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Ultrasound thermometry using an ultrasound element and deep learning for HIFU

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***Abstract*—High intensity focused ultrasound (HIFU) is a non-invasive therapy used to induce thermal dose to target tissue for desired medical outcomes. With this technique, malignant tissues can be destroyed using high energy with minimal side effects compared to surgery, that can induce more pain and leave permanent scar to patients. Temperature monitoring is crucial to preserve healthy tissues during thermal therapies. Magnetic resonance (MR) thermometry is often used to monitor the ablation process precisely. However, it is costly and some patients have contraindications. Ultrasound is a cost-effective medical imaging modality and suffers from less restrictions on the operating environment and can be used safely with all patients. In this paper, we propose a method to monitor the temperature with ultrasound using a deep learning approach. The system is designed to collect ultrasound channel data during HIFU therapy and alternates ablation phases and monitoring phases. In the monitoring phase, ultrasound elements in the probe receive ultrasound pulses sent from the 256 HIFU elements sequentially. We use convolutional long short term memory (ConvLSTM) neural network to generate temperature images from the ultrasound channel data. The temperature images are compared with the ones collected from MR thermometry. Mean and max difference of each image are calculated to evaluate the performance of designed neural network. We achieve 0.57 $\pm$ 0.33 $^\circ$C of mean difference and 1.99 $\pm$ 1.07 $^\circ$C of max difference in axial plane. In coronal plane, we achieve 0.33 $\pm$ 0.19 $^\circ$C of mean difference and 1.54 $\pm$ 1.04 $^\circ$C of max difference. The results show the potential use of ultrasound and deep learning to reconstruct temperature images.**

***Keywords*—ultrasound, HIFU, temperature monitoring, thermometry, deep learning**

I. Introduction

To remove malignant tissues, surgical excision is often performed but it may leave pain and permanent scar to patients. Also, it generally takes a long time for patients to recover from the surgery. In order to reduce the damage and recovery time for patients after surgery, non-invasive ablation technologies are developed. High intensity focused ultrasound (HIFU) is a widely used one [1], especially for prostate [2] and uterine fibroid treatments [3]. HIFU system focuses acoustic energy to increase temperature at a small target region. Thus, temperature monitoring is essential to guide the ablation process. Magnetic resonance (MR) thermometry is developed based on temperature sensitivity of proton resonance frequency [4]. This provides real time imaging capability with high accuracy, but its high cost and strict requirement of nonmetal environment push for the development of monitoring methods using other medical imaging modalities [5]. For example, R. Seip and E.S. Ebbini developed a method to monitor temperature by measuring acoustic information based on discrete scattering model [6].

In previous works, we showed the feasibility of an ultrasound thermometry method using few ultrasound elements for HIFU therapy monitoring [7] [8]. We collected time of flight (TOF) information obtained from ultrasound elements to reconstruct temperature images. Moreover, deep learning approach was applied to reconstruct temperature images using TOF information at different temperature [9]. However, these methods make use of only one temperature dependent ultrasound property which is the ultrasound propagation velocity. In fact, more properties can be used such as the attenuation coefficient. In order to extract both spacial and temporal features, we use a ConvLSTM network [10] to predict a temperature image. More ultrasound properties may be learned from ultrasound raw data, and this may improve ultrasound thermometry.

II. Method and Experiment

A. Data Collection

The experiment setup is illustrated in Fig. 1. It is composed of an MR-compatible ultrasound probe with 128 elements, an MR machine to collect temperature images, a HIFU system with 256 elements and a phantom made of 2 % agarose and 2 % silicon-dioxide to mimic biological soft tissue. The HIFU surface is covered by mineral oil and degassed water for acoustic coupling. The ultrasound probe is fixed with a holder on top of the phantom to collect ultrasound signals. This setup is fixed in the MR gantry to obtain MR temperature images and ultrasound channel data simultaneously.

In the experiment, the system alternates ablation phase and monitoring phase for six cycles. In the ablation phase, the HIFU elements transmit continuous waves at 78 Watts for 5 seconds. The acoustic wave focuses at the natural focal point and the temperature increases. In the monitoring phase, ultrasound pulses are transmitted at 2 Watts by each HIFU element

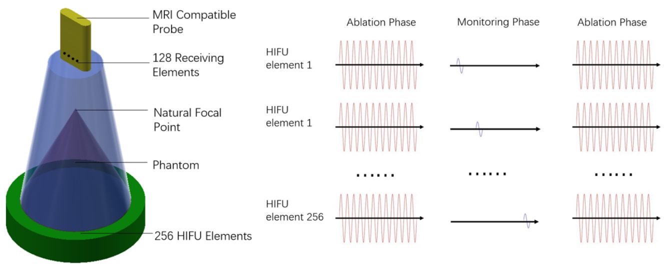

Fig. 1. HIFU experiment setup and timing diagram.

sequentially with a pinging interval of 3 ms. Ultrasound waves propagate through the target region at different speeds due to the temperature evolution. The pulses are captured by an MR-compatible ultrasound probe. We collect 4096 samples at a sampling rate of 62.5 Mhz after 131.072 ms delay. A trigger is generated when the HIFU element transmits the signal and the sampling is synchronized with it. Fig. 2 shows the channel data received by one ultrasound element in the probe at a monitoring phase. The x axis is each HIFU element number transmuted with 3 ms interval, the total time of monitoring phase is 768 ms using 256 HIFU elements. In the monitoring phase, the ultrasound pulse power is low and they are not focused. Therefore, the temperature change during the monitoring phase can be negligible. Temperature images in axial and coronal planes are generated by MR thermometry every 1.5 seconds. We average two MR temperature images which are acquired right before and after a monitoring phase. Before experiment, the initial phantom is at room temperature which is 20 °C. The temperature after the final ablation rise up to 45 °C. We repeat the experiment three times.

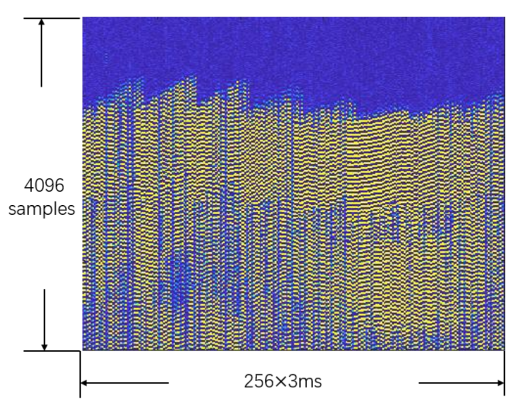

Fig. 2. An example of a channel data in a monitoring phase collected from an ultrasound element.

Since the pitch of ultrasound probe is 0.22 mm, the channel data collected from adjacent elements may have correlation. Therefore, we split training and test dataset by different sampling combinations. For each receiving element, we pick signals transmitted from 128 HIFU elements among 256 HIFU elements randomly for 20 times for training. Since we conduct 3 experiments with 128 probe elements, the size of train set is 128 × 3 × 20 which is equivalent to 7680. Similarly, we generate validation set and test set by randomly picking 128 HIFU elements for three times. The number of validation and test set is 128 × 3 × 3 which is equivalent to 1152.

B. Neural Network Design

The pulse arrives at first 2048 samples, thus we use first 2048 samples to reduce the input image size. The input is the concatenation signal of initial monitoring phase and current monitoring phase. Therefore, the image size of input is 2 × 2048 × 128 since each input image have 128 signals from different HIFU element combinations.

Fig. 3 shows the structure of the designed neural network. TOF shift change is essential to derive the temperature [8]. ConvLSTM network [10] can extract both spacial and temporal features from channel data. We use the raw channel data as a input which contains amplitude and TOF information. We use time series channel data for ConvLSTM block input, thus the network would learn the amplitude and TOF changes at different temperature profiles. Convolution operation is done with the output of ConvLSTM. Location vectors are added in the network as additional input. It contains relative coordinates of HIFU elements with respect to the receiving ultrasound element in the HIFU coordinate system. After passing through few convolution and fully connected layers, the vector is reshaped into a 40 by 40 array. It passes through convolution and transposed convolution layers and is flattened. Finally, it is connected to a fully connected layer with 400 size vector output and is reshaped to be a 20 by 20 image. The output of the network is the temperature image, and the MRI temperature images serve as target images. We use Adam as optimizer. The lose function is the mean square error and the learning rate is 1.5×10^{-4}. The image resolution is 1 mm by 1 mm.

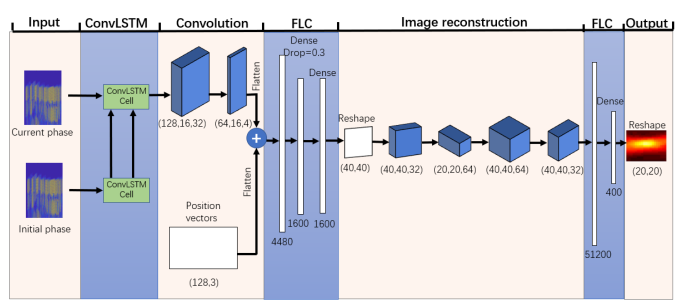

Fig. 3. Designed neural network.

III. RESULT

Two independent networks are trained to reconstruct axial and coronal temperature images. The Network is trained with early stopper to avoid over-fitting. If the validation error does not improve within 10 epochs, the network will stop training. Since accuracy on the temperature in the heating center is more important than in the background, a region of interest (ROI) is defined as a 20 by 20 area centered at the HIFU focal point. Fig. 4 shows the reconstruction results of our neural network. For each output image, we calculate the mean and maximum absolute error in the ROI. On the test set, the mean error of axial image is 0.57 ± 0.33 °C and the maximum error is 1.99 ± 1.07 °C. The maximum error is 9.16 °C. The mean error in coronal image is 0.33 ± 0.19 °C and the maximum error is 1.54 ± 1.04 °C. The maximum error is 9.04 °C. A smaller intersection with the heating area could explain the smaller error in the coronal images than in the axial ones. Fig. 5 is an example of comparison between reconstructed images and MR temperature images in axial plane and coronal plane.

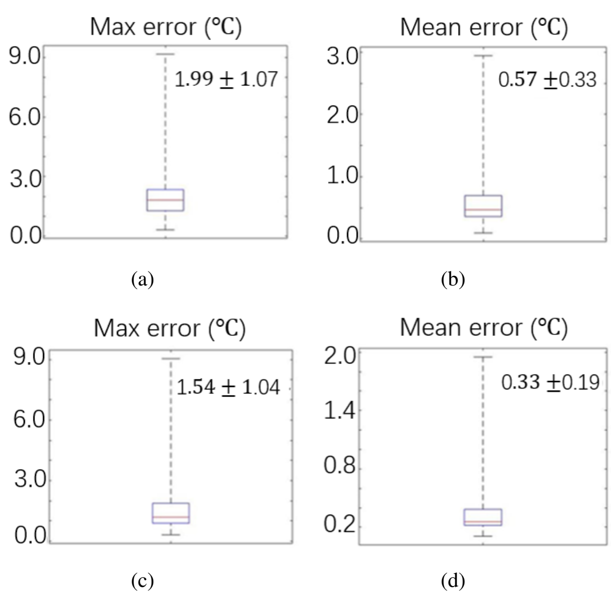

Fig. 4. Pixelwise absolute error in axial images in test set: (a) max error (b) mean error. Pixelwise absolute error in coronal images in test set. (c) max error (d) mean error.

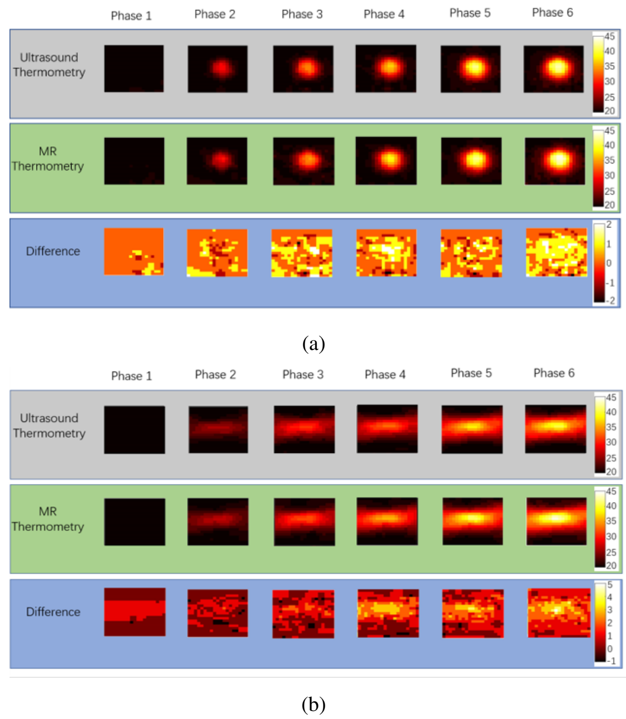

Fig. 5. Example of reconstructed images, MR temperature images in coronal plane and the differences between them. (a) in the coronal plane. (b) in the axial plane. The image size is 20 by 20, and image pixel size is 1 mm by 1 mm. Temperature unit is in °C.

IV. DISCUSSION

We propose a method to reconstruct temperature images from raw ultrasound channel data using deep learning. The setup is simple and affordable since our method only requires to place the ultrasound elements on top of the target. We conduct experiments to collect data and train the neural network. The results show the feasibility of the proposed ultrasound thermometry method using ultrasound channel data and deep learning for HIFU therapy monitoring.

The method uses initial ultrasound data before ablation, therefore patient motion would be challenging since the channel data collected at initial status will be different from the one in our network. In the future, we would not need initial channel data in the input, instead, most recent temperature information before patient motion and relative ultrasound data shift after patient motion could be used together.

One of the limitations of this study is the relatively small data capacity. Future work will include more data collection for training and validation. We will collect more data with various biological tissues and different element positions. To validate the method, *in vivo* and *ex vivo* experiments must also be performed in the future. We believe the accuracy can be further improved by tuning the hyperparameters and modifying the neural network structure using more data. Simulation can also be considered since collecting a sufficient large number of data is difficult. We may be able to use data from both simulation and experiments to train the network.

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