CNN-Based Ultrasound Image Reconstruction for Ultrafast Displacement Tracking

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Abstract—Thanks to its capability of acquiring full-view frames at multiple kilohertz, ultrafast ultrasound imaging unlocked the analysis of rapidly changing physical phenomena in the human body, with pioneering applications such as ultrasensitive flow imaging in the cardiovascular system or shear-wave elastography. The accuracy achievable with these motion estimation techniques is strongly contingent upon two contradictory requirements: a high quality of consecutive frames and a high frame rate. Indeed, the image quality can usually be improved by increasing the number of steered ultrafast acquisitions, but at the expense of a reduced frame rate and possible motion artifacts. To achieve accurate motion estimation at uncompromised frame rates and immune to motion artifacts, the proposed approach relies on single ultrafast acquisitions to reconstruct high-quality frames and on only two consecutive frames to obtain 2-D displacement estimates. To this end, we deployed a convolutional neural network-based image reconstruction method combined with a speckle tracking algorithm based on cross-correlation. Numerical and in vivo experiments, conducted in the context of plane-wave imaging, demonstrate that the proposed approach is capable of estimating displacements in regions where the presence of side lobe and grating lobe artifacts prevents any displacement estimation with a state-of-the-art technique that rely on conventional delay-and-sum beamforming. The proposed approach may therefore unlock the full potential of ultrafast ultrasound, in applications such as ultrasensitive cardiovascular motion and flow analysis or shear-wave elastography.

Index Terms—Biomedical imaging, deep learning, diffraction artifacts, displacement estimation, image reconstruction, speckle tracking, ultrafast ultrasound imaging.

I. INTRODUCTION

ULTRAFAST ultrasound (US) imaging allows reconstructing full-view images from single acquisitions by insonifying the entire field of view at once, using unfocused transmit wavefronts such as plane waves (PWs) or diverging waves (DWs) [1]. Ultrasound images are then reconstructed from the received echo signals using the well-known delay-and-sum (DAS) algorithm. Ultrafast US imaging thus breaks with the trade-off between field of view and frame rate inherent to conventional transmit-focused line-by-line scanning. This allows imaging large tissue regions at very high frame rates of multiple kilohertz, limited only by the round-trip propagation time of single acoustic waves. High frame rates are imperative for studying and analyzing rapidly changing physical phenomena inside the human body, such as highly complex motions occurring inside the cardiovascular system [2]–[5] or the propagation of shear waves through tissue [6]–[10]. Several breakthrough US imaging modes based on motion estimation within a large field of view rely on ultrafast US imaging, such as shear-wave elastography [6], ultrasensitive flow imaging [3], and functional US neuroimaging [11].

Because of the absence of transmit-focusing, images obtained from ultrafast acquisitions are of low quality, suffering heavily from poor lateral resolution and low contrast [4], [7]–[9], [12], [13]. Both effects are related to the point spread function (PSF) of ultrafast US imaging systems, characterized by a broader main lobe (lower lateral resolution) and stronger diffraction artifacts (lower contrast) caused by side lobes (SLs), grating lobes (GLs), and edge waves (EWs), compared with conventional focused-US imaging systems. Naturally, low-quality images also limit the accuracy of subsequent displacement estimation methods involved in ultrafast US imaging modes [5], [7], [9]. The state-of-the-art solution for increasing the quality of ultrafast US imaging is coherent compounding, where a series of low-quality images, reconstructed from multiple, differently steered, unfocused wavefronts, are coherently summed [7], [12].

In [7], an image quality surpassing state-of-the-art multi-focus imaging was obtained by compounding 71 PW acquisitions, increasing the frame-rate by a factor of approximately seven.

However, for analyzing motion at very high frame rates, coherent compounding suffers from two considerable disadvantages. Firstly, the increase in image quality is directly linked to the number of compounded acquisitions, which in turn is limited by the minimum frame rate necessary to analyze the underlying physical phenomenon of interest. Secondly, coherent compounding assumes, similarly to line-by-line scanning, that the region of interest is stationary for the duration of an acquisition sequence used to reconstruct a single frame. This assumption does not hold when imaging fast-moving tissue regions or complex flows, for which coherent compounding
suffers from strong motion artifacts [13], [14].

The first issue is well exemplified in [7], in which Montaldo et al. demonstrated, in the context of shear-wave elastography, that the quality of estimated elasticity maps is directly linked to the number of compounded acquisitions, which in turn was limited to a maximum of twelve acquisitions to ensure a minimum frame rate of 1 kHz. In particular, displacement estimation in highly heterogeneous tissue regions, where the aforementioned diffraction artifacts were dominant, was a major obstacle. Issues due to diffraction artifacts hindering accurate displacement estimates were reported for several methods, all of them suffering from the trade-off between image quality and frame rate [7], [9], [15].

The occurrence of severe motion artifacts when compounding multiple acquisitions of rapidly evolving physical phenomena (inter-frame displacement close to the effective wavelength) was discussed in [13], [14], [16], and motion compensation techniques were proposed to tackle this problem. They consist of estimating inter-acquisition displacement, using either conventional Doppler [14], [16] or 1-D correlation methods [13], and compensate for it before compounding all acquisitions to produce a motion-compensated high-quality image. However, these motion compensation techniques can also suffer from strong diffraction artifacts [13], as they are themselves based on displacement estimation from low-quality images, obtained from unfocused wavefronts. It thus remains unclear if such methods could help improve motion estimation in regions plagued by such artifacts.

Consequently, there exists a great need for a robust displacement estimation technique that does not rely on multiple acquisitions to reconstruct consecutive frames. This is of particular interest in extreme conditions, when analyzing rapidly evolving physical phenomena in zones with highly heterogeneous echogenicities.

In [17], we introduced a method for reconstructing high-quality US images from single unfocused acquisitions. It consists of a backprojection-based DAS operation followed by the application of a convolutional neural network (CNN), specifically trained to reduce the diffraction artifacts inherent to the deployed ultrafast US imaging setup. Strong artifact reduction was demonstrated in simulated, in vitro, and in vivo environments. The CNN-based image reconstruction method works strictly on an frame-by-frame basis and relies on the spatial information of each image only. Hence, it is completely agnostic to the time dimension and thus to any displacement between consecutive frames, making it a perfect fit for combination with state-of-the-art image-based displacement estimation techniques. In a preliminary work [18] we showed that a CNN-based image reconstruction method may preserve the time-coherence of speckle patterns between consecutive frames, which is essential to any image-based displacement estimation technique.

In this work, we propose an approach for estimating 2-D inter-frame displacements at maximum frame rates, by combining our single-shot CNN-based image reconstruction method [17] with a state-of-the-art 2-D speckle tracking algorithm. Although estimating the axial displacement (only) remains the standard in US imaging, 2-D displacement estimation is increasingly gaining attention in both flow and tissue motion applications [5], [19], [20], as it allows the analysis of more complex motion patterns. In elastography, 2-D displacement maps may be of interest to increase the quality and robustness of the estimated elasticity maps [21]. Also, 2-D speckle tracking represents an optimal fit for high-frame-rate displacement estimation since, unlike vector Doppler techniques, it does not rely on multi-angle acquisitions. Moreover, displacement estimation can be performed accurately from two consecutive frames only, whereas Doppler-based techniques usually require multiple consecutive frames to estimate the phase accurately.

Since our aim is to tackle displacement estimation at maximum frame rates, the proposed approach relies only on single unfocused acquisitions to reconstruct consecutive frames and on two consecutive frames only to obtain 2-D displacement estimates. The primary goal of this work was to assess whether the diffraction artifact reduction and speckle restoration capabilities of our CNN-based image reconstruction method [17] could allow accurate estimation of displacements in zones initially shadowed by GL, SL, and EW artifacts. This work was conducted in the context of PW imaging with a linear transducer array (Section II). The accuracy of proposed approach was evaluated both in numerical and in in vivo experiments, and was compared with a state-of-the-art coherent plane wave compounding (CPWC)-based displacement estimation approach (Section III). Results, implications, and limitations of the experiments carried out are analyzed and discussed in Sections IV and V, respectively. Concluding remarks are given in Section VI.

II. MATERIALS AND METHODS

A. Imaging Configurations

We considered a US acquisition system composed of a 9L-D transducer (GE Healthcare, Chicago, Illinois, USA) and a Vantage 256 system (Verasonics, Kirkland, WA, USA), identical to the one considered in [17]. Relevant imaging configuration parameters are summarized in Table I. The 9L-D is a 192-element linear transducer array with a center frequency of 5.3 MHz and a bandwidth of 75% (at −6 dB). A typical speed of sound in soft tissue of 1540 m/s was assumed, resulting in an element spacing (i.e. pitch) of ∼0.78λ at that frequency. Note that, as a result, images reconstructed with this transducer in the context of ultrafast imaging by conventional DAS algorithms will inevitably be contaminated by GL artifacts. All pulse-echo measurements were carried by transmitting a single-cycle tri-state waveform of 67% duty cycle centered at 5.208 MHz, with leading and trailing equalization pulses of quarter-cycle durations and opposite polarities. The received echo signals were sampled at 20.833 MHz, guaranteeing a Nyquist sampling rate up to a bandwidth of 200%. To reconstruct images up to a depth of 60 mm, we considered a maximum pulse repetition frequency (PRF) of 9 kHz.

All image reconstruction methods considered in this study rely on PW acquisitions performed without transmit apodization. Single PW acquisitions with normal incidence were used for the proposed CNN-based image reconstruction method (Section II-B), and steered PW acquisitions were used for CPWC-based
TABLE I

| Parameter                  | Value                        |
|----------------------------|------------------------------|
| Center frequency           | 5.3 MHz                      |
| Bandwidth                  | 75%                          |
| Aperture                   | 43.93 mm                     |
| Element number             | 192                          |
| Pitch                      | 230 µm                      |
| Element width              | 207 µm                      |
| Element height             | 6 mm                        |
| Elevation focus            | 28 mm                       |
| Transmit frequency         | 5.208 MHz                    |
| Excitation cycles          | 1                            |
| Sampling frequency         | 20.833 MHz                   |

\(^a\) Guessed (no official data available).

\(^b\) Single excitation cycle with equalization pulses.

comparison methods (Section II-C). For each transmit-receive event, echo signals were recorded on all transducer elements (i.e., full aperture).

B. CNN-Based Image Reconstruction Method

To obtain high-quality images from single-shot unfocused acquisitions, we relied on our CNN-based image reconstruction method proposed in [17], briefly summarized hereafter.

The method consists of first reconstructing a (vectorized) low-quality estimate \( \tilde{x} \in \mathbb{R}^n \) from the (vectorized) transducer elements measurements \( y \in \mathbb{R}^m \), obtained from a single unfocused sonification, by means of a backprojection-based DAS operator \( D : \mathbb{R}^m \rightarrow \mathbb{R}^n \) as \( \tilde{x} = Dy \). The operator \( D \) is composed of the adjoint of a linear measurement model (backprojection) and a pixel-wise reweighting operator (image equalization). The measurement model is based on linear acoustics and is derived from the spatial impulse response (SIR) model [22], assuming far-field approximation both for the transmitter (e.g., ideal wavefront) and the receiver (e.g., narrow transducer element), an ideal Dirac pulse-echo wavefront, and neglecting tissue attenuation. Before summation, measurement values were interpolated using a B-spline approximation of order three [23]. Analytic (complex) images, also called in-phase quadrature (IQ) images, were reconstructed on a \( \lambda/4 \times \lambda/8 \) (Cartesian) grid, with a width spanning the 9L-D aperture (Table I) and a depth from 1 mm to 60 mm. The image grid resolution was chosen to guarantee Nyquist sampling of radio frequency (RF) content of US images in both dimensions, resulting in images of 596 × 1600 pixels. The process was implemented with PyUS,\(^1\) a graphics processing unit (GPU)-accelerated Python package for US imaging developed in our laboratory.

In a second step, the low-quality estimate \( \tilde{x} \) is fed to a CNN \( f_\theta : \mathbb{R}^n \rightarrow \mathbb{R}^n \), with parameters \( \theta \), trained to recover a high-quality estimate as \( x = f_\theta(\tilde{x}) \), with strongly reduced diffraction artifacts and well-preserved speckle patterns. The CNN architecture is based on the popular U-Net [24] and on [25], with several improvements such as the use of residual convolutional blocks (RCBs) and additive intrinsic skip connections [17]. It is a residual CNN with multi-scale and multi-channel filtering properties, composed of 2-D convolutional layers (CLs) and rectified linear units (ReLUs) arranged in symmetric downsampling and upsampling paths. As real-time displacement estimation was not a primary goal of this work, we used the best-performing CNN architecture analyzed in [17], with 32 initial expansion channels. The CNN was trained precisely as detailed in [17], namely in a supervised manner using a dataset composed of 30 000 simulated image pairs (i.e., input and ground-truth). The well-known Adam optimizer [26] was used to minimize the mean signed logarithmic absolute error (MSLAE) loss, introduced in [17] to account for both the high dynamic range (HDR) and the RF property of US images. A total of 500 000 iterations were performed with a batch size of 2 and a learning rate of \( 5 \times 10^{-5} \). The same training dataset of simulated images was used. It is composed of low-quality input images reconstructed from single PW acquisitions with normal incidence. High-quality reference images were reconstructed from the complete set of synthetic aperture (SA) acquisitions using a spatially-oversampled version of the transducer array to ensure the absence of GL artifacts (only possible in a simulation environment). To reconstruct both input and reference images, element raw-data were simulated using an in-house 3-D SIR simulator, validated against the well-known Field II simulator [27]. Each numerical phantom was composed of random scatterers with a density that ensured fully-developed speckle patterns throughout the resulting images. The simulated images composing the training dataset are characterized by overlapping ellipsoidal zones of random size, position, and orientation, with mean echogenicitics spanning an 80-dB range.

C. Comparative Image Reconstruction Methods

For the CPWC-based comparison methods, acquisitions to reconstruct consecutive frames consisted of sequential transmit-receive events of \( N_a \) differently steered PWs, fired at maximum PRF. The PW steering angle spacing was evaluated as [7], [13]

\[
\Delta \beta = \arcsin \left( \frac{\lambda}{L} \right) \approx 0.38^\circ ,
\]

where \( \lambda \) is the wavelength of transmit excitation and \( L \) is the transducer aperture. We restricted ourselves to odd acquisition numbers, thus the linearly increasing sequence of steering angles can be expresses as

\[
\beta_n = n \Delta \beta , \quad n = -M, -M + 1, \ldots, 0, \ldots, M - 1, M ,
\]

where \( M = (N_a - 1)/2 \). We deployed an alternate steering angle sequence \((-\beta_M, \beta_M, -\beta_{M-1}, \beta_{M-1}, \ldots, -\beta_1, \beta_1, 0)\), as proposed in [13].

In particular, we considered single PW acquisitions with normal incidence, used both with the proposed CNN-based image reconstruction method and with DAS beamforming, as well as sequences of 3, 9, 15, and 87 steered PW acquisitions used with DAS beamforming. Comparison DAS-based methods are denoted CPWC-1, CPWC-3, CPWC-9, CPWC-15, and CPWC-87. The parameters for each imaging acquisition sequence considered are summarized in Table II. The CPWC-87 was used for reference purposes only, in settings not suffering

\(^1\)https://gitlab.com/pyus/pyus
Also, images obtained from CPWC-1 are identical to input with an F-number $F$ (B-spline interpolation) using the estimated displacements to (PIV). Speckle tracking is fundamentally linked to PIV. How-

To evaluate the accuracy of displacement estimates throughout the experiments, we relied on the well-known endpoint error (EPE), a quality metric commonly used in flow estimation techniques [38], [39]. Considering a vector displacement estimate $\hat{u} \in \mathbb{R}^2$ and its true counterpart $u \in \mathbb{R}^2$, the EPE can be expressed as

$$EPE = \| \hat{u} - u \|_2,$$

where $\| \cdot \|_2$ represents the Euclidean norm. We also relied on a normalized version of EPE, denoted relative endpoint error

### Table II

| Method   | $N_a$ | $\Delta \beta$ | $\beta_M$ | Type          | Frame Rate |
|----------|-------|-----------------|-----------|---------------|------------|
| CNN      | 1     | $\times^a$     | $\times^a$ | $\times^a$    | 9 kHz      |
| CPWC-1   | 1     | $\times^a$     | $\times^a$ | $\times^a$    | 9 kHz      |
| CPWC-3   | 3     | 0.38°          | $\times^a$ | $\times^a$    | 9 kHz      |
| CPWC-9   | 9     | 1.52°          | $\times^a$ | $\times^a$    | 9 kHz      |
| CPWC-15  | 15    | 2.66°          | $\times^a$ | $\times^a$    | 9 kHz      |
| CPWC-87  | 87    | 16.34°         | $\times^a$ | $\times^a$    | 9 kHz      |

$^a$Single PW with normal incidence.
(REPE), which is expressed as

\[
\text{REPE} = \frac{\|\hat{u} - u\|_2}{\|u\|_2}.
\]  

(5)

### III. Experiments

We conducted two experiments (numerical and in vivo) to assess the performance of the proposed 2-D displacement estimation approach, which combines our CNN-based image reconstruction methods [17] (Section II-B) to reconstruct consecutive frames with single PW acquisitions and the deployed speckle tracking algorithm (Section II-D). In both experiments, we compared the proposed CNN-based displacement estimation method to CPWC-based tracking, which consists of applying the same speckle tracking algorithm to consecutive frames reconstructed using conventional CPWC (Section II-C). For CPWC, a larger number of compounded acquisitions results, in the absence of motion artifacts, in better image quality and consequently in improved displacement estimation, at the cost of a reduced achievable frame rate. Thus, by studying different numbers of compounded acquisitions (Table II) we compared the proposed approach to multiple levels of displacement estimation accuracy.

#### A. Numerical Experiment

For the first experiment, we used computer simulations to control the motion pattern, the relative echogenicities of tissue-mimicking structures, and the diffraction artifact levels precisely. The goal was to show the quality of displacement tracking that can be achieved using the proposed method in rapidly moving, highly heterogeneous tissue, where strong diffraction artifacts hinder proper motion analysis with conventional CPWC-based tracking. All simulations were conducted using the same SIR simulator used to generate the training dataset (Section II-B).

We designed a dynamic numerical test phantom composed of scatterers randomly positioned within four cylinders [A, B, C, and D in Fig. 1(a)], embedded in an anechoic background. Each cylinder has a radius of 6.86 mm and a height of 1.0 mm, the latter corresponding to the resolution cell size in elevation evaluated for the imaging configuration considered [17]. Within each of the four zones, an average of ten scatterers per resolution cell was used to ensure fully-developed speckle patterns in the resulting images [40, Sec. 8.4.4]. The cylinders were centered such that cylinder A spawns distinct and spatially separable diffraction artifacts onto cylinders B, C, and D. Cylinders B, C, and D were positioned such that they are maximally covered by EW, SL, and GL artifacts, respectively [Fig. 1(b)]. The mean amplitudes of scatterers located within cylinders B, C, and D were chosen to blend in with the amplitude of EW, SL, and GL artifacts arising from cylinder A [Fig. 1(b)]. Specifically, the mean amplitudes in cylinders A, B, C, and D were set to 20 dB, −20 dB, −20 dB, and 0 dB with respect to an arbitrary 0 dB reference, respectively. Between successive simulated transmit-receive events, the scatterers were rotated with a constant counter-clockwise angular velocity around the center of the cylinder within which they are positioned. The same angular velocity was used for all cylinders.

**TABLE III**

| Method     | Frame Rate | Large Ranges | Small Ranges |
|------------|------------|--------------|--------------|
|            | D. (µm)    | V. (cm/s)    | D. (µm)      | V. (cm/s)    |
| CNN        | 9 kHz      | 33–600       | 29.7–540     | 3.3–60       | 2.97–54      |
| CPWC-1     | 9 kHz      | 33–600       | 29.7–540     | 3.3–60       | 2.97–54      |
| CPWC-3     | 3 kHz      | 33–600       | 9.9–180      | 3.3–60       | 0.99–18      |
| CPWC-9     | 1 kHz      | 33–600       | 3.3–60       | 3.3–60       | 0.33–6       |
| CPWC-15    | 0.6 kHz    | 33–600       | 2.0–36       | 3.3–60       | 0.20–3.6     |

This experiment was designed to evaluate the accuracy of displacement estimates, obtained using the same speckle tracking algorithm on consecutive frames reconstructed with the different image reconstruction methods considered, within prescribed inter-frame displacement ranges. Inter-frame displacements ranging from 3.3 µm to 600 µm (i.e. approximately from 1/10 to 2.1) were analyzed, covering a range from the small displacements that typically occur in shear-wave elastography [7] or acoustic radiation force imaging [41], up to the large displacements that typically occur in external compression-based elastography [41]. Furthermore, when analyzed at a frame rate of 9 kHz, these ranges correspond to velocities up to 5.4 m/s, which are close to the peak velocities inside the cardiovascular system [42]. To this end, two different sets of numerical phantoms were simulated for each image reconstruction method considered and associated frame rate, covering two inter-frame displacement ranges, namely 3.3 µm to 60 µm and 33 µm to 600 µm. The respective angular velocities were determined such that the maximum inter-frame displacement occurred at a radius of 6.5 mm. The resulting border of 0.36 mm was used to avoid speckle tracking border effects in the quality evaluation. It corresponds to the approximate average resolution cell size in the transducer plane. A similar zone was ignored in the center of each cylinder. Displacement ranges and corresponding cross-radial velocity ranges are made explicit in Table III for each image reconstruction method considered.

Inter-frame displacements were estimated using the proposed CNN-based approach, as well as CPWC-1, CPWC-3, CPWC-9, and CPWC-15 at their respective maximum frame rates. For all test configurations considered (i.e. method and displacement range), 50 statistically independent scatterer realizations were simulated, resulting in 50 inter-frame displacement estimate maps for each configuration. The accuracy of each method was measured locally in terms of REPE, by computing (5) for each displacement estimate (grid point) and corresponding true (analytical) value. The mean local REPE was also computed over the 50 independent realizations (in each displacement estimate grid point).

#### B. In Vivo Experiment

For the second experiment, we applied the proposed approach to in vivo acquisitions, to analyze the natural tissue motion around the carotid artery. The goal of this experiment was to test the robustness and translatability of the results obtained in the numerical experiment to the full complexity of in vivo acquisitions. To assess the performance of the proposed 2-D displacement estimation approach, which combines our CNN-based image reconstruction methods [17] (Section II-B) to reconstruct consecutive frames with single PW acquisitions and the deployed speckle tracking algorithm (Section II-D). In both experiments, we compared the proposed CNN-based displacement estimation method to CPWC-based tracking, which consists of applying the same speckle tracking algorithm to consecutive frames reconstructed using conventional CPWC (Section II-C). For CPWC, a larger number of compounded acquisitions results, in the absence of motion artifacts, in better image quality and consequently in improved displacement estimation, at the cost of a reduced achievable frame rate. Thus, by studying different numbers of compounded acquisitions (Table II) we compared the proposed approach to multiple levels of displacement estimation accuracy.
imaging. As the natural motion induced by cardiac pulsations is slow, it allowed us to obtain reference inter-frame displacement estimates, at maximum PRF. For the methods to be compared, the analysis was performed at a low frame rate, selected to result in inter-frame displacement ranges of interest.

We analyzed the slow-moving tissue between the skin and the carotid artery of a healthy volunteer. In particular, motion within a specific tissue region of size $5 \times 5 \text{ mm}$ (Fig. 3) was analyzed at 10 Hz, resulting in inter-frame displacements similar to those studied in the numerical experiment (Section III-A), namely ranging from $5 \mu\text{m}$ to $125 \mu\text{m}$ approximately. Therefore, identical speckle tracking settings were used (Section II-D). Speckle tracking was performed on full images, but we restricted our analysis to a specific zone characterized by fully-developed speckle patterns, plagued by diffraction artifacts mainly originating from the highly echogenic carotid walls when imaged using CPWC-1 [Fig. 3(a)]. The mean echogenicity of the analyzed speckle zone was approximately $20 \text{ dB}$ lower than the echogenicity of the carotid walls, thus similar to the relative echogenicity between cylinders A and D studied in the numerical experiment.

To obtain reference displacement estimates of the image zone considered, we reconstructed consecutive frames using CPWC-87 (Table II). As compounded acquisitions were performed at a PRF of $9 \text{ kHz}$, inter-frame displacements were negligible. Hence, consecutive frames reconstructed using CPWC-87 were considered free of motion artifacts and displacement estimates obtained by speckle tracking were considered as reference. We compared displacement estimates obtained using the proposed approach with the ones obtained using CPWC-1 and CPWC-15. For each method being compared, consecutive frames were reconstructed using the relevant subset of steered PW acquired for the reference CPWC-87 method (Section II-C). Therefore, CPWC-15 was also free of any motion artifacts.

A total of 30 frames were obtained at a frame rate of $10 \text{ Hz}$ from acquisitions performed at a PRF of $9 \text{ kHz}$ resulting in 29 inter-frame displacement estimate maps. For each inter-frame displacement estimate map, the accuracy of each method was measured locally in terms of EPE, by computing (4) for each displacement estimate (grid point) and corresponding reference value (CPWC-87). The quality of the displacement estimates for each frame-pair was assessed by computing the mean endpoint error (MEPE) obtained within the region of interest.

### IV. Results

#### A. Numerical Experiment

Fig. 2 displays local REPE values, averaged over the 50 independent realizations performed in each configuration considered (Section III-A). To facilitate the analysis, we deemed as invalid any displacement estimate resulting in an averaged local REPE value exceeding $100 \%$. From each set of valid estimates we computed two global evaluation metrics, namely the ratio of valid estimates (RVE) and the mean relative endpoint error (MREPE). These global evaluation metrics are reported in Table IV.

Zone A was designed such that it did not suffer from diffraction artifacts and could be used to assess displacement estimation in pure speckle zones. In the large-displacement case [Fig. 2(a)], CPWC-based tracking suffered from increasing motion artifacts with the number of compounded acquisitions when tracking identical inter-frame displacements (i.e., at decreasing frame rates), reaching a stable motion artifact level after nine compounded acquisitions. The proposed method performed best and improved over CPWC-1 both in terms of local and global metrics. In the small-displacement case [Fig. 2(b)] motion artifacts were negligible and all methods performed efficiently. A typical comparison of CPWC with and without motion artifacts is shown in Fig. 1(d) and 1(e) for CPWC-9.

Zone B was designed to suffer from EW artifacts. The proposed method was not capable of restoring speckle patterns shadowed by EW artifacts accurately, resulting in performance metrics only slightly improved compared with CPWC-1. Inaccurate restoration of speckle patterns plagued by EW artifacts can be observed in Fig. 1(c) (e.g., clipped values). These artifacts could only be progressively resolved in the small displacement case [Fig. 2(b)] with the increase in compounded acquisitions, because of the absence of motion artifacts.

Zone C was designed to suffer from SL artifacts. In the large displacement case [Fig. 2(a)], the reduction in SL artifacts achieved by compounding several acquisitions was counteracted by the induced motion artifacts, except in zones of pure lateral movement, making proper tracking impossible using
CPWC-based tracking. The proposed method was capable of properly estimating displacements, with a quality only slightly worse than in artifact-free zone A. In the small displacement case [Fig. 2(b)], CPWC-based tracking was improved with the increase in compounded acquisitions, thanks to a more efficient SL reduction than with motion artifacts. The proposed method achieved a quality slightly worse than CPWC-15 but significantly better than CPWC-9.

Zone D was designed to suffer from GL artifacts, that increase in strength towards the right edge of the image. In the large displacement case [Fig. 2(a)], compounding multiple acquisitions reduced GL artifacts. Yet, motion artifacts prevented accurate displacement estimation except in zones of pure lateral movement. The proposed method significantly improved the displacement estimation quality over CPWC-1 and was the only method to allow tracking displacements in this case. In the small displacement case [Fig. 2(b)], the increase in compounded acquisitions allowed CPWC-based tracking to reduce the effect of GLs and restore the underlying speckle patterns, progressively resulting in an increased RVE with higher MREPE. The proposed method performed slightly better than CPWC-15.

### TABLE IV

**Global Evaluation Metrics of the Numerical Experiment**

| Zone | Metric | Large Displacement Range | Small Displacement Range |
|------|--------|--------------------------|--------------------------|
|      |        | CPWC-1 | CPWC-3 | CPWC-9 | CPWC-15 | CNN | CPWC-1 | CPWC-3 | CPWC-9 | CPWC-15 | CNN |
| A    | RVE\(^a\) (%) | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
|      | MREPE\(^b\) (%) | 4.45  | 7.24  | 12.99 | 12.84 | 3.62  | 7.34  | 6.91  | 5.25  | 4.36  | 5.81  |
| B    | RVE (%) | 63.00 | 69.58 | 63.10 | 68.96 | 74.41 | 57.76 | 73.79 | 99.38 | 99.69 | 67.42 |
|      | MREPE (%) | 19.67 | 29.41 | 39.53 | 38.35 | 19.83 | 18.79 | 25.58 | 26.15 | 19.08 | 18.19 |
| C    | RVE (%) | 85.27 | 77.59 | 51.56 | 65.15 | 100.00 | 29.25 | 81.64 | 100.00 | 100.00 | 100.00 |
|      | MREPE (%) | 52.82 | 45.91 | 41.98 | 38.35 | 4.98  | 39.36 | 36.28 | 17.64 | 8.29  | 9.61  |
| D    | RVE (%) | 44.59 | 44.08 | 34.81 | 49.74 | 100.00 | 22.14 | 42.02 | 82.29 | 99.69 | 99.59 |
|      | MREPE (%) | 36.54 | 46.38 | 50.94 | 41.80 | 5.51  | 47.61 | 45.12 | 36.41 | 17.54 | 15.25 |

\(^a\)Ratio of valid estimates (RVE); an estimate was considered valid when its local REPE was below 100 %.

\(^b\)Mean relative endpoint error (MREPE) evaluated from the set of valid estimates.

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**B. In Vivo Experiment**

From the example images and corresponding displacement estimates [Fig. 3(a) to 3(d)], one can observe that CPWC-1 suffers from diffraction artifacts (mainly caused by GLs and SLs arising from the carotid walls), disturbing both the speckle patterns and the resulting displacement estimates. These artifacts were strongly reduced using CPWC-15, leading to speckle patterns similar to the reference ones (CPWC-87), resulting in accurate displacement estimates. The proposed CNN-based imaging approach also reduced these artifacts, restoring the underlying speckle patterns accurately. This resulted in local displacement estimates with a quality similar to that obtained with CPWC-15.
The analysis of the MEPE values over time [Fig. 3(f)] shows that, while CPWC-1 was generally unable to estimate inter-frame motion properly, the proposed method resulted in high and stable displacement estimation quality, similar (though slightly worse) to CPWC-15. This observation matches the results of the numerical experiments for small-displacements case (see Section IV-A). Over the entire sequence a MEPE of 41.8 µm, 7.5 µm, and 11.1 µm was achieved using CPWC-1, CPWC-15, and the proposed method, respectively. As the reference mean displacement over time was 64.8 µm, this corresponds to error percentages of 65%, 12%, 17% for CPWC-1, CPWC-15, and the proposed method, respectively.

V. DISCUSSION

In this work, we proposed a 2-D motion estimation approach based on single unfocused acquisitions to reconstruct consecutive frames and on pairs of consecutive frames to estimate local displacements. This approach relies on our CNN-based image reconstruction method [17] to reconstruct full-view US frames from single unfocused acquisitions. It consists of first reconstructing low-quality images using a backprojection-inspired DAS algorithm and then feeding them to a CNN, specifically trained to reduce diffraction artifacts inherent to ultrafast US imaging. Inter-frame displacements are estimated by applying a state-of-the-art 2-D speckle algorithm on consecutive-frame pairs only.

A. Performance in Numerical Conditions

An important observation was that the proposed approach could not estimate displacements accurately in zones dominated by EW artifacts (Fig. 2, zone B). This is directly related to the fact that the CNN deployed is not capable of restoring the underlying speckle patterns accurately [Fig. 1(c)]. Slight improvements were observed compared with conventional single PW imaging (CPWC-1), but far less striking than in zones dominated by SL and GL artifacts (Fig. 2, zones C and D). In [17] we already observed that EW artifacts were the most difficult artifacts to deal with, but also that the restoration quality improved with the increase of the CNN capacity. The latter implies that the reduction of these artifacts might be further improved using a more efficient CNN-architecture or training process.

When analyzing large displacements, we observed that compounding multiple acquisitions in an attempt to improve the obtained image quality induces strong motion artifacts, mainly due to destructive interferences caused by axial motion. In the presence of motion artifacts, conventional CPWC-based speckle tracking was generally incapable of providing valid displacement estimation, in particular in zones plagued by strong diffraction artifacts. Consequently, compounding multiple acquisitions decreased the displacement estimation quality compared with single PW acquisitions (CPWC-1). While motion compensation techniques have been proposed to tackle this issue [16], it remains unclear if motion-compensated coherent compounding can be deployed in zones plagued by diffraction artifacts (as it is based on inter-acquisition motion estimation), and if it actually improves displacement estimation quality in artifact-free zones compared with single unfocused acquisitions. We demonstrated that the proposed single PW CNN-based approach is capable of providing high-quality displacement estimates in artifact-free zones, as well as in zones plagued by SL and GL artifacts.

In the case of small displacements, increasing the number
of compounded acquisitions using CPWC-based tracking progressively increased, as expected, the accuracy of displacement estimation. The proposed CNN-based approach achieves a displacement estimation quality comparable to CPWC-15 in zones suffering from SL and GL artifacts and comparable to CPWC-9 in artifact-free zones. It can be noted that the relative estimation precision achieved by the proposed approach was generally worse when analyzing small inter-frame displacements than in larger displacement cases. This was also observed for conventional CPWC-based tracking in artifact-free zones [e.g. compare CPWC-1, zone A in Fig. 2(a) and 2(b)]. This mainly comes from the fact that the minimum estimation error of correlation-based tracking converges to a minimum value (Cramér-Rao lower bound), which, relatively speaking, becomes more significant for smaller displacements [41]. For quantifying very small displacements, applying speckle tracking to RF data instead of envelope data may improve precision [33], [35, Sec. 14.2.1], at the expense of a reduced robustness to speckle decorrelation.

B. Performance in Physical Conditions

We demonstrated that the proposed CNN-based approach, which rely on single PW acquisitions, significantly improved over conventional single PW imaging (CPWC-1). It also achieved an accuracy of inter-frame displacement estimation similar to that of 15 compounded acquisitions (CPWC-15), in conditions where motion artifacts were negligible. Overall, the quantitative evaluations performed in the in vivo experiment were comparable to those of the numerical experiment in the absence of motion artifacts. This does not only show that the proposed method can be applied to in vivo data successfully, even though the CNN used for image reconstruction was trained on simulated data only, it also suggests that the results of the numerical experiments are robust and translatable (to some extent) to experimental conditions.

It should be noted that the experiment was intentionally carried out on a slow moving tissue zone. This allowed us to obtain reference displacement estimates for evaluation purposes, and to select a frame rate, identical for all methods considered, resulting in inter-frame displacements within the ranges of interest. However, as speckle tracking is agnostic to the underlying frame rate, the results are fully translatable to fast motion cases, analyzed at higher frame rates, with similar inter-frame displacement ranges, provided that the desired frame rate is achievable by the method deployed.

C. Potential, Perspectives, and Limitations

The proposed approach is able to provide high-quality estimates for a wide range of 2-D inter-frame displacements, even in tissue regions dominated by SL and GL artifacts. As it only relies on single unfocused acquisitions to reconstruct consecutive frames, it is immune to motion artifacts. Moreover, it is limited only by the propagation time of acoustic waves, making it especially interesting for the analysis of rapidly changing events at very high frames rates, such as the propagation of shear waves in tissue or complex flow patterns within the cardiovascular system, where displacement estimation techniques based on multi-acquisition image reconstruction methods may not be deployable.

The major limitation is that the current implementation of the proposed approach was not able to provide accurate displacement estimates in regions dominated by EW artifacts, most probably because these artifacts closely resemble speckle patterns. Both the EW behavior and the general performance of the approach might be further improved by augmenting the performance of the CNN used for image reconstruction. For instance, the use of a higher-capacity CNN or a more efficient training process may improve the restoration of tissue structures hidden by EW artifacts. Another way to tackle this limitation would be to use transmit apodization [43]. This technique can significantly reduce EW artifacts, at the cost of limited energy towards the image borders. However, its effectiveness is limited by the apodization-capability of US system, in particular by the transmitter complexity. If the method is not used at maximum achievable frame rate, and in the presence of sufficiently stationary motion, the robustness and precision of the displacement estimation could be improved such as by averaging multiple displacement estimates or by using ensemble correlation [28].

This study was limited to tracking fully-developed speckle patterns, hence no insights about tracking tissue structures arising from specular or diffractive scattering should be drawn from it directly. Yet, carotid-wall movement was observed to be similar to that of conventional methods (see animation of Fig. 3, supplementary material). The training set was also limited to simulated images of fully-developed speckle zones resulting from diffusive scattering, and in [17] we observed that while reconstructing other tissue structures is generally possible, the performance may be less potent than in fully-developed speckle zones. Using a versatile training set may be considered to widen the applicability of both the reconstruction approach and the displacement tracking method proposed here.

On a more general perspective, this work further validates the potency of the CNN-based image reconstruction method introduced in [17]. Indeed, this method not only provides high-quality images from single unfocused acquisitions, but also preserves the information of underlying physical phenomena that can be further exploited for estimating inter-frame displacements accurately.

VI. Conclusion

In this work we proposed an approach for estimating 2-D inter-frame displacements in the context of ultrafast US imaging. The approach consists of a CNN trained to restore high-quality images from single unfocused acquisitions and a speckle tracking algorithm to estimate inter-frame displacements from two consecutive frames only. Compared with conventional multi-acquisition strategies, this approach is immune to motion artifacts and allows accurate motion estimation at maximum frames rates, even in highly heterogeneous tissues prone to strong diffraction artifacts. Numerical and in vivo results demonstrated that the proposed approach is capable of estimating displacement vector fields from single PW acquisitions accurately, including in zones initially hidden by SL and GL
artifacts. The proposed approach may thus unlock the full potential of ultrafast US, with direct applications to imaging modes that depend on accurate motion estimation at maximum frame rates, such as shear-wave elastography or ultrasonic echocardiography.

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