Ultrasound Multiple Point Target Detection and Localization using Deep Learning

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Abstract—Super-resolution imaging (SRI) can achieve sub-wavelength resolution by detecting and tracking intravenously injected microbubbles (MBs) over time. However, current SRI is limited by long data acquisition times since the MB detection still relies on diffraction-limited conventional ultrasound images. This limits the number of detectable MBs in a fixed time duration. In this work, we propose a deep learning-based method for detecting and localizing high-density multiple point targets from radio frequency (RF) channel data. A Convolutional Neural Network (CNN) was trained to return confidence maps given RF channel data, and the positions of point targets were estimated from the confidence maps. RF channel data for training and evaluation were simulated in Field II by placing point targets randomly in the region of interest and transmitting three steered plane waves. The trained CNN achieved a precision and recall of 0.999 and 0.960 on a simulated test dataset. The localization errors after excluding outliers were within ±46 µm and ±27 µm in the lateral and axial directions. A scatterer phantom was 3-D printed and imaged by the Synthetic Aperture Real-time Ultrasound System (SARUS). On measured data, a precision and recall of 0.976 and 0.998 were achieved, and the localization errors after excluding outliers were within ±101 µm and ±75 µm in the lateral and axial directions. We expect that this method can be extended to highly concentrated microbubble (MB) detection in order to accelerate SRI.

I. INTRODUCTION

Super-resolution imaging (SRI), often referred to as ultrasound localization microscopy (ULM), has demonstrated that it is possible to surpass the diffraction limit of conventional ultrasound imaging. Microvessels laying closer than a half-wavelength apart have been resolved by deploying microbubbles (MBs) as a contrast agent and using SRI [1]–[5]. The centroids of individual MBs can be easily found as MB echoes are much stronger than surrounding tissues when insonified, and their sizes are much smaller than a wavelength. Sub-wavelength imaging is achieved by accumulating the detected MB positions over time, revealing the fine structure of the microvasculature.

The MB detection in SRI, however, is still diffraction-limited because it is performed in conventional ultrasound images which are commonly formed by delay-and-sum (DAS) beamforming [6]. For accurate and reliable detection and localization, the MBs need to be more than a wavelength apart to avoid the overlaps of MB point spread functions (PSFs). Diluted concentrations of MBs are commonly used to satisfy this criteria as the behavior of MBs is hard to control. The number of detectable MBs, therefore, is constrained and this leads to very long data acquisition times in order to map the entire microvasculature.

In this work, we propose a deep learning-based method for detecting and localizing multiple ultrasound point targets. The method especially aims to identify high-density point targets whose PSFs are overlapping, by feeding radio frequency (RF) channel data directly as input. A fully convolutional neural network (CNN) was designed to return 2-D confidence maps given RF channel data. The pixel values of the confidence maps correspond to the confidence of point targets existing in the pixels. The point target positions were extracted from the confidence maps by identifying local maxima. The CNN was trained and evaluated using simulated RF channel data. To further investigate the method on measured data, a phantom experiment was performed using a 3-D printed PEGDA 700 g/mol hydrogel phantom [7].

II. METHOD

A. Simulated Dataset

1) RF channel data: The Field II ultrasound simulation program [8], [9] was used to simulate RF channel data for generating a training and a test datasets. The datasets were composed of a certain number of frames. One frame was created by transmitting three steered plane waves after placing 100 point targets randomly within a region of 6.4 × 6.4 mm² (an average target density of 2.44 mm⁻²) where the center was 18 mm away from a transducer. The transducer was modeled after a commercial 192-element linear array, and the measured impulse response [10], [11] was applied to make the RF data as close to real measured data as possible. The parameters used in simulation are listed in Table I.

The simulated raw RF data were not beamformed but delayed, based on the time-of-flight calculated by

\[ \tau_i(x, z) = \left( \sqrt{(x - x_i)^2 + z^2 + z} \right) / c \]  \quad (1)

where \( \tau_i \) is the time-of-flight of the \( i \)-th transmission, \( (x, z) \) is the point, \( x_i \) is the center of the \( i \)-th transmission aperture, and \( c \) is the speed of sound. The delayed RF data were then sampled to have the same number of samples as that of confidence maps along the axial direction. The size of resulting RF data for one frame was 256 × 64 × 3.
TABLE I
RF CHANNEL DATA SIMULATION PARAMETERS

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transducer</td>
<td>Center frequency</td>
<td>5.2 MHz</td>
</tr>
<tr>
<td></td>
<td>Pitch</td>
<td>0.20 mm</td>
</tr>
<tr>
<td></td>
<td>Element width</td>
<td>0.18 mm</td>
</tr>
<tr>
<td></td>
<td>Element height</td>
<td>6 mm</td>
</tr>
<tr>
<td></td>
<td>Number of elements</td>
<td>192</td>
</tr>
<tr>
<td>Imaging</td>
<td>Number of TX elements</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>Number of RX elements</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>Steering angles</td>
<td>−15°, 0°, 15°</td>
</tr>
<tr>
<td>Environment</td>
<td>Speed of sound</td>
<td>1480 m/s</td>
</tr>
<tr>
<td></td>
<td>Field II sampling frequency</td>
<td>120 MHz</td>
</tr>
<tr>
<td></td>
<td>RF data sampling frequency</td>
<td>29.6 MHz</td>
</tr>
<tr>
<td>Scatter</td>
<td>Number of scatterers</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Lateral position range</td>
<td>(−3.2, 3.2) mm</td>
</tr>
<tr>
<td></td>
<td>Axial position range</td>
<td>(14.8, 21.2) mm</td>
</tr>
</tbody>
</table>

2) Confidence Map: Non-overlapping Gaussian confidence maps were used as labels for training CNNs. Initially, binary confidence maps were created, where pixel values of one indicated a point target and the remaining pixel values were zero. A 21 × 21 Gaussian filter with a standard deviation of six was then applied at each point target position in the binary confidence maps. The filter values from the targets will be zero. A 21

precision and recall that are defined by

\[ \text{Precision} = \frac{TP}{TP + FP} \] (2)

\[ \text{Recall} = \frac{TP}{TP + FN} \] (3)

where \( TP \) is the number of true positives, \( FP \) is the number of false positives, and \( FN \) is the number of false negatives. The positive and negative detections were determined by comparing estimated target positions with true target positions based on their pair-wise distances. The CNN method achieved

A. Simulation Experiment

The trained CNN was initially evaluated on a simulated test dataset. It was simulated in the same way as the training dataset in Field II, and consisted of 3,840 frames. In Fig. 3 the result of applying the CNN method to a test frame is compared with simply using the conventional DAS beamforming. The 3-D printed phantom was scanned by the Synthetic Aperture Real-time Ultrasound System (SARUS) [20] to acquire RF channel data. The same imaging scheme and transducer described in Table I were used. The phantom was placed on a motion stage at a step of 50 μm in the lateral direction. A total of 33 frames were obtained.

C. 3-D Printed Scatterer Phantom

A PEGDA 700 g/mol hydrogel scatterer phantom [7] was 3-D printed to investigate the proposed method on measured data. The phantom contained water-filled cavities which acted as scatterers. A total of 100 scatterers were placed on a 10 × 10 grid with a spacing of 518 μm in the lateral direction and 342 μm in the axial direction, as illustrated in Fig. 2.

The 3-D printed phantom was scanned by the Synthetic Aperture Real-time Ultrasound System (SARUS) [20] to acquire RF channel data. The same imaging scheme and transducer described in Table I were used. The phantom was placed on a motion stage and scanned at different positions by moving the motion stage at a step of 50 μm in the lateral direction. A total of 33 frames were obtained.
a precision and recall of 0.999 and 0.960, while DAS beamforming achieved a precision and recall of 0.986 and 0.756.

Localization uncertainties in the lateral and axial position were calculated using the positive detections, and is illustrated using a box-and-whisker plot in Fig. 4a. The bottom and top edges of the blue box indicate the 25th ($q_1$) and 75th percentiles ($q_3$) and the center red edge indicates the median. The vertically extended line from the box (whisker) indicates the range of inliers which are smaller than $q_3 + 1.5 \times (q_3 - q_1)$ and greater than $q_1 - 1.5 \times (q_3 - q_1)$. The inliers were within $\pm 46 \mu m$ (0.16$\lambda$) in the lateral direction and $\pm 27 \mu m$ (0.09$\lambda$) in the axial direction.

B. Phantom Experiment

The CNN trained for the simulation experiment was not effective on the measured data because the scatterers in the phantom are not infinitesimally small point targets. The ultrasound beam is actually scattered twice at each scatterer in the phantom. Therefore, the RF data in the training dataset were simulated a second time by modeling a target using two points. In addition, the first scattering was phase reversed since the acoustic impedance is higher in the phantom than in the water inside the targets.

A new CNN was trained using the modified training dataset, and it successfully identified scatterers from the measured data as shown in Fig. 5. The achieved precision and recall were 0.976 and 0.998. The inliers were within $\pm 101 \mu m$ (0.33$\lambda$) in the lateral direction and $\pm 75 \mu m$ (0.25$\lambda$) in the axial direction, as illustrated in Fig. 4b.

IV. CONCLUSION

A CNN-based ultrasound multiple point target detection and localization method was demonstrated. The CNN was trained
to learn a mapping from RF channel data to non-overlapping Gaussian confidence maps, and point target positions were estimated from the confidence maps by identifying local maxima. The non-overlapping Gaussian confidence maps were introduced to relax the sparsity of binary confidence maps while maintaining local maxima as target positions. The CNN method resolved point targets closer than the diffraction limit, while maintaining local maxima as target positions. The CNN introduced to relax the sparsity of binary confidence maps, and point target positions were to learn a mapping from RF channel data to non-overlapping Gaussian confidence maps, and point target positions were estimated from the confidence maps by identifying local maxima. The non-overlapping Gaussian confidence maps were introduced to relax the sparsity of binary confidence maps while maintaining local maxima as target positions. The CNN method resolved point targets closer than the diffraction limit, while maintaining local maxima as target positions. The CNN introduced to relax the sparsity of binary confidence maps, and point target positions were estimated from the confidence maps by identifying local maxima. The non-overlapping Gaussian confidence maps were introduced to relax the sparsity of binary confidence maps while maintaining local maxima as target positions.

It is also shown that the CNN method is applicable to real-world data, as well as simulated data, through the phantom experiment. It is notable that the training was performed solely using simulated data because it is nearly impossible to obtain a large number of measurements with ground truth for these kinds of work. It was also imperative to employ the measured impulse response and model targets following realistic physical modeling in the simulation.

We expect that this method can be extended to MB detection and potentially shorten the data acquisition time of SRI by detecting a greater number of MBs in a shorter amount of time.

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REFERENCES