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Locating the Interface between Different Media Based on Matrix Ultrasonic Sensor Data Using Convolutional Neural Networks

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Abstract

Introduction. The study focuses on modelling the process of ultrasound medical examination in a heterogeneous environment with regions of significantly different sound speeds. Such scenarios typically arise when visualizing brain structures through the skull. The aim of this work is to compare possible approaches to determining the interface between acoustically contrasting media using convolutional neural networks.

Materials and Methods. Numerical modelling of the direct problem is performed, obtaining synthetic calculated ultrasonic images based on known geometry and rheology of the area as well as sensor parameters. The calculated images reproduce distortions and artifacts typical for setups involving the skull wall. Convolutional neural networks of 2D and 3D structures following the UNet architecture are used to solve the inverse problem of determining the interface between media based on a sensor signal. The networks are trained on computational datasets and then tested on individual samples not used in training.

Results. Numerical B-scans for characteristic setups were obtained. The possibility of localizing the aberrator boundary with good quality for both 2D and 3D convolutional networks was demonstrated. A higher quality result was obtained for the 3D network in the presence of significant noise and artifacts in the input data. It was established that the 3D architecture network can provide the shape of the interface between media in 0.1 seconds.

Discussion and Conclusions. The results can be used for the development of transcranial ultrasound technologies. Rapid localization of the skull boundary can be incorporated into imaging algorithms to compensate for distortions caused by differences in sound velocities in bone and soft tissues.

Keywords: transcranial ultrasound, matrix probe, aberrations, mathematical modelling, grid-characteristic method, convolutional networks

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Оригинальное теоретическое исследование

Определение границы раздела сред по трёхмерным данным матричного ультразвукового датчика с использованием свёрточных нейронных сетей

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Аннотация

Введение. Работа посвящена моделированию процесса ультразвукового медицинского исследования в гетерогенной среде, в которой присутствуют области с существенно разной скоростью звука. Такие постановки задач

возникают, например, при визуализации структур мозга через череп. Целью данной работы является сравнение возможных подходов к определению границы раздела акустически контрастных сред с использованием свёрточных нейронных сетей.
Материалы и методы. В работе выполняется численное моделирование прямой задачи — получение синтетических расчётных ультразвуковых изображений по известной геометрии и реологии области, а также параметрам датчика. На расчётных изображениях воспроизводятся искажения и артефакты, типичные для постановок со стенкой черепа. Для решения обратной задачи определения границы раздела сред по сигналу с датчика используются свёрточные нейронные сети 2D и 3D структуры, следующие общей архитектуре UNet. Сети обучаются на наборах расчётных данных, после чего тестируются на отдельных примерах, не использованных при обучении.
Результаты исследования. Получены расчётные B-сканы для характерных постановок. Показана возможность локализации границы аберратора с хорошим качеством как для 2D, так и для 3D свёрточных сетей. Показано более высокое качество результата для 3D сетей в случае наличия значительного шума и артефактов во входных данных. Установлено, что сеть 3D архитектуры может обеспечить получение формы границы раздела сред за 0,1 секунды.
Обсуждение и заключения. Результаты работы могут быть использованы для развития технологий транскраниального ультразвукового исследования. Быстрая локализация границы стенки черепа может быть включена в алгоритмы построения изображения для компенсации искажений, вызванных различием скоростей звука в костных и в мягких тканях.

Ключевые слова: транскраниальное УЗИ, матричный датчик, аберрации, математическое моделирование, сеточно-характеристический метод, сверточные сети

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Introduction. This study addresses the problem of ultrasound image formation in a heterogeneous medium with regions of significantly different sound speeds. This setup is aimed at applications in visualizing brain structures through the skull bones. Despite years of medical technology development, this specific task remains extremely challenging, as existing methods have many limitations and require highly skilled specialists.

The problem arises from the fact that typical algorithms used in commercially available equipment assume that the sound speed in the area of interest changes minimally. This assumption is valid for soft tissues. However, when examining the brain through the skull, this basic assumption fails, leading to highly distorted images using traditional ultrasound approaches [1].

This study focuses on determining the boundary between two media-rigid (model skull wall) and soft (model brain tissue). The proposed solution method must operate in near real-time to ensure practical application. In the future, rapid localization of the skull boundary could be included in imaging algorithms to compensate for distortions caused by differences in sound velocities between bone and soft tissues.

Convolutional neural networks are considered for this task due to their extensive use in related biomedical tasks and their ability to operate at high speeds. Previous studies [2–6] have demonstrated the effectiveness of convolutional networks for ultrasound imaging and elastography. However, using this general approach requires careful calibration for each specific task [7].

Materials and Methods. For the direct problem, numerical modelling of the ultrasound pulse propagation in a sample is performed to obtain synthetic calculated ultrasonic images based on known geometry and rheology of the area and sensor parameters.

The medium is described using the acoustic approximation [8], a significant simplification compared to the full system of elastic equations, including only longitudinal waves. This approach is widely used for describing ultrasound pulses in biological tissues, as the attenuation coefficient for shear waves in ultrasound is four orders of magnitude higher than for longitudinal waves [9].

The numerical solution of the direct problem uses the ray tracing method with wavefront reconstruction [1], allowing the calculation of ultrasound images qualitatively and quantitatively corresponding to experimental data. The method describes reflections from extended boundaries and point reflectors. In this study, the boundary between layers and large pores are modeled as extended boundaries, while small reflectors are considered point sources. After recording the reflected signal, it is processed, and B-scans are constructed using algorithms from [10].

The inverse problem is to determine the shape of the boundary between acoustically contrasting layers based on the sensor's recorded signal. The input data for the inverse problem is the response from the medium registered by the matrix ultrasonic sensor. The output is the position of the boundary between the two media.

Convolutional neural networks are used to solve the inverse problem of determining the boundary based on the sensor signal. A synthetic dataset was generated from 1024 direct problem calculations for network training. Separate examples not included in the training set were used for testing.

This study investigates both 2D and 3D networks to compare results. All convolutional networks follow the UNet architecture [11]. The depth of both 2D and 3D networks is four blocks.

For the 2D network, the three-dimensional data is represented as a set of two-dimensional slices. Each slice is processed with three channels — the target slice and two adjacent slices — providing the network with some three-dimensional context [12, 13].

For the 3D network, three-dimensional data is input using a patch-based approach [14, 15], allowing flexible memory management on the GPU when processing large input data.

Results. The direct problem setup involves calculating the propagation of the ultrasound signal in an area containing a boundary between acoustically contrasting layers. The calculation area is a parallelepiped. The upper face corresponds to the external boundary of the area where the matrix ultrasonic sensor is located. Outside the contact zone with the sensor, the upper face is modeled as a free surface. The other three boundaries are set as non-reflective boundary conditions.

The boundary between the two acoustically contrasting layers is assumed to be smooth and may have an arbitrary shape. Additionally, the upper layer contains many small reflectors, creating background noise in the final ultrasound image, and several large pores whose response intensity is comparable to the boundary reflection.

The sound speed in both layers is constant. The upper layer is more rigid, with a sound speed of 30 km/s. The lower layer is softer, with a sound speed of 15 km/s. The number of small reflectors varied from 100 to 2500, and the number of large pores from 5 to 50.

The matrix sensor has a square shape of 24×24 elements, emitting a signal at 3 MHz. The sampling frequency for signal reception is 45 MHz. The final data dimension is 24×24×1024, where 24×24 are the physical dimensions of the sensor and 1024 are the time samples recorded during the experiment by each sensor element.

Fig. 1 shows the profile of the medium interface in one of the calculations is presented. Four slices of the complete three-dimensional data are shown — the position of the interface under the rows of sensor elements from the 5th to the 8th. The vertical axis represents the 24 elements of the matrix sensor in the given slice. The horizontal axis represents time samples. The image is cropped to the first 400 samples out of a full set of 1024 samples.

Fig. 2 shows the raw ultrasound image for this calculation is demonstrated. The overall "noise", visually seen as fluctuations in the intensity of the gray background, is associated with a large number of small reflectors in the medium. The interface between media is visible as an area of intense response with varying amplitude. Individual bright responses from large pores can be seen at depths of 50, 70, 90, 110, 130, and especially 230 (the last two slices in the figure). These bright responses significantly interfere with the automatic image processing, as they even exceed the intensity of the response from the desired boundary.

Figs. 3 and 4 show the results of the 2D convolutional network. Figs. 5 and 6 present the results for the 3D network.

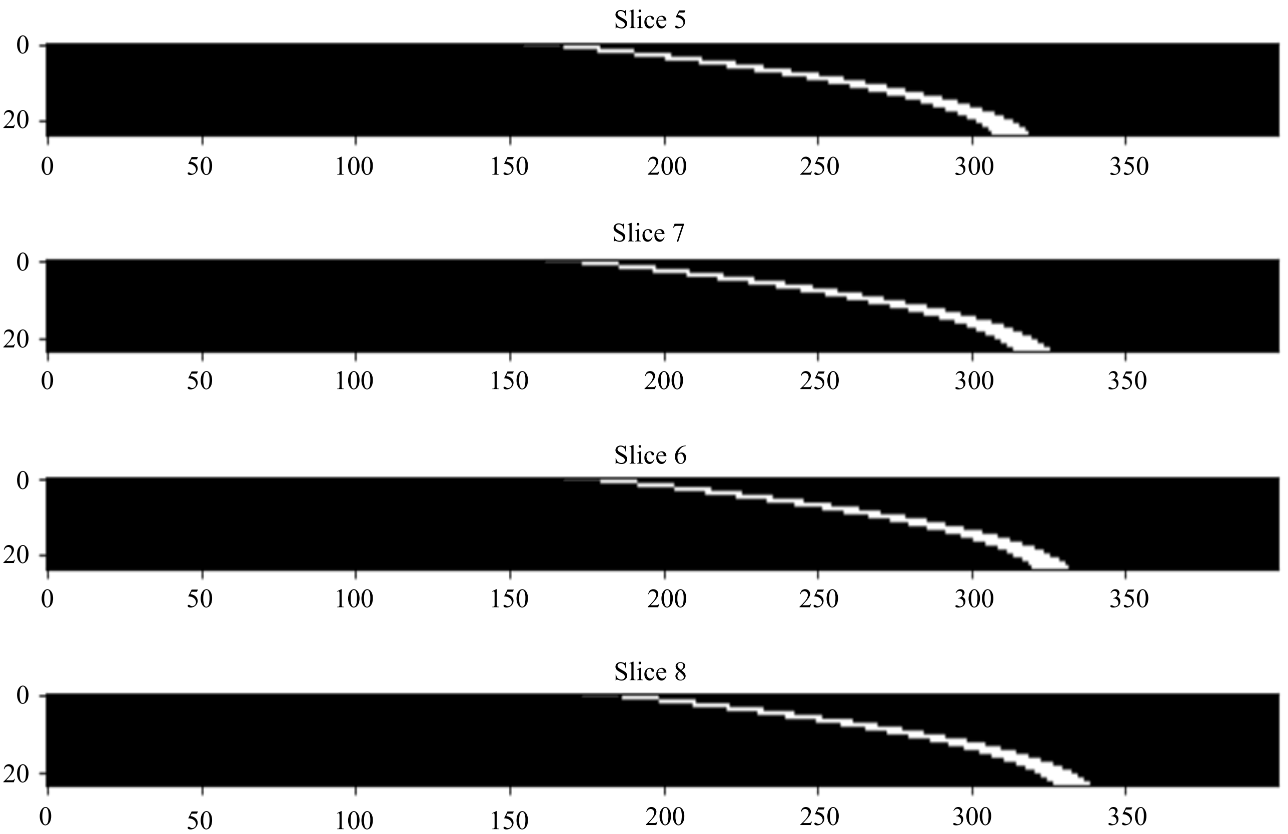

Fig. 1. Location of the medium interface

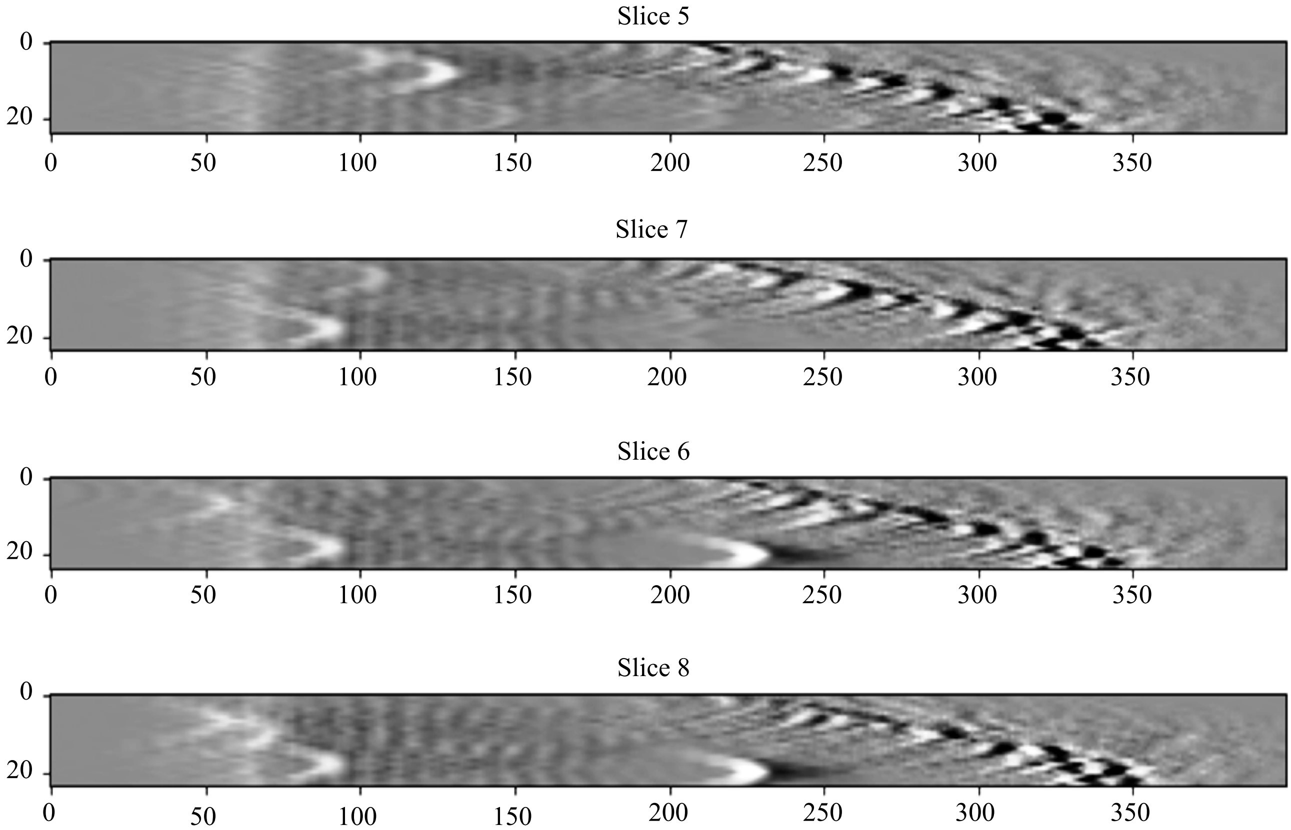

Fig. 2. Ultrasound image (B-scan)

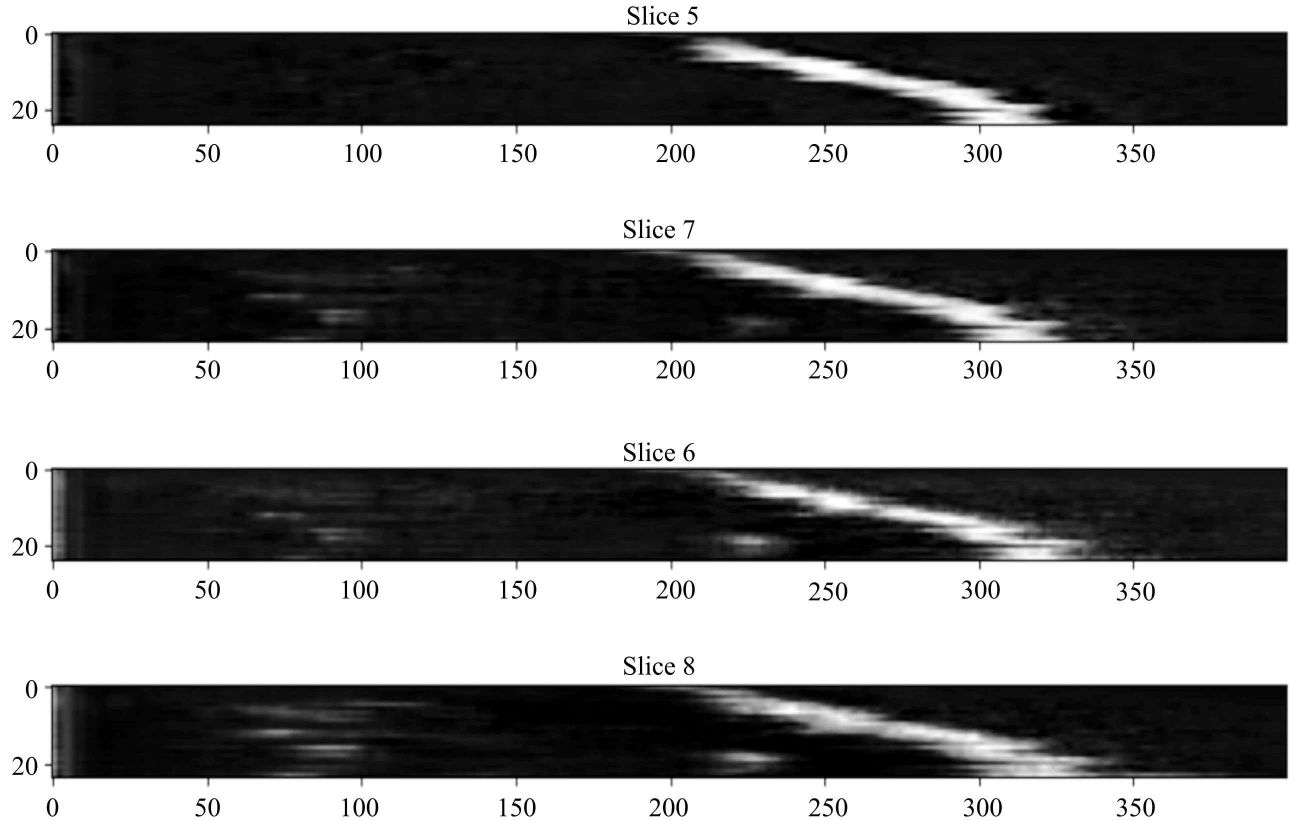

Fig. 3. Predictions of the 2D network in the original form

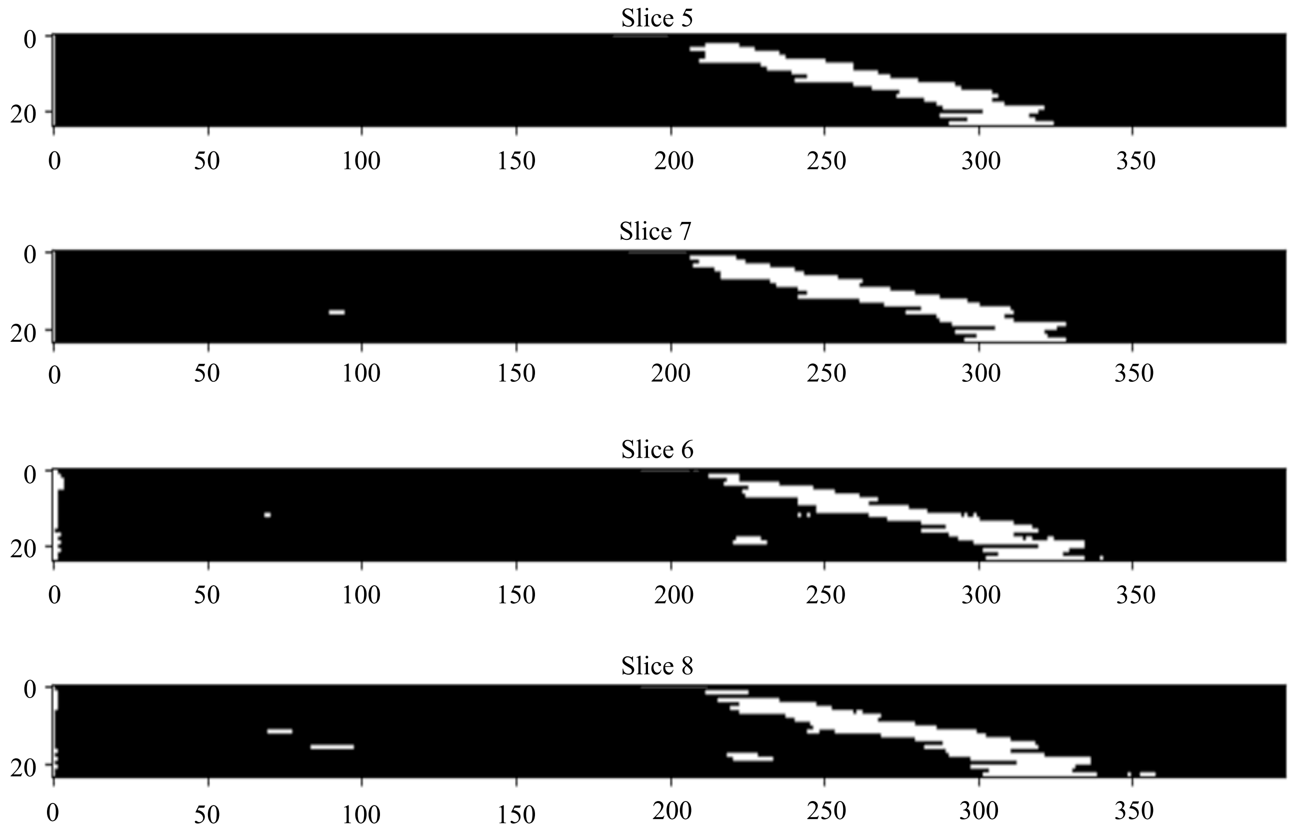

Fig. 4. Predictions of the 2D network after binarization

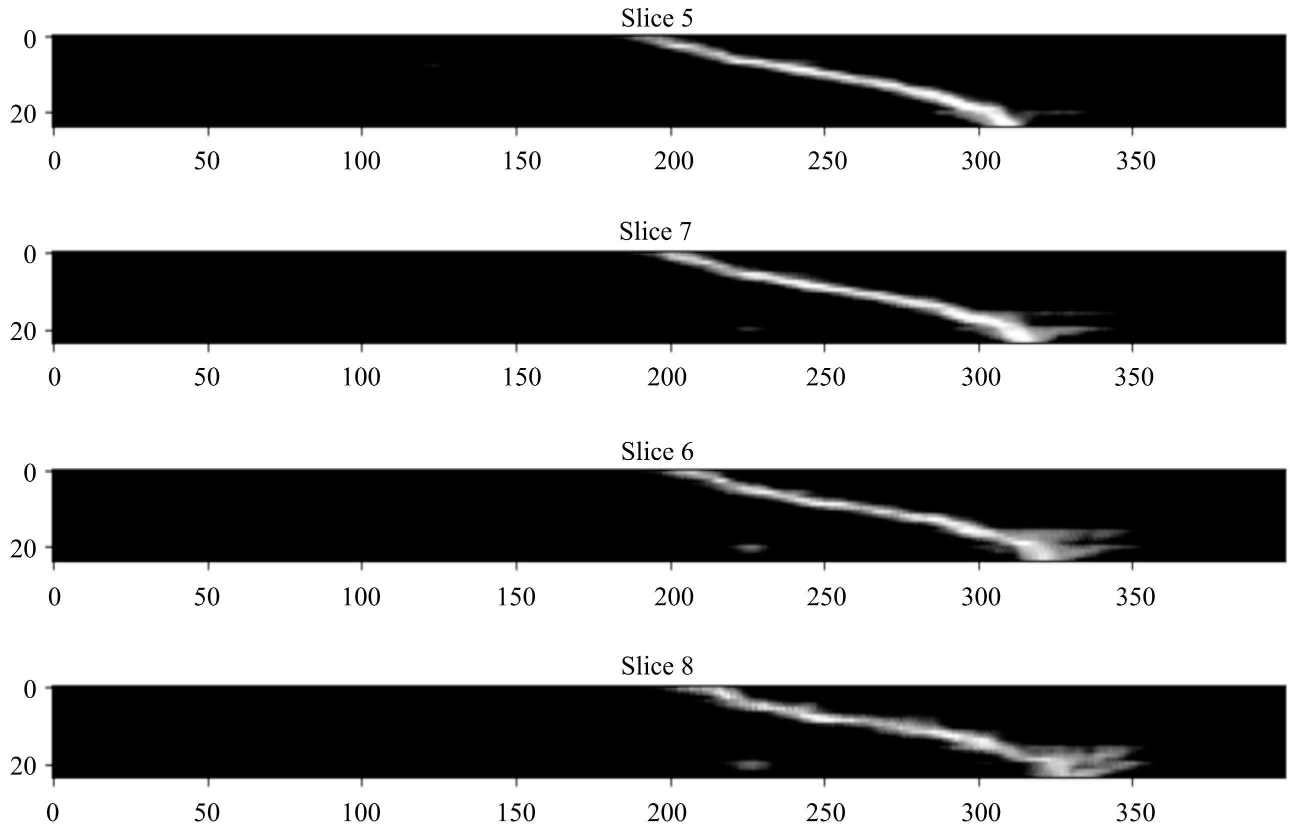

Fig. 5. Predictions of the 3D network in the original form

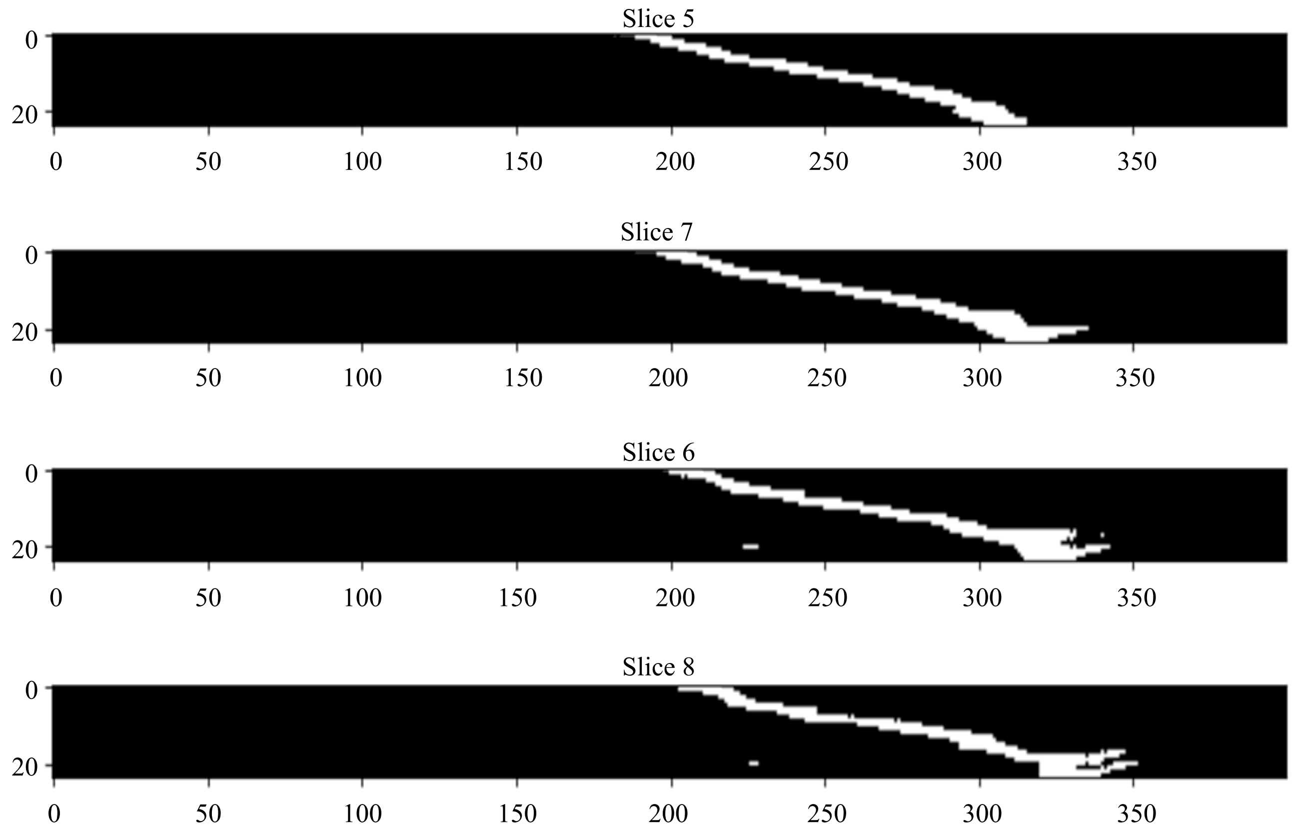

Fig. 6. Predictions of the 3D network after binarization

Discussion and Conclusions. The results show that the 3D convolutional network significantly outperforms the approach of processing three-dimensional data as slices using 2D networks in determining the shape and position of the boundary. Qualitatively, the boundary is generally correctly identified in both scenarios, but the 3D network exhibits substantially less blurring. Notably, the 3D network is almost unaffected by noise and interference in the input signal, both random and those caused by the presence of large bright reflectors. The results of the 2D network (Figs. 3 and 4) show a significant number of detections in the area before the desired boundary — where large pores were located in the object. This is not a random error; the network solves the segmentation task by aiming to detect acoustically contrasting boundaries, and the boundaries of the pores also fall into this category. However, this effect is undesirable. When using the 3D network (Figs. 5 and 6), such problems are virtually eliminated. This is because the three-dimensional structure of the input data allows the convolutional network to fully utilize the spatial information about the reflectors and learn to ignore geometrically small objects.

The total processing time for a single three-dimensional image using the 3D network was about 0.1 seconds on commercially available GPUs. Thus, the possibility of real-time localization of the aberrator boundary with good quality has been demonstrated. This fact can be further used to create new ultrasound imaging algorithms employing methods for compensating distortions caused by differences in sound speeds in tissues.

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Conflict of interest statement

The author does not have any conflict of interest.

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