Real-Time Quantitative Ultrasound and Radar Knowledge-Based Medical Imaging

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Abstract

Ultrasound and radar signals are useful for medical imaging due to their non-invasive, non-radiative, low-cost, and accessible nature. However, traditional imaging techniques lack resolution, contrast, and physical interpretation. Quantitative medical imaging is necessary for this purpose, as it provides a visual representation of physical characteristics. However, current techniques have drawbacks, including convergence to local minima and delayed results, which can lead to unsatisfactory outcomes. To address these limitations, we propose a neural network that incorporates the symmetries and properties of the received signals to achieve real-time quantitative mappings of physical properties. Our method achieves high accuracy using several numerical metrics for complex shapes with less than 0.15 seconds per test sample, compared to 0.75-2 hours for the competing method.

Keywords: ultrasound, radar, quantitative imaging, U-net, FWI, ISP, channel data

1. Introduction

Ultrasound (US) and radar signals are two primary signals used in non-invasive and non-radiative medical imaging. US and radar imaging produce images based on the received signals, referred to as channel data (CD), obtained from the received echoes (for US) or microwave signals (for radar) scattered by the scanned medium (Van Veen and Buckley, 1988; Li et al., 2005), as illustrated in Fig. 1.a-c. However, current imaging techniques using US or radar signals provide limited physical interpretation, hence quantitative medical imaging (QMI) is needed. QMI has the potential to visualize various quantitative physical properties (QPPs) of the scanned medium, such as speed-of-sound (SoS), density, and permittivity, which can be beneficial for diverse medical applications such as fatty liver diagnosis, and stroke imaging (Ruby et al., 2019; Lee, 2017; Hopfer et al., 2017; Ireland and Bialkowski, 2011; Wei and Chen, 2018).

To obtain quantitative images, a non-linear inverse scattering problem (ISP) must be solved for reconstructing the QPPs of the scanned medium using the received CD. Full Waveform Inversion (FWI) is one such method that utilizes an iterative optimization algorithm to solve the ISP (Shultzman and Eldar, 2022; Guasch et al., 2020). The goal of FWI is to minimize the loss between the measured and predicted CD according to the QPPs estimation. However, FWI can be time-consuming and may converge to a local minimum. Furthermore, an initial guess close to the real solution based on some prior knowledge is required, which is often unavailable in realistic settings. To address these limitations, deep learning techniques have been proposed as a potential solution for solving the ISP (Guo et al., 2022; Chen et al., 2020; Wei and Chen, 2018; LeCun et al., 1998). Nevertheless, previous works only reconstructed one QPP and tested it on simple synthetic tests.

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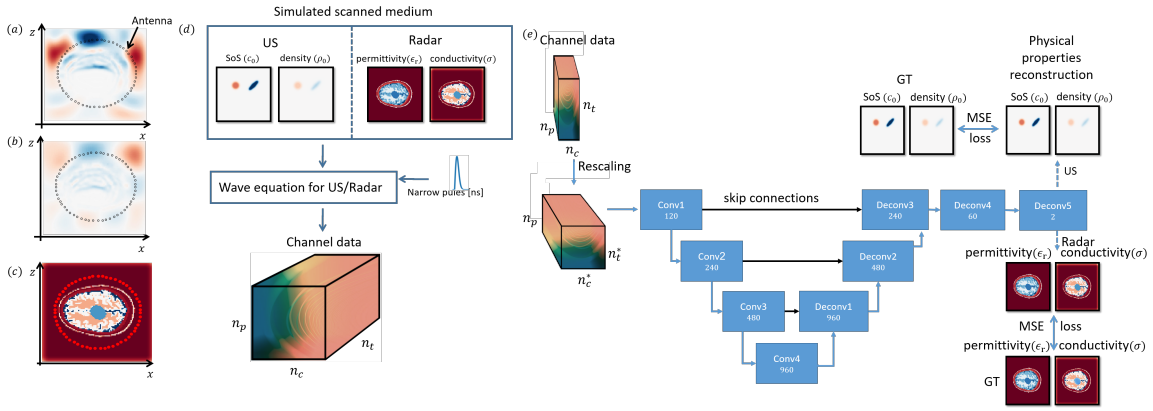


Figure 1: (a)-(b) depict the wave propagation from one antenna over two successive time samples. (c) depicts a medium with 60 antennas surrounding a stroke-affected brain. (d) displays the training set creation process from simulation, utilizing the QPPs of the grid and known pulse to obtain the channel data for network input. (e). QUARK-MI architecture for both radar and US schemes. The channel number of each convolution block is displayed.

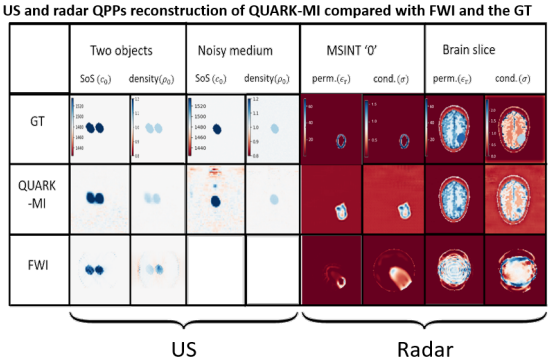
Our contribution is twofold. First, we propose a neural network (NN) for real-time reconstruction of multiple QPPs from measured CD. By incorporating the physical meaning of the input CD, our method achieves more accurate reconstructions and avoids converging to a local minimum, as occurs in FWI. Second, we demonstrate the versatility of our proposed network by showing its ability to reconstruct physical properties using either radar signals or US signals. Additionally, we demonstrate the network's ability to reconstruct more than one property for each case, and to handle complex nonhomogeneous domains such as a realistic human brain with random stroke.

2. Data and Method

We introduce QUARK-MI (Quantitative-Ultrasound-and-Radar Knowledge-based Medical Imaging), a real-time NN solution that can accurately reconstruct the medium's QPPs from either US or radar signals. QUARK-MI has a U-Net based architecture with skip connections, stride convolution, and batch normalization, enabling the NN to learn from different signal channels and capture fine details while preserving information from the entire CD tensor. The input to the NN is the CD tensor consists of the receiving signals over time for each transmission. Our training set includes one random object in a sample with liver properties for the US case, and different training sets for the radar case: MNIST digit (LeCun et al., 1998) in a random position and blood properties as the object, and realistic brain slices (Qureshi and Mustansar, 2017) with a random stroke. We use the known wave equations to create the CD inputs (Fig. 1.d).

Our approach integrates the CD physical interpretation into the network architecture. Each transmission channel offers complementary information about the QPPs and treated as the convolution channels, while the time and receiving signal dimensions are treated as the spatial image dimensions in traditional U-Net. Additionally, as illustrated in Fig.1.e, we employ derivable rescaling to achieve square spatial dimensions. The final convolution

(a)



(b)

US and radar accuracy scores of QUARK-MI compared with FWI and the GT

Scenario	Property	Method	NRMSE	PSNR	SSIM	
2 objects	SoS	**QUARK-MI**	**0.073**	**62.08**	**0.82**	US
		FWI	0.087	61.93	0.97	
	Density	**QUARK-MI**	**0.072**	**6.30**	**0.97**	
		FWI	0.162	5.60	0.86	
Noisy medium	SoS	**QUARK-MI**	**0.06**	**62.13**	**0.60**	
		FWI	NaN	NaN	NaN	
	Density	**QUARK-MI**	**0.103**	**5.85**	**0.88**	
		FWI	NaN	NaN	NaN	
MNIST '0'	Perm.	**QUARK-MI**	**0.076**	**35.55**	**0.95**	Radar
		FWI	0.075	35.57	0.91	
	Cond.	**QUARK-MI**	**0.078**	**7.83**	**0.87**	
		FWI	0.11	7.50	0.38	
Brain slice	Perm.	**QUARK-MI**	**0.027**	**36.35**	**0.98**	
		FWI	0.202	34.63	0.62	
	Cond.	**QUARK-MI**	**0.062**	**7.64**	**0.48**	
		FWI	0.175	6.75	0.43	

Figure 2: (a) The comparison of QUARK-MI and FWI methods for the reconstruction with respect to the ground-truth (GT). (b) The accuracy performance.

block in our model sums the transmission channels over the spatial dimensions, generating two channels that depict two mappings of the medium's QPPs.

3. Evaluation and Results

We conducted a comprehensive evaluation of our QUARK-MI method and compared it with the FWI algorithm using numerical metrics (NRMSE, PSNR, and SSIM), to assess the accuracy of object shape and position as well as quantitative values of pixels, as shown in Fig.2. Our NN accurately reconstructs QPPs from challenging US signals scenarios, including two scattering objects with a uniform background (trained on only one object in each sample), and a noisy medium (where FWI diverge). Additionally, for the radar case, we reconstructed non-defined objects from the MNIST dataset with QPPs, and a realistic brain slice with a generated stroke. QUARK-MI outperforms FWI in most scenarios (highlighted in green), except for one case where FWI has as the initial guess the homogeneous background value (highlighted in grey). Our NN shows a generalization ability to reconstruct multiple objects even though the training set contained only one random object in each image, and reconstruction of highly complex shapes, even in the case of a human brain where the skull causes a significant decrease in signal quality, in which both the outline of the brain and the location and size of the stroke were restored with great success. Our method achieves high accuracy in complex and realistic objects, with less than 0.15 seconds per sample, compared to 0.75-2 hours for FWI.

4. Conclusion

In conclusion, our proposed NN that incorporates the symmetries and properties of received signals can achieve real-time mappings of QPPs for medical imaging. This method provides improved physical interpretation and can lead to the accomplishment of new clinical goals such as fast stroke imaging and cancer detection. With high accuracy and fast computational time, this approach has the potential to significantly impact the field of medical imaging.

References

Xudong Chen, Zhun Wei, Maokun Li, and Paolo Rocca. A review of deep learning approaches for inverse scattering problems (invited review). *Progress In Electromagnetics Research*, 167:67–81, 2020.

Lluís Guasch, Oscar Calderón Agudo, Meng-Xing Tang, Parashkev Nachev, and Michael Warner. Full-waveform inversion imaging of the human brain. *NPJ digital medicine*, 3 (1):28, 2020.

Rui Guo, Tianyao Huang, Maokun Li, Haiyang Zhang, and Yonina C Eldar. Physics embedded machine learning for electromagnetic data imaging. *arXiv preprint arXiv:2207.12607*, 2022.

Markus Hopfer, Ramon Planas, Abouzar Hamidipour, Tommy Henriksson, and Serguei Semenov. Electromagnetic tomography for detection, differentiation, and monitoring of brain stroke: A virtual data and human head phantom study. *IEEE Antennas and Propagation Magazine*, 59(5):86–97, 2017.

David Ireland and Marek Bialkowski. Microwave head imaging for stroke detection. *Progress In Electromagnetics Research M*, 21:163–175, 2011.

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

Dong Ho Lee. Imaging evaluation of non-alcoholic fatty liver disease: focused on quantification. *Clinical and molecular hepatology*, 23(4):290, 2017.

Xu Li, Essex J Bond, Barry D Van Veen, and Susan C Hagness. An overview of ultra-wideband microwave imaging via space-time beamforming for early-stage breast-cancer detection. *IEEE Antennas and Propagation Magazine*, 47(1):19–34, 2005.

Awais Munawar Qureshi and Zartasha Mustansar. Levels of detail analysis of microwave scattering from human head models for brain stroke detection. *PeerJ*, 5:e4061, 2017.

Lisa Ruby, Sergio J Sanabria, Katharina Martini, Konstantin J Dedes, Denise Vorburger, Ece Oezkan, Thomas Frauenfelder, Orcun Goksel, and Marga B Rominger. Breast cancer assessment with pulse-echo speed of sound ultrasound from intrinsic tissue reflections: Proof-of-concept. *Investigative radiology*, 54(7):419–427, 2019.

Avner Shultzman and Yonina C. Eldar. Nonlinear waveform inversion for quantitative ultrasound, 2022.

Barry D Van Veen and Kevin M Buckley. Beamforming: A versatile approach to spatial filtering. *IEEE assp magazine*, 5(2):4–24, 1988.

Zhun Wei and Xudong Chen. Deep-learning schemes for full-wave nonlinear inverse scattering problems. *IEEE Transactions on Geoscience and Remote Sensing*, 57(4):1849–1860, 2018.