Supplementary Materials for Displacement Estimation in Ultrasound Elastography using Pyramidal Convolutional Neural Network

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I. Effect of input images on the proposed networks

In this experiment, different signals are used as the input of our networks for the case that the strides of the first feature extraction layer are set to 1. Fig. 1 shows the strain of using only RF (a), B-mode (b) and concatenation of all (c) for an experimental phantom. As depicted in Fig. 1, RF data produces the highest quality strain image but there are some unreliable and outlier regions. The reason of these outlier regions is that in MPWC-Net there are different pyramidal levels for displacement estimation and in low pyramid levels, MPWC-Net fails to extract useful information from RF data. It should also be noted that B-mode image can result in fair approximation of the displacement and there is no outlier regions since in B-mode image, the high frequencies are removed and it can be downsampled without any unreliable regions. B-mode image lacks high quality information of RF data and reliable displacement cannot be obtained by RF data in entire regions due to loss of information from downsampling.

In MPWC-Net, this problem is mitigated by concatenating RF data, B-mode and envelope which is shown in Fig. 1 (c). The Network uses the information of B-mode and envelope in low resolutions where RF data cannot provide useful information and the network exploits RF data in the final resolution to have a high quality displacement estimation. It is also clear from the results that using only RF data produces slightly higher quality strain image compared to using concatenation of RF, B-mode and envelope. This fact motivated us to develop RFMPWC-Net which exploits RF data, B-mode and envelope in all pyramid levels except for the final one and uses only RF data for the final pyramid level. The results of this network is shown in Fig. 1 (d). The strain quality is as high as using only RF data without unreliable regions of using only RF data and has higher quality compared to MPWC-Net (c).

II. Effect of removing strides on the networks

The effect of strides of the first feature extraction layer for different inputs is investigated and shown in Fig. 2. In (a), both strides are 2 and only RF data is used as input. As shown in (a), there is no outlier region but the accuracy is poor. In (2), strides of 2 are removed and only RF data is used as input. The obtained strain has high quality but there are failure regions which are not present when concatenation (c) is employed. By using the concatenation of RF data, B-mode and envelope, the outlier regions are removed but the strain quality is slightly degraded. RFMPWC-Net (d) not only removes the outlier regions but also has the same accuracy and quality as using only RF data (b).

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TABLE I: Number of parameters of the networks

Network	Number of parameters (Approximately). M represents million.
FlowNet2	162M
PWC-Net	9M
MPWC-Net	9M
RFMPWC-Net	11.7M

III. Number of Learnable parameters

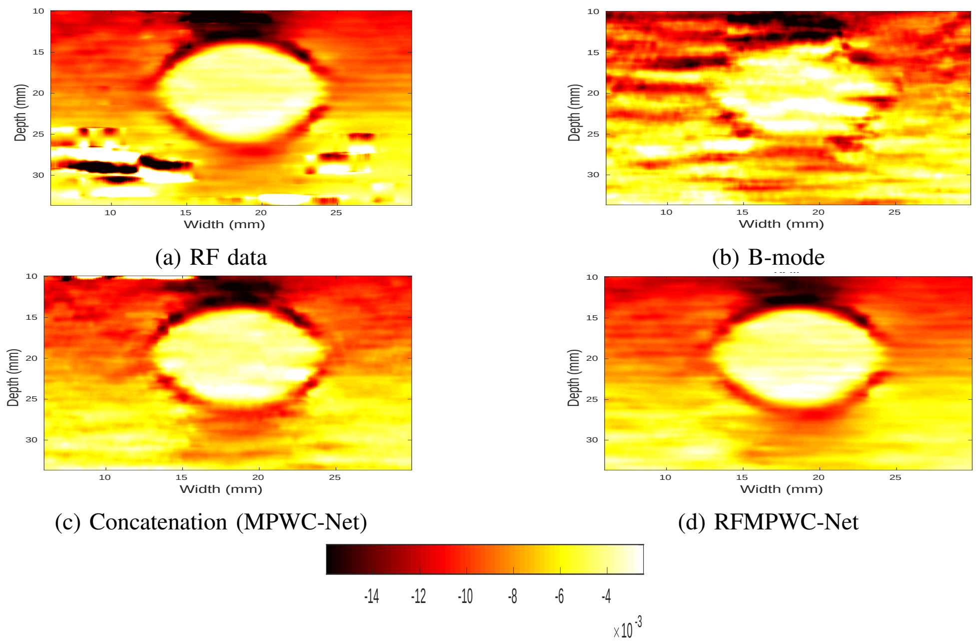
All networks are implemented on Pytorch version 0.4 and CUDA 9.1. The number of trainable parameters are given in Table I. As shown in the Table, FlowNet2 has at least 10 times more parameters than PWC-Net. While, the networks based on PWC-Net require much lower amount of memory due to having substantially fewer trainable parameters compared to FlowNet2. RFMPWC-Net has 2.7M more trainable parameters than PWC-Net and MPWC-Net.

IV. Results for different imaging parameters

The sampling and center frequency of simulated data are 50 MHz and 5 MHz, respectively. In this section results of three networks (RFMPWC-Net, FlowNet2 and PWC-Net) are given for different combination of sampling frequencies (25, 50 MHz) and center frequencies (5, 10 MHz).

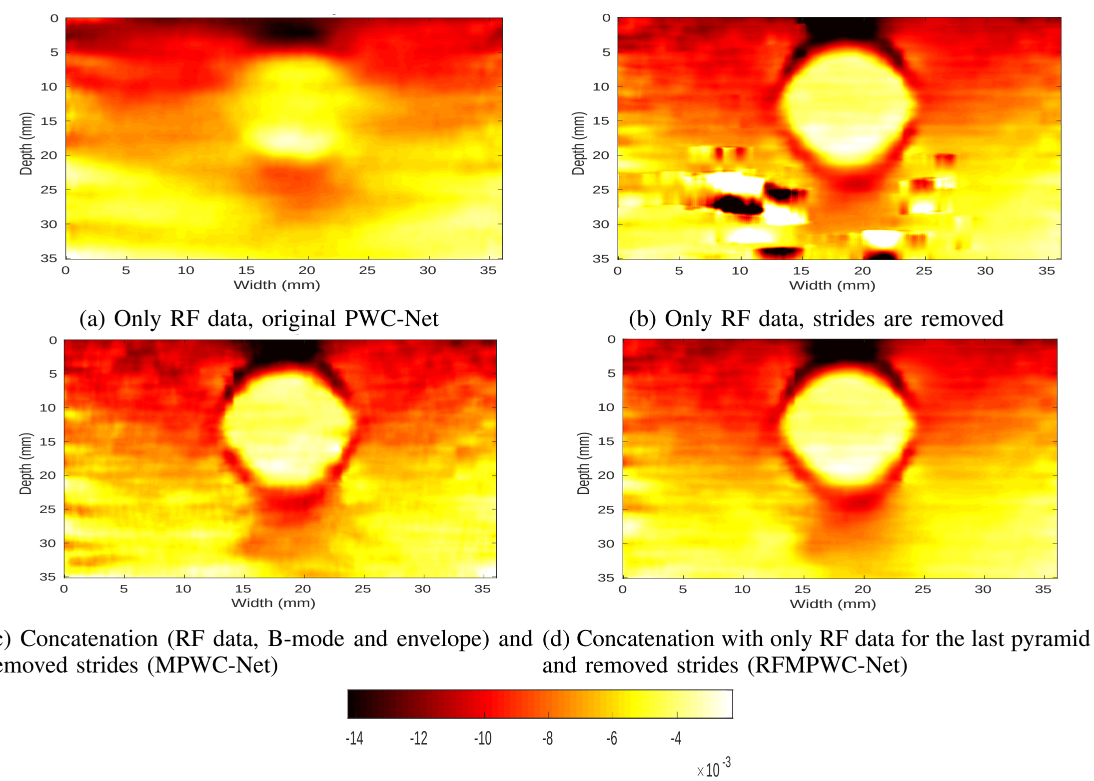
V. Result for different strain (%)

The CNR value for different strain value is computed and shown in Fig. 4. Strain is changed from 0.5 to 4% for all CNN methods and GLUE for a simulated phantom. We see that the two proposed networks (especially RFMPWC-Net) work well and comparable to GLUE.



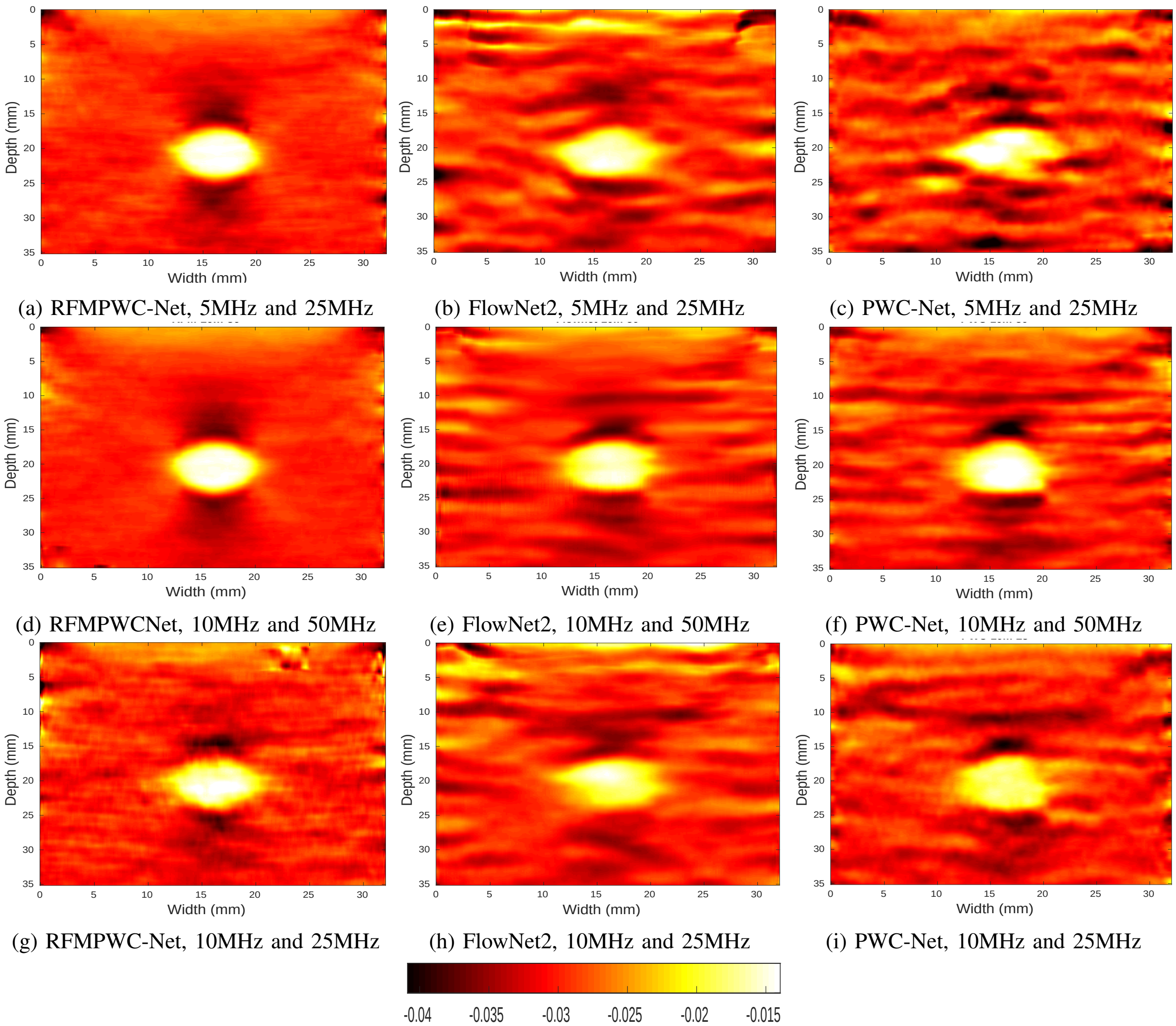
(a) RF data
(b) B-mode
(c) Concatenation (MPWC-Net)
(d) RFMPWC-Net

Fig. 1: Results of different input signals for an experimental phantom. Note the high accuracy but failure of (a), low accuracy without failure of (b), Concatenation (c) removes outliers presented in (a), and RFMPWC-Net (d) is closer to RF results compared to simple concatenation (MPWC-Net) (c).



(a) Only RF data, original PWC-Net
(b) Only RF data, strides are removed
(c) Concatenation (RF data, B-mode and envelope) and removed strides (MPWC-Net)
(d) Concatenation with only RF data for the last pyramid and removed strides (RFMPWC-Net)

Fig. 2: Effect of strides removal with different input signals. Note the low accuracy without failure of (a), high accuracy with failure of (b), and RFMPWC-Net (d) is closer to RF results compared to simple concatenation (MPWC-Net) (c).



(a) RFMPWC-Net, 5MHz and 25MHz (b) FlowNet2, 5MHz and 25MHz (c) PWC-Net, 5MHz and 25MHz

(d) RFMPWCNet, 10MHz and 50MHz (e) FlowNet2, 10MHz and 50MHz (f) PWC-Net, 10MHz and 50MHz

(g) RFMPWC-Net, 10MHz and 25MHz (h) FlowNet2, 10MHz and 25MHz (i) PWC-Net, 10MHz and 25MHz

Fig. 3: Simulation results of RFMPWC-Net and FlowNet2 for different center and sampling frequencies. (Network, Center frequency and Sampling frequency)

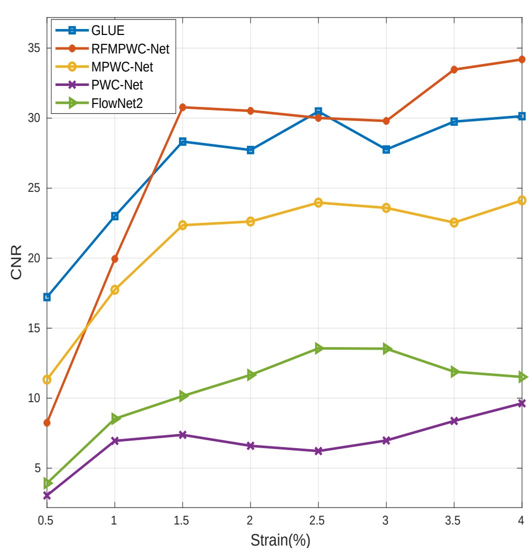


Fig. 4: Strain (%) versus CNR for a simulated phantom.

VI. Fine-Tuning PWC-Net

In order to demonstrate that fine-tuning is not sufficient and modifying the structure is necessary, we perform the following experiment. PWC-Net is fine-tuned and compared with RFMPWC-Net and PWC-Net. Fig. 5 shows the strain images of an *in vivo* data. As shown in Fig. 5, fine-tuned PWC-Net performs better than PWC-Net but inferior to RFMPWC-Net which is not fine-tuned on ultrasound data. The fact that PWC-Net even with fine-tuning is still far behind state-of-the-art methods, inspired us to modify the structure of the network to adopt the model to ultrasound data.

VII. Positive strain results

The network is fine-tuned on negative strain (second image is the post-compression image) only. In this experiment, the results of positive and negative strain for RFMPWC-Net and the fine-tuned version are given for a simulated phantom. As shown in Table. II, the network that is fine-tuned on negative strain only, performs inferior to pre-train network.

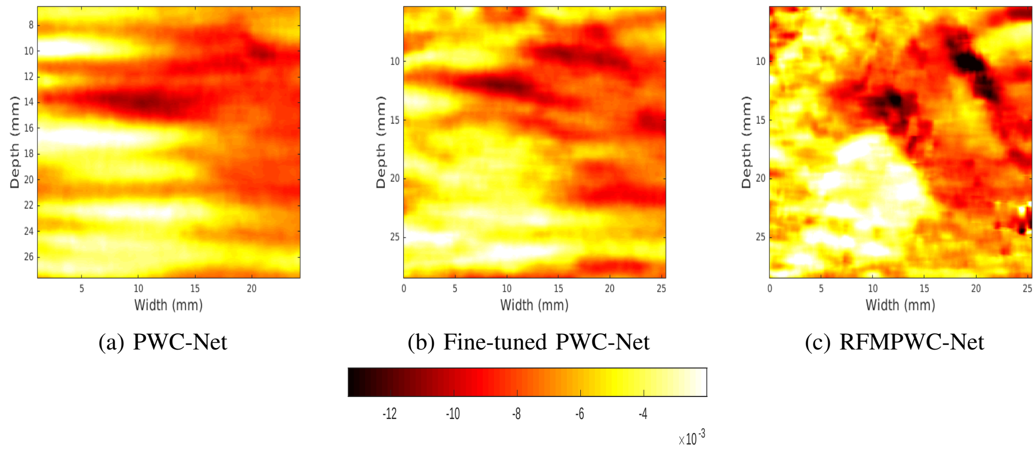


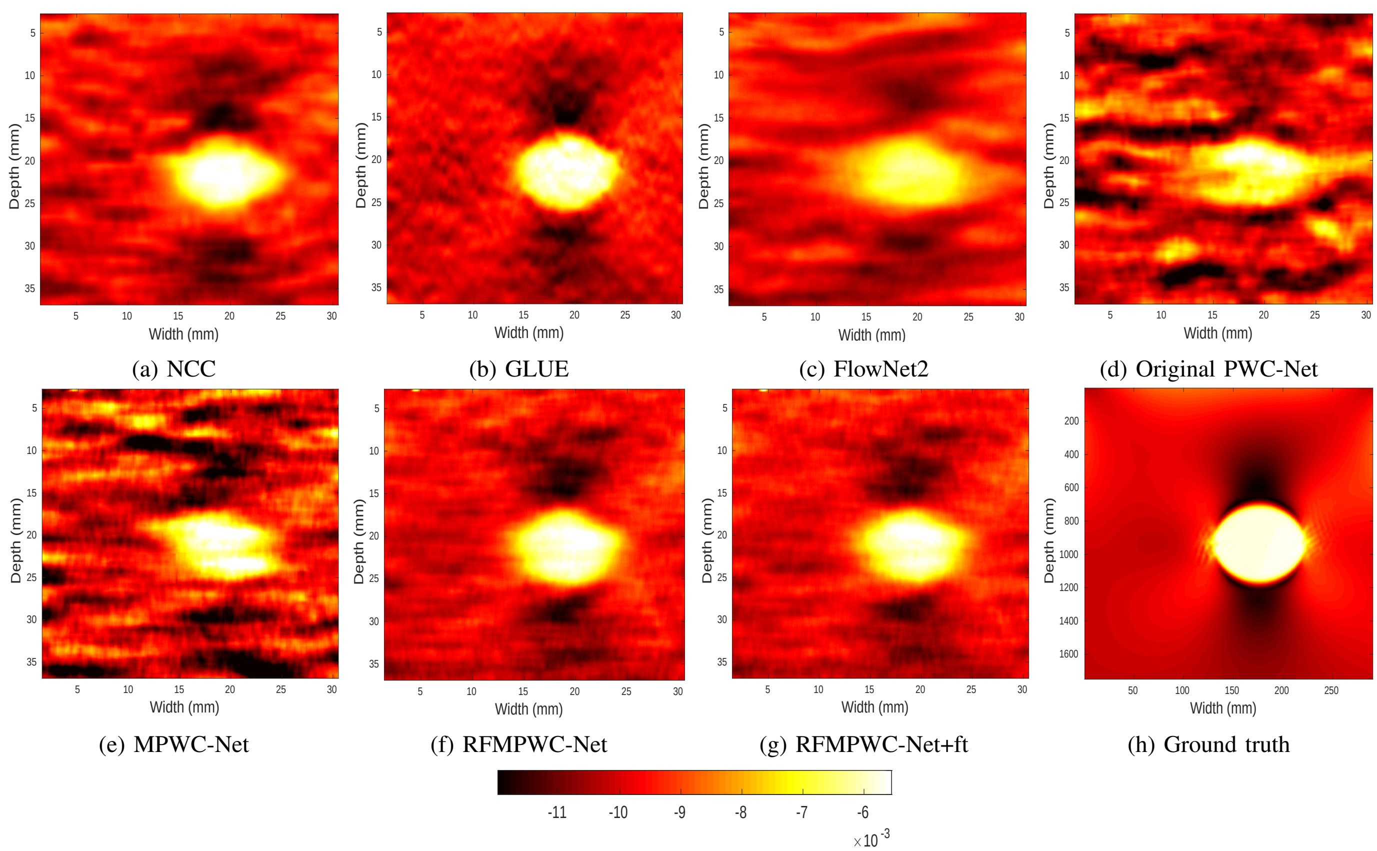
Fig. 5: *In vivo* results of PWC-Net (a), Fine-tuned PWC-Net (b) and RFMPWC-Net (c).

TABLE II: Positive and negative displacement NRMSE (%)

Network	Positive (%)	Negative (%)
RFMPWC-Net	0.62	1.17
RFMPWC-Net+ft	1.06	0.97

VIII. Additional experiments

Fig. 6 shows the strain of a simulated phantom from the test set with $PSNR = 35$ dB. According to Fig. 6, MPWC-Net strain result degrades for the noisy input. While, RFMPWC-Net strain result remains well in the noisy condition.



(a) NCC (b) GLUE (c) FlowNet2 (d) Original PWC-Net

(e) MPWC-Net (f) RFMPWC-Net (g) RFMPWC-Net+ft (h) Ground truth

Fig. 6: A simulated phantom strain result with $PSNR = 35$. RFMPWC-Net ((f) and (g)) has high quality in contrast to MPWC-Net (e).