound is one of the most popular modalities for instrument guidance, which can provide simultaneous images of human anatomy and the tool in real time using non-ionizing radiation. Moreover, the required equipment and devices are relatively mobile and of low cost. However, ultrasound suffers from a low signal-to-noise ratio, anisotropy, imaging artifacts and the distorted appearance of medical instruments, which complicate the interpretation of the data. Furthermore, in a guided intervention using 2D US, bi-manual coordination of the tool and US transducer for maintaining the perfect alignment is challenging and an inadequate view of the tool leads to an erroneous placement. For this reason, medical specialists need considerable practicing and training to increase the success of interventions and yet they may become too much focused on finding the tool in the ultrasound field rather than the treatment itself [1].

As an alternative, 3D US with a computer-aided instrument-tracking system can overcome 2D limitations in image-guided interventions [2] and minimize the manual coordination. In such a system, after positioning the transducer to identify the target and obtain the best image quality, the instrument is conveniently placed in the larger 3D US field of view and transducer need not to be further adjusted. Instead, the processing unit automatically detects and visualizes the entire instrument, so that full attention can be given to the intervention to correct any misalignment of the instrument and the target. This automatic localization of the instrument creates further opportunities. First, it can be used to select the optimal region of interest for visualization. Second, US beams can be steered for best instrument visibility. Third, accurate information regarding the position of the instrument with respect to important vessel or nerve structures in the body can minimize risks to the patient and improve health outcomes.

Instrument-localization techniques in US images can be divided into *image-based* detection algorithms [3] and *external* tracking devices. Examples of external tracking are robot-assisted navigation, optical needle localization, and electromagnetic tracking systems [4]. Although these systems are shown to improve the guidance accuracy in interventional procedures [5], they are not widely used in practice. This is because they require additional equipment, request specific skills and they add costs to the US system and the needle or catheter. Therefore, image-based localization techniques are more appealing in 3D US, as they can potentially overcome these limitations. Furthermore, alternative imaging techniques such as photoacoustic needles [6] improve needle visibility and can be supported by image-based techniques [7] for accurate

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localization. We will now briefly discuss the state-of-the-art instrument detection techniques based on image processing.

A. Image-based instrument detection in US data

Various algorithms have been proposed for image-based instrument detection in US data. Despite the diversity in choice of the methods, they typically have the following three main stages: pre-processing, candidate-point selection and instrument-position estimation.

Pre-processing: Normalization of the acquired US volumes is required prior to any automated analysis. However, this requirement varies for different approaches. One example is adaptation of 2D techniques for implementation in 3D US by projecting the 3D volume on 2D planes [8], [9]. Another example is regarding the model-based detection algorithms that require intensity normalization of training samples to represent similar structures based on the same reference [10].

Speckle noise and acoustic clutter are the primary factors that limit the detectability of small, low-contrast structures in US data. Primitive denoising techniques such as mean and median filtering [11], [12] are used considering the speckle noise as impulse noise. Methods based on anisotropic diffusion [13], [14] smooth the data to minimize the speckle effect, while enhancing important features such as edges. Other studies [15], [16] concentrate on separating and suppressing the multiplicative noise component in the wavelet domain. Depending on the clinical application and objective measures, various methods are shown to be superior in different studies [11], [14]. However, as these techniques may alternate or obscure small details in the acquired data, they have not yet become a standard part of the US data processing framework. Alternatively, modified US image formation methods, such as apodization [17], adaptive beamforming [18] and short-lag spatial coherence [19] are shown to reduce the acoustic clutter. Although clutter overlay the needle by diffused echoes [20], the global shape of instruments can still be predicted [21].

Despite the limitations of noise reduction techniques for clinical diagnosis, they can be useful for instrument detection purposes. Information regarding the cylindrical structure of surgical instruments can be used to enhance their appearance, while reducing the imaging artifacts. This can be achieved by Hessian-based line filtering methods [21] or employing second-order derivative of Gaussian filters [22].

Candidate-point selection: In order to increase the detection accuracy, candidate points of the instrument are selected prior to estimating the tool axis. Generally, the intensity of the instrument is assumed to be higher than the surrounding tissues in the US field. Therefore, intensity-based thresholding [23], edge detection [12] and phase grouping [24] are common methods for pre-selection of the data. However, the occurrences of other highly echogenic structures in the field of view, such as bones and fat tissues, complicate the detection. Another method is to detect moving objects by observing intensity changes in needle-based interventions. These movements can be caused by oscillatory motion of the stylus [25], or associated with displacement and strain of nearby tissue [26]. The requirement of having a fixed transducer and stationary subject, makes this approach not appealing for our case.

Other methods involve a supervised classification approach to more robustly model the differences between the instrument and other echogenic structures. Descriptors such as Frangi's line filtering [27], Gabor [28], and log-Gabor features [29] are used to create a data representation that is invariant to small changes in brightness and appearance. A combination of intensity and line filtering descriptors is proposed in [30].

Our previously published evaluation [31] suggests that the performance of descriptors in discriminating the instrument is highly influenced by instrument type and diameter, type of the dataset, as well as the resolution parameters of the 3D transducer. Therefore, in this study, we incorporate these influencing factors and present solutions for a generic and robust instrument detection algorithm in 3D US data.

Instrument Detection and Axis Estimation: Several algorithms for instrument localization in 3D are based on accumulating voxel intensities via projection techniques on to the orientation planes of the data cube. Afterwards, 2D line detection techniques are applied, such as Principle Component Analysis (PCA) [32] and Hough transformation [33]. However, depending on instrument orientation and visibility, projection may obscure some of the parts, which makes detection difficult or even impossible. Similarly, extensions of Radon transformation are used for detecting a line, which models an interventional instrument in 3D. Examples are 3D Hough transform [34] and modified Radon transform [35], also called Parallel Integral Projection (PIP) [36]. Nevertheless, these transformations are also not robust to cluttered backgrounds because they lack the discriminative information regarding the instruments shape to be distinguished from other structures with similar brightness in noisy US data.

Due to detection challenges, localization needs to be robust to false detections and outliers. Therefore, it is proposed to fit a model of the instrument by means of RANdom SAMple Consensus (RANSAC), which enables also a real-time performance on a GPU [37]. Furthermore, processing only in the region of interest and tracking over time is shown to limit the computational complexity and increase robustness in phantom data [38]. Nevertheless, arbitrary movements of the transducer and subject must be avoided for a successful tracking. In this study, we apply RANSAC [28] on full still volumes for a generic and robust localization.

B. Novelty of the approach

To the best of our knowledge, the state-of-the-art methods on image-based instrument detection, either fall short in validating on realistic datasets, use highly echogenic [32] and modified tools [23], [35], or require specific acquisition conditions, such as a fixed transducer [39]. In our previous work [28], we have introduced a robust algorithm for automatic detection of a conventional needle in 3D US, using a directionally sensitive spectral transformation and validated this concept on a limited *ex-vivo* dataset. In a follow-up study, the performance was shown to largely deviate for different needles and phantoms as the instrument appearance varies [31]. As these variations are mainly local in nature without abrupt global changes, they can be overlooked in

Fig. 1: Block diagram of the proposed system.

clinical trainings, e.g. as in [40]. However, for automated detection and positioning of instruments, these local variations should be identified and the design of specific methods should be made robust against them.

In this paper, we present a novel and generic method for detecting medical instruments, such as a needle or a catheter, in 3D US data volumes to support various US-guided procedures. Our method is based on extraction of instrument voxels, using 3D structure directions and robust approximation of the dominant tool axis in the volume. More specifically, the main contributions of this paper are: (1) proposing a generic automated method to detect various types of medical instruments in 3D US and validating the robustness in challenging settings, including *in-vivo* datasets acquired from patients during interventions, (2) novel technique for normalization the contrast visibility of the instrument and its appearance for detection to improve the performance of the supervised detection, (3) novel usage and design of the 3D Gabor transformation to exploit the instrument voxels in static or sequences of full US volumes, (4) in-depth analysis of medical instrument characteristics under different circumstances, which influences the automated detection in the intended US-guided procedure.

The remainder of this paper starts with a detailed description of the individual processing stages of our approach in Section II. Afterwards, the performed experiments and results are presented in Section III. Section IV provides discussions and recommendations for future work. Lastly, mathematical background is presented in the Appendix.

II. PROPOSED METHODS

The block diagram in Fig. 1 shows the main stages of our proposed instrument detection system. In the first stage, US data is pre-processed for normalization, noise reduction and enhancement of instrument appearance. Second, the candidate voxels are coarsely selected by classifying the feature vectors implemented for each voxel. Finally, a predefined model of the instrument is fitted to the candidate voxels. We now present the detailed description of various subsystems at each stage.

Fig. 2: Visualization of the composite beam lines, (left) in longitudinal and transverse views with respect to the probe, (middle) depicting the original beam lines and instrument, and (right) the transformed beam lines and instrument. Effective beam widths are assumed to remain consistent with depth.

A. Pre-processing

We introduce several enhancement and normalization processes to improve the performance of the automated detection.

1) *Beam-line transformation*: The differences between the axial, lateral and elevational resolutions of a 3D US transducer result in a deformed representation of objects. For example, a needle cross-section appears horizontally stretched in the acquired data, as depicted in the bottom-middle subfigure of Fig. 2. This deformation also varies with depth due to two different principles in the ultrasound data acquisition, which are briefly detailed now. First, since the beam width varies along the beam path, the best resolution occurs over the focal zone and degrades as distance increases. However, in the state-of-the-art commercial devices, beam width consistency is improved by methods such as multiple focal zones, aperture growth and synthetic aperture imaging. Second, in the curved and phased-array transducers, density of scan lines decreases with depth, which decreases the lateral and elevational resolutions. Therefore, the needle cross-section is circular at shallow and ellipsoid at deeper positions (see Fig. 4a). In this paper, we propose a method to correct for the latter cause of resolution degradation to minimize the depth-related deformations. Therefore, while using different transducers, we normalize the situation for instrument detection to a standard case, so that the instrument properties are also normalized.

In order to maintain the density of the scan lines to be consistent with depth, we propose to transform the data from a hypothesized pyramidal to a rectangular field. This way, the cylindric nature of instruments can be restored, increasing the uniformity of the data. This transformation is achieved by mapping the voxel coordinates from the standard spherical coordinate system to a new coordinate system, where the radial

distance ρ is varied in the vertical direction and the polar angle ω in the horizontal direction (see Fig. 2). Although this transform reverses the predictable deformation of the instrument cross-section, it also deforms other objects in the volume, as well as the instrument straightness. Therefore, the volume is transformed back to the original coordinate system after enhancement and selection of the instrument voxels.

2) *Adaptive histogram equalization*: Our proposed system is based on supervised detection of instrument voxels. In such algorithms, it is very important that training samples are represented similarly for the same structures. However, the acquired US data are highly dependent on the relative position and orientation of the reflecting structures to the US beams. Therefore, the intensity of structures in the acquired data have to be normalized based on the same reference. We propose to normalize the visibility of structures (including the medical instrument), based on the Contrast Limited Adaptive Histogram Equalization (CLAHE) [41]. In this approach, a mapping function is calculated for each region in the data based on its cumulative intensity distribution. We evaluate the performance of different mapping functions such as uniform, Gaussian and Rayleigh in enhancing the visibility of the instrument in cases of large angles. In conclusion, the histogram equalization normalizes the visibility of structures and thus the instrument within it, leading to a high-quality instrument detection independent of the type of instrument.

3) *Vessel enhancement filtering*: Based on the assumption that medical instruments are locally one-dimensional straight structures in the US field, their appearance can be enhanced with vesselness filtering. Therefore, we use Eq. (A.3) as a pre-processing stage to enhance the instrument in the volume for improved detection. Thresholds α , β , and c are chosen by an exhaustive search to yield the best classification performance. The output of the vesselness estimate, $\mathcal{V}$, is the speckle-reduced data for further processing and instrument detection.

B. Instrument-voxel classification

After pre-processing, candidate voxels for instruments are selected prior to the tool-axis estimation using a supervised classifier. The only assumption that we start with is the cylindrical section of the considered instrument. It will appear later that this assumption is sometimes too simple to offer a reliable instrument detection, so that additional processing will be added. This extra processing will eliminate outliers and better forecast the dominant instrument structure.

Let us first work on the cylindrical shape assumption and using that for initial detection. For this purpose, a discriminative model of the instrument is constructed from its local features. To select the correct voxels for the instrument finding, different descriptors are used to create a discriminant representation of the instrument that is invariant to small changes in shape, size and brightness. For this purpose, we study the implementation of different descriptors based on the raw voxel values (ξ), pre-processed vesselness-filtered values ($\mathcal{V}$), and Gabor transformation (subscript $\mathcal{G}$) responses. We define four feature vectors for which we evaluate the performance for voxel classification. These feature vectors are combinations

of the previous three fundamental descriptors and are denoted by: $\mathbf{F}_{\mathcal{L}}(\mathbf{x}_0) = [\xi(\mathbf{x}_0) \ \mathcal{V}(\mathbf{x}_0)]$, implemented based on the line filtering technique proposed in [30], $\mathbf{F}_{\mathcal{G}}$, implemented based on the Gabor transformation, and $\mathbf{F}_{\mathcal{C}}(\mathbf{x}_0) = [\mathcal{V}(\mathbf{x}_0) \ \mathbf{F}_{\mathcal{G}}(\mathbf{x}_0)]$ and $\mathbf{F}_{\mathcal{E}}(\mathbf{x}_0) = [\xi(\mathbf{x}_0) \ \mathcal{V}(\mathbf{x}_0) \ \mathbf{F}_{\mathcal{G}}(\mathbf{x}_0)]$, where $\mathbf{x}_0 \in \xi$.

Obtaining the feature vector elements for classification is straightforward for raw voxel values $\xi(\mathbf{x}_0)$ and for vesselness $\mathcal{V}(\mathbf{x}_0)$ from Eq. (A.3). However, for Gabor responses further processing is required to construct the feature vector elements, which will fill the middle part of this subsection.

In order to exploit the discriminant local shape information of instruments, we use the wavelet transformation with directional sensitivity, so that the instrument detection is amplified along one of the possible orientations of the transform [42]. This novel approach makes the instrument detection inherently more robust and reliable compared to projection techniques due to the noisy nature of US signals. In this paper, the 3D Gabor transformation of Eq. (A.4) is chosen to be specific to frequencies corresponding to the instrument diameter. Furthermore, we propose a unique design of 3D Gabor wavelets for directional sensitivity to elongated structures. The transformation is calculated for several ϕ and θ angles to cover all possible orientations of instruments. We refer the readers to the Appendix for more details on our design. Gabor responses are then sub-sampled in the spatial domain to be more tolerant to shift and size of the instrument. This is done for each filter scale and orientation, by taking the maximum response of all voxels in a small cell grid with length of a few voxels. To this end, transformations for all filter orientations form a response matrix $\mathcal{M}_{\mathbf{x}_0}$ at each point, which is the basis of the feature vector to be used for classification. Further processing is required to implement feature vectors invariant to the instrument orientation. Therefore, we perform circular shifts in the response matrix (periodic to the size of the matrix), so that the maximum value is located at the center of the matrix. We expect that this value corresponds to the instrument Gabor representation. Finally, the response matrix is reshaped to form a feature vector $\mathbf{F}_{\mathcal{G}}(\mathbf{x}_0)$ based on the Gabor transformation analysis for each point.

Having the voxel representations and descriptors from the above approaches, a classifier is trained to model the discriminative features between the voxels belonging to the instrument and other regions. We evaluate two well-known algorithms for classification of voxel structures: Linear Discriminant Analysis (LDA) and Linear Support Vector Machine (LSVM). LDA is a generative method that assumes a Gaussian mixture distribution for each class and maximizes the inter-class variance relative to the intra-class variance. LSVM is a discriminative model, which separates the samples by finding a hyperplane such that the separation margin is maximized. Both of the methods are fast and have good generalization capability. We set the misclassification costs equal for all classes and use uniform prior probabilities when evaluating their accuracies and comparing their performances.

C. Axis estimation and optimization

Occurrence of the misclassified voxels in the detection results is inevitable because of the relatively simple cylindrical

TABLE I: Specifications of 3D US volumes used for evaluation.

Tissue	Instrument	Diameter	# of Vols.	Ultrasound system	Transducer type and frequency range	Processing resolution	Volume voxel size elev. $\times$ lat. $\times$ ax.
PVA cryogel (<i>in vitro</i>)	Electrode	0.60 mm	8	Voluson 530D [†]	Curved Arr. 5-8 MHz	0.44 mm	156 $\times$ 156 $\times$ 204
Silicon heart (<i>in vitro</i>)	Catheter	2.3 mm	50	CX50 CompactXtreme [‡]	Phased Arr. 2-7 MHz	0.40 mm	248 $\times$ 180 $\times$ 172
Chicken breast (<i>ex vivo</i>)	Needle	1.47 mm 0.72 mm	10 10	iU22 xMATRIX [‡]	Linear Arr. 5-13 MHz	0.22 mm	156 $\times$ 168 $\times$ 160 136 $\times$ 168 $\times$ 184
Popliteal fossa (<i>in vivo</i>)	Needle (echogenic*)	0.72 mm	5	iU22 xMATRIX [‡]	Linear Arr. 5-13 MHz	0.20 mm	204 $\times$ 188 $\times$ 208
Axillary fossa (<i>in vivo</i>)	Needle (echogenic*)	0.72 mm	4	iU22 xMATRIX [‡]	Linear Arr. 5-13 MHz	0.20 mm	156 $\times$ 192 $\times$ 204

[†] From Kretztechnik, Austria. Currently available from GE Healthcare, UK

[‡] Available from Philips Healthcare, Bothell, WA, USA

* Sonoplex available from Pajunk Medizintechnologie, Geisingen, Germany

Fig. 3: Example of (a) Tip-Reverberation-Artifact (TRA) and (b) the corresponding vesselness filter outcome showing enhanced artifacts and increased probability of false detections.

shape assumption. Therefore, we first examine the detections based on size and shape of blobs fitted on the classified voxels. Falsely detected voxels are usually scattered and rarely form connected regions that can resemble a needle or a catheter tip. Furthermore, reverberation artifacts and few other structures in the volume may locally appear as parts of a medical instrument. Fig. 3 shows an example of such region with a so-called tip reverberation artifact (TRA) at the catheter tip in water [40]. Although the TRA strength can be different for other instruments and mediums, it always appears adjacent to the instrument on the opposite side of the US beam incident location, reproducing the cylindrical shape of the instrument. Therefore, vesselness filtering of Eq. (A.3) enhances TRA and increases the probability of a false detection.

In order to robustly detect the instrument axis in the presence of outliers, we fit a model ℓ , to the remaining voxels using the RANSAC algorithm [43]. Because we search for a needle or catheter tip, a straight line can represent the instrument as:

$$\ell = \{\mathbf{r} \in \xi, \mathbf{r}_0 \in \xi, t \in \mathbb{R}, \mathbf{v} \in \mathbb{R}^3 : \mathbf{r} = \mathbf{r}_0 + t\mathbf{v}\}. \quad (1)$$

The straight-line constraint is an instrument rule applied to the detected voxels. By taking other rules like thickness, curvature, shape, the type of instrument can be varied and the system can be tuned to detect another type of instrument. For example, we could exchange the straight-line constraint by a parabolic segment for localizing a deflected needle or a curved catheter [44]. Hence, the description rules form a second stage in a general method for detecting instruments. The model with the highest number of inliers is chosen to be the instrument axis. Whether or not a voxel $\mathbf{x}_0$ is an inlier can

be determined by computing its Euclidean distance from the model $d(\mathbf{x}_0; \ell)$.

Due to the presence of false detections, Gaussian smoothing in the Hessian method and Gabor transformation, and pre-processing steps, accuracy of the proposed technique is limited. Smoothing can reduce the noise in the volume but removes sharp edges of the instrument that are required for fine localization in noisy US data. Therefore, detection results need to be adjusted locally and optimized for higher accuracy. Optimization is performed with a Gradient Descent strategy by minimizing the detection error function, $E(\ell)$, defined as:

$$E(\ell) = 255 - \frac{1}{L} \sum_{\mathbf{x} \in \ell} \xi(\mathbf{x}), \quad (2)$$

where L is the length of the line ℓ . The maximum range value of ξ is 255, which is subtracted from average intensity of ℓ .

III. EXPERIMENTAL RESULTS

This section presents three types of results: shape and brightness normalization of voxels as classification input (Subsection A), voxel classification to serve instrument detection (Subsection B), and axis estimation of the instrument (Subsection C). The motivation for this separation is as follows. We have evaluated the pre-processing outcome separately in order to study their contribution and find the optimal settings. Then, classification of the instrument voxels is elaborated to determine the best descriptors. Third, detection of the instrument is evaluated and compared with the state-of-the-art studies on *in-vitro*, *ex-vivo* and *in-vivo* patient datasets.

Evaluation is performed on 3D datasets acquired from PolyVinyl Alcohol (PVA) cryogel [21], silicon heart and chicken breast phantoms, as well as *in-vivo* data acquired from patients. In order to prove the robustness and adaptability of the methods, datasets are acquired with different transducers and ultrasound devices. Properties and specifications of each dataset are summarized in Table I. Ground-truth data is created by manually annotating the voxels belonging to the instrument. Evaluated approaches are implemented in MATLAB and tested on a quad-core CPU with 3.7-GHz clock frequency. Depending on size and complexity, the execution takes 2–4 minutes.

Fig. 4: Beam-line transformation of a compound volume, constructed from 15 deliberately positioned catheters; (a) transverse cross-section shows deformation of deep catheters; (b) corresponding vesselness values decrease with depth; (c) cross-section of the transformed volume; and (d) depth independent vesselness responses in the transformed volume.

A. Pre-processing

The proposed beam-line transformation is an intermediate step aiming at minimizing the depth-dependent deformation of instruments and improving the detectability. After classification of individual voxels, the coordinate system will be transformed back to the original pyramidal field for localization of the instrument. In order to evaluate the contribution of this sub-system, we study the output of the vessel enhancement filtering applied to the beam-line transformed data. For this purpose, a different set of data is used, which contains a catheter placed at 15 pre-defined positions in water using a holder. For visualization purposes, we construct an artificial compound volume by accumulating all 15 volumes resulting from the various catheter positions into one volumetric data field. Fig. 4a shows the transverse slice through the middle of this volume, while crossing the catheter tips. As shown, with a phased-array transducer, deformation of the catheter increases with depth as the lateral and elevation resolutions decrease. Therefore, vessel enhancement filtering is unable to produce high responses for deeply positioned catheters. However, after transforming the beam lines to a rectangular field (see Fig. 4c), the actual cylindrical section of the catheter is restored to be enhanced by vesselness filtering. It is worth noting that the accuracy of instrument localization is determined by the visibility of data structures in the acquired volume. Only if the transformation would be applied outside of this framework, then its accuracy would need to be explicitly evaluated.

Further pre-processing is performed to normalize the visibility of the instrument for stabilizing detection behavior further in the processing chain. Therefore, we pursue a uniform representation for the appearing brightness of training data

Fig. 5: The 8-bin histogram of instrument voxels (top) before intensity normalization and (bottom) CLAHE processed. For identifying the optimal normalization, the highest 6 intensity bins are considered, which correspond to the instrument voxels that are brighter than at least one-fourth of the intensity range. Average of standard deviations is then 0.041, 0.040 and 0.046 for uniform, Gaussian and Rayleigh distributions, respectively.

in different conditions. We evaluate the performance of this module by comparing the histogram values and deviation of the instrument voxels before and after applying CLAHE processing for different volumes. As the brightness variations of the instrument are maximal with linear array transducers, we only use the data with linear array transducers (see Table I). Furthermore, the uniform, Gaussian and Rayleigh CLAHE mapping functions are compared. As shown in Fig. 5, after adaptive normalization of the histograms, variations in brightness of instrument voxels are considerably decreased (bottom part). The three studied mapping functions show comparable behavior in normalizing the histogram of instrument voxels. The Gaussian function reaches the least standard deviation and is therefore most suited for intensity normalization of our data.

B. Voxel-wise classification

The capability of the classifiers to distinguish instrument voxels from other tissue structures results from the discriminative power of the extracted features. We implement and evaluate the performance of our proposed feature vector, $\mathbf{F}_G$, the feature vector taken from the state-of-the-art [30], $\mathbf{F}_L$, and feature vectors based on the combinations of the two, $\mathbf{F}_C$, and $\mathbf{F}_E$. The implemented feature vectors are classified using the LDA and LSVM classifiers, which are simple and suitable for fast analysis of a large set of data points. To this end, we perform leave-one-out cross-validation (LOOCV) for each dataset to make training and testing data completely distinct at each trial. The average performances are reported on Receiver Operating Characteristic (ROC) and Recall-Precision (RP) spaces. The values in Table II are the raw classification results in the full-size volume without any post-processing or removal of the isolated detections. The column with feature $\mathbf{F}_L$ [30] serves as state-of-the-art for comparison.

TABLE II: Average classification performance in the full volume. Recall is set at the highest F-2.

Dataset		Linear Discriminant Analysis (LDA)				Linear Support Vector Machine (LSVM)				
		F_L [30]	F_G	F_C	F_E	F_L [30]	F_G	F_C	F_E	
in vitro	PVA cryogel 0.6-mm electrode	Recall	67.0	81.7	80.0	80.3	67.5	79.0	78.3	74.6
		Precision	32.1 ± 6.8	39.0 ± 6.6	42.7 ± 7.9	38.8 ± 7.6	26.1 ± 6.0	37.3 ± 6.2	41.1 ± 9.0	41.1 ± 8.5
		Specificity	98.7 ± 0.4	98.6 ± 0.5	98.8 ± 0.5	98.7 ± 0.5	98.5 ± 0.5	98.1 ± 1.1	98.3 ± 1.0	98.5 ± 0.9
	Silicon heart 2.3-mm catheter	Recall	47.6	56.0	54.0	49.4	31.7	60.9	61.1	57.3
		Precision	8.0 ± 0.3	24.0 ± 3.4	31.9 ± 3.6	8.6 ± 0.1	9.6 ± 0.7	22.1 ± 2.9	32.1 ± 3.6	26.8 ± 2.8
		Specificity	97.2 ± 0.2	95.5 ± 1.2	98.7 ± 0.2	70.0 ± 2.7	98.7 ± 0.1	92.0 ± 2.5	97.7 ± 0.9	97.9 ± 0.7
ex vivo	Chicken breast 1.47-mm needle	Recall	12.4	72.9	68.7	69.7	83.4	91.7	85.9	86.6
		Precision	1.6 ± 0.4	44.5 ± 10.1	39.3 ± 7.1	38.4 ± 6.7	0.4 ± 0.1	52.3 ± 10.9	55.5 ± 8.6	54.1 ± 8.3
		Specificity	95.5 ± 1.3	98.7 ± 0.5	98.9 ± 0.7	99.0 ± 0.5	20.3 ± 2.3	97.8 ± 1.7	98.7 ± 1.1	98.9 ± 0.9
	Chicken breast 0.72-mm needle	Recall	11.8	64.3	60.3	63.1	14.2	80.9	90.6	73.6
		Precision	3.7 ± 1.9	21.6 ± 7.8	22.5 ± 8.6	22.0 ± 8.2	0.3 ± 0.1	36.2 ± 12.5	27.4 ± 10.9	28.9 ± 10.4
		Specificity	97.6 ± 0.7	95.6 ± 1.8	96.0 ± 2.1	97.4 ± 0.9	92.5 ± 1.0	95.3 ± 2.1	90.1 ± 5.5	97.4 ± 1.0
in vivo	Popliteal fossa 0.72-mm needle	Recall	35.5	70.5	67.9	61.7	17.6	81.5	73.6	66.9
		Precision	1.5 ± 0.6	39.9 ± 16.4	23.0 ± 8.2	22.8 ± 8.3	0.7 ± 0.2	38.6 ± 14.4	28.3 ± 11.0	23.1 ± 10.7
		Specificity	91.3 ± 2.2	97.8 ± 1.6	97.8 ± 1.0	98.4 ± 0.7	92.8 ± 1.9	97.0 ± 2.4	96.4 ± 2.0	97.3 ± 1.3
	Axillary fossa 0.72-mm needle	Recall	26.5	75.8	70.7	69.9	26.5	82.7	77.0	75.0
		Precision	18.6 ± 4.4	51.9 ± 17.1	52.3 ± 20.8	53.4 ± 21.1	15.2 ± 8.1	57.0 ± 19.3	55.6 ± 14.6	57.7 ± 15.0
		Specificity	99.7 ± 0.1	99.2 ± 0.6	99.2 ± 0.5	99.2 ± 0.6	99.4 ± 0.2	98.8 ± 1.0	99.6 ± 0.3	99.6 ± 0.3

Values corresponding to the highest F-2 score are **bold**.

After a noisy voxel classification, a high recall increases the accuracy of the instrument detection. Therefore, we aim at high recall values in our evaluation and employ the F-2 score, which weights recall higher than precision, as defined by:

$$\text{F-2 score} = \frac{5 \cdot \text{recall} \cdot \text{precision}}{\text{recall} + 4 \cdot \text{precision}}. \quad (3)$$

During these experiments, parameters for feature extraction methods are identified by an exhaustive search to deliver the best classification performance. The Gabor filter banks are constructed with an angular spacing of 15° for both ϕ and θ rotation angles, which results in F_G with size of 144.

Because of the better classification performance of LSVM, we only show the performance curves of LSVM classifiers. The *in-vitro* classification performance of LSVM for different feature vectors is shown in Fig. 6. The PVA cryogel and silicon heart phantoms mainly consist of uniform non-echogenic structures, which create a low complexity in distinguishing the instrument. As shown, in these datasets the classification performance is improved in cases of combined vesselness and Gabor-based features, as few other structures in the volume have a cylindrical shape. However, adding intensity values for constructing F_E slightly degrades the performance.

The classification performances for the *ex-vivo* datasets that are acquired in chicken breast are shown in Fig. 7. In these cases, vesselness features alone, F_L , perform very poorly compared to Gabor results. Furthermore, combinations of vesselness and Gabor show degraded performances compared to Gabor alone. This can be explained by the increased complexity of detecting the instrument in these datasets. In chicken breast phantom, muscle fascicles appear as small linear features and are difficult to locally distinguish from voxels belonging to a thin needle. Therefore, as shown in Fig. 7, the performance for the 0.72-mm needle is degraded compared to the thicker 1.47-mm needle. As a result, intensity and vesselness values are unable to capture the discriminative

Fig. 6: LOOCV performance curves for *in-vitro* datasets.

information between needle voxels and other vessel-like structures. However, Gabor-based features, F_G , are tuned to a pre-defined frequency range, which corresponds to the diameter of the needle. This ability to extract the shape information of the object in different orientations increases the discriminative information and significantly improves the performance.

Fig. 8 shows the classification performance for *in-vivo* patient datasets. As shown, the overall performance degrades slightly. This is due to different preferences for the acquisition

Fig. 7: LOOCV performance curves for *ex-vivo* datasets.

Fig. 8: LOOCV performance for *in-vivo* patient datasets.

parameters, such as gain and frequency, which vary amongst medical specialists for different patients and lighting conditions. Therefore, intensity of the needle and its surroundings are subject to variation per physician, which increases the complexity of the automated detection.

In the dataset of axillary fossa, the ROC performance of the vesselness features F_L is improved compared to the chicken breast dataset. The reason is the presence of additional structures in patient scans that are easier to classify from the needle for vesselness features, i.e. bone, artery, vein and nerve. Therefore, the false positive rate is considerably reduced, but the precision still remains low. Nevertheless, the classification performance improves significantly when Gabor-based features are combined with vesselness.

As discussed, the performance of the studied methods varies among different datasets. This is largely due to the fact that the combination of each tissue, instrument and acquisition parameters generates a certain level of complexity for the supervised detection system. Depending on these combinations, a specific solution exists for each application that is optimal for distinguishing the instrument from other objects and the surrounding environment. Therefore, the dataset and instrument need to be *a-priori* identified for the best performing method.

C. Instrument Axis Estimation

Although the voxel-wise classification performance is not perfect, the *a-priori* information regarding the global shape of the instrument and clustering the detected voxels assist for the correct axis estimation. In this section, we evaluate the final error of our proposed system in estimating the instrument axis. After transforming the classified voxels back from the

rectangular to the original pyramidal field, the position and orientation of the instrument in 3D are estimated and optimized for the minimum axis detection error of Eq. (2).

Similar to the voxel-wise classification evaluation, we perform leave-one-out cross-validation to make training and testing data distinct. The LSVM classifier and feature vectors with the highest F-2 scores are used for classification in each dataset. Table III shows the performance of our proposed system in detecting the instrument. The instrument position error (ε_p) is calculated as the average of the point-line distances between the two end-points of the ground-truth axis and the detected axis. The orientation error (ε_v) is the angle between the detected and the ground-truth orientation vectors.

As reported in Table III, the detection position error is always less than the diameter of the instrument, which shows a very good detection accuracy. For the silicon heart dataset,

TABLE III: Average performance of the proposed system in detecting the instrument axis in full volumes of 3D US.

Tissue	Instrument diameter	Feature	ε_p	ε_v	Time* (min)
PVA cyogel	0.60 mm	F_C	0.49 mm	2.9°	3.37
Silicon heart	2.30 mm	F_C	1.46 mm	9.2°	3.68
Chicken breast	1.47 mm	F_G	0.74 mm	4.4°	2.68
Chicken breast	0.72 mm	F_G	0.65 mm	3.7°	2.56
Popliteal fossa	0.72 mm	F_G	0.60 mm	2.2°	3.39
Axillary fossa	0.72 mm	F_G	0.68 mm	3.7°	2.13

* Measured in MATLAB on a 3.7-GHz quad-core CPU.

Fig. 9: Examples of (left) detected candidate needle voxels in the full volume and (right) detected needle planes in 3D US. Yellow lines show the position of ground-truth needles. Red lines represent detected needle axes using the Gabor features, F_G .

the short length of the catheter's tip in comparison to its width complicates the orientation estimation. Therefore, we observe a relatively large orientation error in those cases.

Computational cost of the proposed system highly depends on the size of the data and complexity of the feature extraction. As shown in Table III, the complete system takes approximately 2–4 minutes to execute in MATLAB without any programming optimization. Although the measured runtime does not immediately reflect the applicability of the system to real-time instrument detection, several approaches are proposed in Section IV for improving the speed with respect to the performance. Nevertheless, implementation on efficient programming languages or parallel computation methods certainly facilitate much faster executions.

Fig. 9 shows a few examples of the detected planes in 3D US containing the instrument. As shown, after a careful selection of the feature extraction method, a simple classification technique such as linear SVM can reliably detect and extract the instrument voxels in the volume. Although this classification (shown at the left) is noisy, the *a-priori* information regarding the global shape of the instrument leads to the correct instrument axis estimation. The detected cross-section contains the optimal view of the tool that is visualized without manually maneuvering the transducer.

IV. DISCUSSIONS AND CONCLUSIONS

Ultrasound-guided interventions are increasingly used to minimize risks to the patient and improve health outcomes.

However, the multi-fold coordination of the medical instrument and US plane is extremely challenging and furthermore, developed external guidance tools add even more complexity and costs. Therefore, an automated localization of the instrument in 3D US can overcome 2D limitations and facilitate the ease of use of such transducers while ensuring accurate instrument usage and improving the intervention quality.

In this paper, we have introduced a novel and robust system for detecting medical instruments in 3D US data. We have contributed to this system in four aspects: (1) a system solution that is purely based on image processing techniques using existing transducers and instruments, (2) a novel normalization of the US data that improves the performance of the supervised detection, (3) a novel design of the 3D Gabor transformation, which extracts instrument voxels in the volume, and (4) in-depth analysis of medical instruments under different circumstances, which leads to a generic identification system to learn new instruments to be used in a broad set of interventions.

System/procedure implementation: In the proposed procedure, the physician is placing the 3D transducer at the desired position on the patient. When advancing the needle or catheter, the system will automatically detect the best instrument view, so that the physician can entirely focus on the intervention. This eliminates the need for advanced manual coordination of the equipment and facilitates accurate clinical interventions under a broad range of circumstances. Validating the robustness for *in-vivo* datasets acquired from patients not only proved clinical feasibility but also yielded a high clinical value for intervention support.

Data normalization: We have proposed a novel normalization of the US data that improves the performance of the supervised detection by minimizing the variations in the shape and brightness of the structures. This is achieved in two steps, where first a beam-line transformation is introduced to minimize the depth-related shape variations and second, the contrast of structures is locally enhanced to be represented based on the same reference. Experiments on datasets that have the maximum variance in shape and intensity of instruments show significant appearance normalization. For example, three frequency ranges are explored for phased and linear-array transducers, as well as several corresponding processing resolutions (see Table I). For each of these transducers and their typical settings, we have been able to perform accurate instrument detection.

3D Gabor transformation: For classification of the instrument voxels, several feature vectors are proposed including responses to a novel design of the 3D Gabor transformation exploiting instrument voxels in the volume. A thorough comparison is made for the classification in all datasets at the voxel level, which shows the elevated contribution of the proposed Gabor transformation with respect to discriminative power.

In-depth analysis of conditions: The optimal choice of methods at each stage for the intended US-guided procedure has been presented in Table IV. For cardiac ablation, where the catheter is placed within blood, limited linear structures occur in the volume apart from the catheter itself. Therefore, vesselness filtering is able to distinguish the instrument from other heart tissue. In contrast, in regional anesthesia, the needle is inserted into muscular tissue, where muscle fascicles appear frequently surrounding the instrument so that detection becomes complicated. Therefore, Gabor transformation is required to benefit from the precise space-frequency analysis leading to better classification performance.

The final stage of processing covers the instrument-axis extraction by fitting a proposed model of the instrument to the classified voxels by means of the RANSAC algorithm. The position and orientation of the estimated instrument axis is optimized by minimizing the detection error. Quantitative evaluation shows a very high detection accuracy with position errors being smaller than the instrument diameter. This means that the scan plane presented to the medical specialist always contains the entire instrument and tip for all the experimented phantoms and instruments, yielding a high clinical accuracy.

Further improvements are still possible. For example, increasing robustness to various acquisition settings, such as gain

and focal depth. Furthermore, detecting very short instruments in the acquired volume can be achieved by further increasing voxel-wise recall and precision. Moreover, the high computational complexity of 3D Gabor transformations remains a challenge and needs to be addressed for embedding this technology as a real-time application. However, there are multiple techniques to modify the chosen approach towards real-time operational performance. One technique is to limit the number of processed voxels by analyzing the optimal subsampling factors, limiting the search region and/or incorporating a coarse-fine search strategy. Furthermore, the number of 3D convolution operations can be reduced by optimizing the complexity of the filter bank with respect to the estimation accuracy. Besides, conventional ways of optimizing algorithms and parallel computing options are also possible.

When realizing the real-time operation, it would be possible to implement repetitive detection of the instrument so that moving instruments can also be found. In this way, tracking of moving instruments is implemented by repeated detection with sufficient time resolution. This will result in detection per volume in a 4D US sequence without the need for having a fixed transducer and a stationary subject.

APPENDIX MATHEMATICAL BACKGROUND

Our method is based on extraction of linear features in the volume to robustly select instrument voxels. Therefore, we provide a brief overview of the two methods employed: the Hessian method using second-order differentiations, and the Gabor transformation providing space-frequency analysis.

A. Hessian Method

In the Hessian method, local widths of structures are derived from second-order directional derivatives along the principal directions of the structures. Given a volume ξ , its Hessian matrix at the point $\mathbf{x}_0(x, y, z)$ is

$$\mathcal{H}_s = \begin{bmatrix} \xi_{xx} & \xi_{xy} & \xi_{xz} \\ \xi_{yx} & \xi_{yy} & \xi_{yz} \\ \xi_{zx} & \xi_{zy} & \xi_{zz} \end{bmatrix}. \quad (\text{A.1})$$

The partial derivatives in Equation (A.1) are computed as a convolution with derivatives of an isotropic 3D Gaussian kernel at scale s , which corresponds to the approximate diameter of the instrument [27]. Therefore, the second derivative of the Gaussian function (Fig. 10, Left) is the filtering kernel to construct elements of the Hessian matrix $\mathcal{H}_s$.

The directions given by the Eigenvectors, v_k , of the Hessian are along the principal directions of a structure at $\mathbf{x}_0$ and the magnitudes of the respective Eigenvalues $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$ are reciprocally corresponding to local widths of the structure. In case of a needle or catheter, this means that λ_1 is related to the Eigenvector in the primary orientation of the needle, whereas λ_2 and λ_3 are related to the Eigenvectors in the plane perpendicular to the needle direction. In the presence of acoustic clutter, needle is overlaid by diffused echoes [20] and surface representations is irregular. However, the global shape of the instrument can still be detected [21] and similar

TABLE IV: Optimal choice of methods proposed at each stage for the intended US-guided procedure.

Procedure	Pre-processing	Classification features	Classifier
Cardiac ablation [†]	Beam-line transformation	Vesselness filtering + Gabor transform	LSVM
Regional anesthesia [‡]	CLAHE	Gabor transform	LSVM

[†] Typically performed with a curved or phased-array transducer

[‡] Typically performed with a linear-array transducer

Fig. 10: (Left) second order derivative of a 3D Gaussian kernel, and (right) even-symmetric component of a 3D Gabor kernel.

to the cylindrical structures [27], a voxel from the instrument in the 3D US volume must satisfy the following conditions:

$$\lambda_1 \approx 0 \quad , \quad \lambda_2 \ll 0 \quad , \quad \lambda_3 \ll 0 \quad . \quad (\text{A.2})$$

Frangi *et al.* [27] proposed a combination of Hessian eigenvalues to obtain a probability-like estimate of vesselness according to Eq. (A.2), which is defined as:

$$\mathcal{V} = \left(1 - e^{-\mathcal{R}_A^2/2\alpha^2}\right) \left(e^{-\mathcal{R}_B^2/2\beta^2}\right) \left(1 - e^{-\mathcal{S}^2/2c^2}\right), \quad (\text{A.3})$$

where $\mathcal{R}_A = \frac{|\lambda_2|}{|\lambda_3|}$, $\mathcal{R}_B = \frac{|\lambda_1|}{\sqrt{|\lambda_2\lambda_3|}}$, $\mathcal{S}^2 = \sum_k \lambda_k^2$, and α, β and c are thresholds to control the sensitivity of the vesselness filter to $\mathcal{R}_A$, $\mathcal{R}_B$ and $\mathcal{S}$, respectively. As the instrument is acquired as a bright structure on dark background in the US field, $\mathcal{V}$ is set to zero when $\lambda_2 \geq 0$ or $\lambda_3 \geq 0$.

B. Gabor Transformation

Gabor transformation is used to compute the space-frequency representation of the data, providing localized frequency information of the objects and structures. As a result, objects can be localized in space from their fundamental frequencies, which represent their shape information. A Gabor filter is a complex sinusoidal plane wave modulated by a Gaussian envelope (Fig. 10, right) and can be defined in 3D space by:

$$\mathcal{G}_{\phi,\theta}(x, y, z) = \left(e^{-(\gamma_x^2 x^2 + \gamma_y^2 y^2 + z^2)/2\sigma^2}\right) \left(e^{j2\pi f_0 z_r}\right), \quad (\text{A.4})$$

where $[x_r, y_r, z_r] = \mathbf{R}_x(\phi) \mathbf{R}_z(\theta) [x, y, z]$. Here, $\mathbf{R}_x$ and $\mathbf{R}_z$ are 3D rotation matrices around x -axis and z -axis, for ϕ and θ rotation angles, respectively. Parameters γ_x and γ_y are the spatial aspect ratios of the Gaussian envelope. Standard deviation of the Gaussian function σ is calculated from the desired half-response spatial frequency bandwidth b as:

$$\sigma = \frac{1}{f_0 \pi} \sqrt{\frac{\ln(2)}{2}} \times \frac{2^b + 1}{2^b - 1}. \quad (\text{A.5})$$

For the purpose of instrument detection, the central frequency of the sinusoidal plane wave f_0 is specified as $f_0 = 1/2d$, where d is the diameter of the instrument [45]. Furthermore, γ_y is chosen to be a positive number much smaller than 1 to increase the sensitivity to elongated instrument voxels. To this end, a 3D Gabor transformation is calculated from the convolution of the filter kernel $\mathcal{G}_{\phi,\theta}$ with the volume ξ .

As shown in Fig. 10, the Gabor filter kernel can be made very similar to the second derivative of the Gaussian. However, the Gabor transform extracts richer information from the oscillation frequencies of the data. At each point, localized frequencies as well as discontinuities are gathered from all directions of the neighborhood [46]. Moreover, design of the Gabor wavelets can be adjusted to be sensitive to the shape of specific objects for a discriminant analysis. Nevertheless, the Gabor transform is computationally complex and efficient implementations are necessary to allow for real-time execution.

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