

Real-Time Passive Acoustic Mapping Using Sparse Matrix Multiplication

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Abstract—Passive acoustic mapping enables the spatiotemporal monitoring of cavitation with circulating microbubbles during focused ultrasound (FUS)-mediated blood–brain barrier opening. However, the computational load for processing large data sets of cavitation maps or more complex algorithms limit the visualization in real-time for treatment monitoring and adjustment. In this study, we implemented a graphical processing unit (GPU)-accelerated sparse matrix-based beamforming and time exposure acoustics in a neuronavigation-guided ultrasound system for real-time spatiotemporal monitoring of cavitation. The system performance was tested *in silico* through benchmarking, *in vitro* using nonhuman primate (NHP) and human skull specimens, and demonstrated *in vivo* in NHPs. We demonstrated the stability of the cavitation map for integration times longer than 62.5 μ s. A compromise between real-time displaying and cavitation map quality obtained from beamformed RF data sets with a size of $2000 \times 128 \times 30$ (axial pixels \times lateral pixels \times samples) was achieved for an integration time of 1.44 μ s, which required a computational time of 0.27 s (frame rate of 3.7 Hz) and could be displayed in real-time between pulses at PRF = 2 Hz. Our benchmarking tests show that the GPU sparse-matrix algorithm processed the RF data set at a computational rate of $0.03 \pm 0.01 \mu$ s/pixel/sample, which enables adjusting the frame rate and the integration time as needed. The neuronavigation system with real-time implementation of cavitation mapping facilitated the localization of the cavitation activity and helped to identify distortions due to FUS phase aberration. The *in vivo* test of the method demonstrated the feasibility of GPU-accelerated sparse matrix computing in a close to a clinical condition, where focus distortions exemplify problems during treatment. These experimental conditions show the need for spatiotemporal monitoring of cavitation with real-time capability that enables the operator to correct or halt the sonication in case substantial aberrations are observed.

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I. INTRODUCTION

FOCUSED ultrasound (FUS) can drive microbubble-seeded cavitation that enhances drug delivery through the blood–brain barrier (BBB)—a semipermeable structure of the brain vasculature that prevents drug uptake into the central nervous system [1]. FUS-induced cavitation can transiently and locally disrupt the BBB [2] via transcytosis, tight junction opening, and inhibition of active transport proteins in the brain endothelial cells [3]–[5]. Preclinical studies have demonstrated the potential of FUS-mediated BBB opening to deliver variable-sized molecules such as antibody-based anticancer agents [6]–[8], anti-amyloid antibodies [6], [9], [10], brain-derived neurotrophic factor [11]–[13], adeno-associated viruses [14], [15], and stem cells [16]. Currently, clinical studies are assessing the safety and feasibility of the technique for the treatment of Alzheimer’s disease [17] and glioblastoma [18].

Passive cavitation detection (PCD) using single-element transducers has been used to monitor potential harmful cavitation regime in real-time in open-loop and closed-loop systems [19]–[22] inside and outside the magnetic resonance imaging (MRI) scanner [23], [24]. However, single-element PCD limits the monitoring to a temporal analysis, where cavitation activity cannot be resolved spatially. Neuronavigation-guided ultrasound with real-time passive acoustic mapping (PAM) [25] can provide a high precision therapy at lower cost in comparison to magnetic resonance-guided FUS (MRgFUS) systems. The FUS neuronavigation system allows for planning trajectories toward specific brain targets that avoid pre-existent lesions, large vessels, ventricles, and other brain structures to be circumvented while PAM enables spatiotemporal monitoring of cavitation associated with BBB-opening. The spatial mapping of acoustic cavitation recorded by a multielement transducer is reconstructed using delay-and-sum (DAS) beamforming either in the time or frequency domain [26]–[36]. Altogether, this system can help detect beam aberration due to the skull [32], [37], which could be compensated by repositioning the transducer for an efficient

and safe sonication at the prescribed location, especially when multiple sonications are required for covering a larger brain volume.

Modern graphical processing units (GPUs) offer parallel processing designed for high-peak computational throughput in a short period. Previous studies have demonstrated implementations of GPU acceleration, which generated real-time visualization of microbubble activity in the brain at variable frame rates, sample integration times, number of channels, and field-of-view (FOV) (respectively, Collin *et al.* [38]: 5 Hz, 4000 samples, 32 channels, and $40 \times 10 \text{ mm}^2$; Jones *et al.* [37]: 3.3 Hz, 200 samples, 128 channels, and $20 \times 20 \times 20 \text{ mm}^3$; Lyka *et al.* [34]: 3 Hz, N/A samples, 128 channels, and $20 \times 10 \text{ mm}^2$; Lyka *et al.* [39]: 0.25 Hz and 0.625 mHz, 2000 samples, 128 channels, and 660 voxels; Jones *et al.* [40]: 1 Hz, 8000 samples, 256 channels, and $10 \times 10 \times 10 \text{ mm}^3$).

Programmable multiprocessing-unit architectures provide library routines optimized for sparse matrices computations, which improves real-time performance of numerical operations [41], [42]. Data processing with a sparse matrix provides higher performance than a fully sampled matrix because it eliminates operations with zero-valued elements of the matrix. In addition, sparse representation reduces data storage as it stores only the nonzero elements and their row indices. Sparse matrix operations can be accelerated even more when performed in parallel using GPU computing. Sparsity methods have been employed widely in medical imaging [43] to speed up and improve image processing and machine-learning techniques in a variety of imaging methods, such as MRI [44]–[46], digital pathology images [47], [48], computed tomography (CT) [49], [50], and ultrasound [25], [51]–[54].

In this study, we present an implementation of PAM using GPU-accelerated sparse matrix-based beamforming and time exposure acoustics (TEAs) [55], [27], which can be performed in real-time with large maps and short-duration data sets or vice versa. This study builds on prior reports by our group as indicated by Wu *et al.* [25], which employed real-time PAM focusing on the neuronavigation system implementation, where the GPU sparse-matrix implementation was not detailed or compared with other standard methods, and Hou *et al.* [51], where active mapping (harmonic motion imaging using tissue displacement tracking) was employed, but not in passive detection or for microbubble-based therapy monitoring. The novel contributions of this article are the detailed description of the implementation of the sparse matrix-based algorithm for PAM and a benchmarking comparison of the non-sparse and sparse implementations in both CPU and GPU. Tests were performed *in silico* through benchmarking, *in vitro* using skull specimens of human and nonhuman primate (NHP), as well as *in vivo* BBB opening experiments in NHP.

II. MATERIAL AND METHODS

A. Passive Beamforming Algorithm

The passive beamforming algorithm based on TEA [27] was implemented with a conventional 128-channel linear array imaging probe (L7-4, Philips, Bothell, WA, USA; center

frequency: 5.208 MHz). A programmable ultrasound scanner (Vantage 256, Verasonics, Kirkland, WA, USA) recorded the acoustic emissions, with time t , from cavitating bubbles during sonications. The radio frequency (RF) channel data were used to reconstruct the passive cavitation maps using dynamic receive beamforming $[\sum_{n=1}^N S_n(r_n, r, t)]$ and then time-integrated $(\int_0^{T_i} |\cdot|^2 dt)$ over a period T_i defined as the integration time

$$C(r) = \int_0^{T_i} \left| \sum_{n=1}^N S_n(r_n, r, t) \right|^2 dt \quad (1)$$

$$S_n(r_n, r, t) = c_n(t + d(r_n, r)/c) \quad (2)$$

where N is the number of elements in the array, S_n is the channel data for the n th element, r_n is the location of the n th transducer element, r is the location of the pixel to be reconstructed, $c_n[t + d(r_n, r)/c]$ the received cavitation signal for the n th channel after adjusting for the time delay based on the distance between r_n and r , and c is the speed of sound. Skull-specific aberration corrections were not performed.

B. Sparse-Matrix Construction

Although GPU-based sparse matrix beamforming has been described elsewhere [25], [51], its specific implementation and application for TEA-PAM is detailed here. In our previous study, the sparse matrix algorithm was implemented using sequences with short imaging pulses. In contrast, therapeutic pulses used in BBB opening are typically composed of thousands of acoustic cycles. Therefore, the duration of received RF signals during PAM or the total amount of beamformed data is significantly larger than the active imaging described before. The DAS beamforming was accelerated using the fast sparse matrix operation performed on a GPU [Tesla K40 (real-time) or Quadro P6000 (offline processing), NVIDIA, Santa Clara, CA, USA]. All sparse matrix operations were performed in MATLAB (2017b, MathWorks, Natick, MA, USA), which has built-in GPU support for sparse matrices since version 2015a. The computing acceleration was accomplished by implementing the term $\sum_{n=1}^N S_n(r_n, r, t)$ from (1) using a sparse matrix multiplication followed by temporal summation of the squared beamformed RF data. The sparse matrix multiplication can be written as $y = Ax$, where the reconstructed RF data y are the result from the multiplication of A , a sparse matrix associated with the DAS operation, and x , a matrix containing the channel data reshaped into column vectors for each sample of the integration time. The number of rows in A is equal to the total number of pixels in the reconstructed image, which is the product of the lateral map size N_x and the axial map size N_z . The number of columns in A is equal to the product of the number of samples acquired per channel Z , and the number of array elements N . Table I presents all values for the parameters used in this study.

The sparse matrix was built offline prior to the experiments, as it requires minutes-to-hours of calculation. The computational time depends on the number of samples in the acquired channel data, the number of array elements N , as well as the number of pixels in the reconstructed image ($N_x \times N_z$).

TABLE I
PARAMETERS USED FOR GPU-BASED SPARSE MATRIX
MULTIPLICATION IN PASSIVE ACOUSTIC MAPPING

Symbol	Parameter	Value / Units
N_x	Lateral map size	128 pixels
N_z	Axial map size	2,000 pixels
N_T	Integrated samples	10 – 2,000 samples
T_i	Integration time	1.44 – 96.1 μ s
Z	Acquired RF data samples per channel	2,000 samples
N	Number of array elements	128
f_s	Sampling frequency	20.8 MHz
n	Assigned number of transducer element or channel	1-128
l	Iteration number of the standard basis vector	1-256,000

The sparse matrix was designed here using double-precision to compute images of approximately 74 mm (depth, $N_z = 2000$ axial pixels) by 38 mm (width, $N_x = 128$ lateral pixels), with Z equal to 2000 samples acquired by $N = 128$ transducer elements (or channels) at sampling frequency 20.8 MHz (4 times the receiving center frequency of the L7-4 array, which is 5.208 MHz) that can be displayed in real-time once the sparse matrix is built. The sparse matrix needs to be built offline only once and then can just be loaded into memory for real-time beamforming.

The following describes how to build the reconstruction sparse matrix numerically. First, a conventional 3-D matrix representation [Fig. 1(a)] containing the distance D in sample units between each image pixel and transducer element is calculated by

$$D = |\vec{r}_n - \vec{r}|N_w \quad (3)$$

where \vec{r} is the pixel location in the reconstructed image in wavelength units, \vec{r}_n is the location of the n th element in wavelength units, and N_w is the number of samples per wavelength ($N_w = 4$, yielding a sampling frequency four times the center frequency of the receiving array). The speed of sound associated with the wavelength was 1540 m/s, which is equal to the speed of sound in water.

Then, the values in the distance matrix are converted into indices associated with the size of a given data point of channel data provided by Verasonics Vantage (sample segments acquired by each transducer element per frame). The indexed distance [Fig. 1(b)] is given by

$$i(z, x, n) = D(z, x, n) + (n - 1)Z \quad (4)$$

where i is the indexed pixel to element distance in the channel data, and Z is the total depth in sample units, with $Z = 2000$ samples and $n = 1-128$. After that, the DAS operation is performed to compute the matrix $T^l(z, x)$

$$T^l(z, x) = \sum_{n=1}^N ((1 - d(z, x, n)) \cdot B^l(i(z, x, n)) + d(z, x, n) \cdot B^l(i(z, x, n) + 1)) \quad (5)$$

where l is iterated from 1 to 256 000 ($Z \times N$) and

$$d(z, x, n) = \text{mod}[D(z, x, n), 1] \quad (6)$$

where mod is the modulus operator, and B^l is the l th standard basis vector of the 256 000-dimensional Euclidian space, containing zeros everywhere except at the l th position [$B^l(i) = \delta_{il}$, where δ_{il} is the Kronecker delta, Fig. 1(c) and (d)]. Finally, the sparse matrix A is allocated with nonzero values obtained from the matrix T^l , which can be obtained in MATLAB using $[k^l, \sim, s^l] = \text{find}(T^l(:))$, where k^l is the vector of indices of nonzero values in T^l , and s^l is the corresponding vector of nonzero values in T^l . The sparse matrix [Fig. 1(e)] is given by

$$A(k^l, l) = s^l. \quad (7)$$

C. Time Exposure Acoustics Real-Time Processing

Once the sparse matrix is loaded in the computer or GPU memory, the RF data can be beamformed in real-time by simply multiplying the sparse matrix by the channel data. This is the only step in the processing where the sparse matrix is used. The acquired data sets comprise 2000 samples per receiving element, that is, a signal duration of 96.1 μ s and a sampling frequency of 20.8 MHz. To acquire data sets with reduced integration times that would accelerate computation, the beamformed time-domain signal was truncated at the relevant sample after $t = 0$. For example, only the first 30 samples were used for an integration time of 1.44 μ s, the first 300 samples for an integration time of 14.4 μ s. An important property of the multiplication using the sparse matrix is that it can be applied regardless of the number of samples, as it refers to a multiplication involving two 2-D matrices [Fig. 2(a)]. Then, the cavitation map is obtained from the TEAs processing [(1)] using the beamformed data [Fig. 2(b)]. Finally, the image is reshaped in 2-D ($N_z \times N_x$) and displayed in real-time [Fig. 2(c)].

D. In Vitro Experiments

The *in vitro* test of the system with and without the skull specimens (NHP and human and parietal bone) was performed in a silicon phantom with a 4-mm-diameter tube where in-house, lipid-shell, monodisperse microbubbles (median diameter: 4–5 μ m, diluted to 2×10^5 bubbles/mL [56], [57]) circulated at a flow rate of 0.25 mL/s using a syringe pump [Fig. 3(a)]. The skull specimens were degassed 24 h before the experiment. A customized MATLAB code controlled a single-element, 0.5-MHz FUS transducer (diameter: 64 mm and focal depth: 62.6 mm; H-107, Sonic Concepts, Bothell, WA, USA) driven by a function generator (model 33220A, Agilent Technologies, Santa Clara, CA) with 50-dB amplification (A075, ENI, NY, USA). A PCD array (L7-4, Philips, Bothell, WA, USA; center frequency: 5.208 MHz, sampling frequency: 20.8 MHz, and channel data length: 2000 samples) and a single PCD transducer (Y-107, Sonic Concepts; sensitivity: 10 kHz–15 MHz, sampling frequency: 50 MHz) were simultaneously used to monitor the cavitation generated using derated peak-negative pressure (PNP): 100–600 kPa, pulse length: 5000 cycles (10 ms), pulse repetition frequency (PRF): 10 Hz, duration: 2 s. The skull specimen was placed between the phantom and the PCD array immediately after

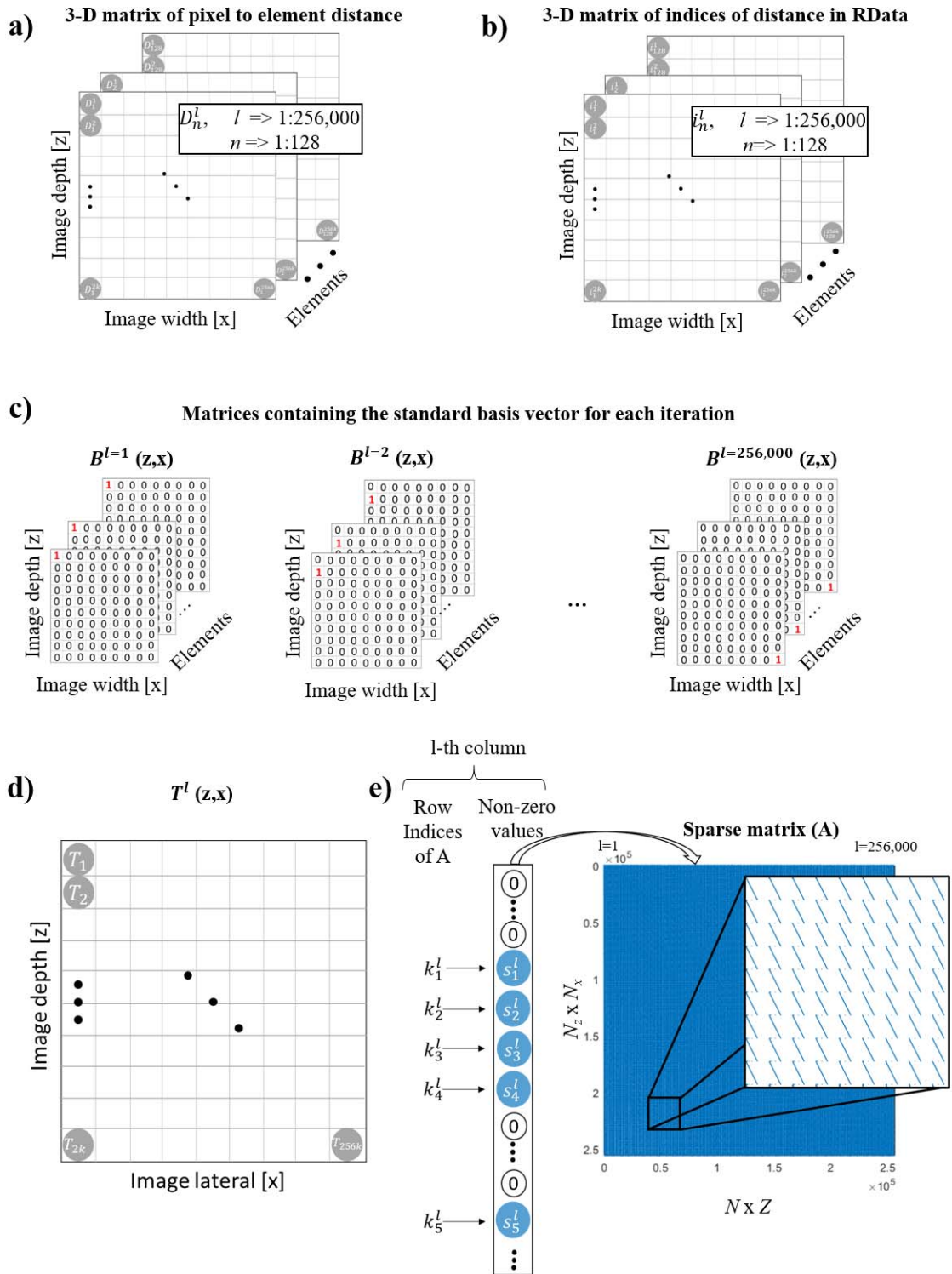


Fig. 1. Sparse matrix construction. (a) 3-D matrix of distance from the pixel to transducer element in sample units calculated for an imaging array with 128 elements, and a reconstructed image of $2000 \times 128 = 256000$ pixels. (b) 3-D matrix of reindexed distance to follow data output by Verasonics Vantage. (c) Standard basis vectors used for the DAS iterative calculation. (d) Matrix resulting from DAS operation on a given standard basis vector. (e) Sparse matrix values allocation following 2-D representation.

280 acquisitions without the skull to assess the skull effects on the
281 PCD data in similar experimental conditions.

282 E. In Vivo NHP Experiments

283 All procedures and experiments with animals were reviewed
284 and approved by the Institutional Animal Care and Use

Committee at Columbia University and the New York State
Psychiatric Institute following the National Institutes of Health
Guidelines for animal research. The *in vivo* experiments were
performed in two male adult macaques (*Macaca mulatta*,
weight: 9–11 kg, age: 18–20 years old). The FUS transducer
was placed on the top of the animal's head using a

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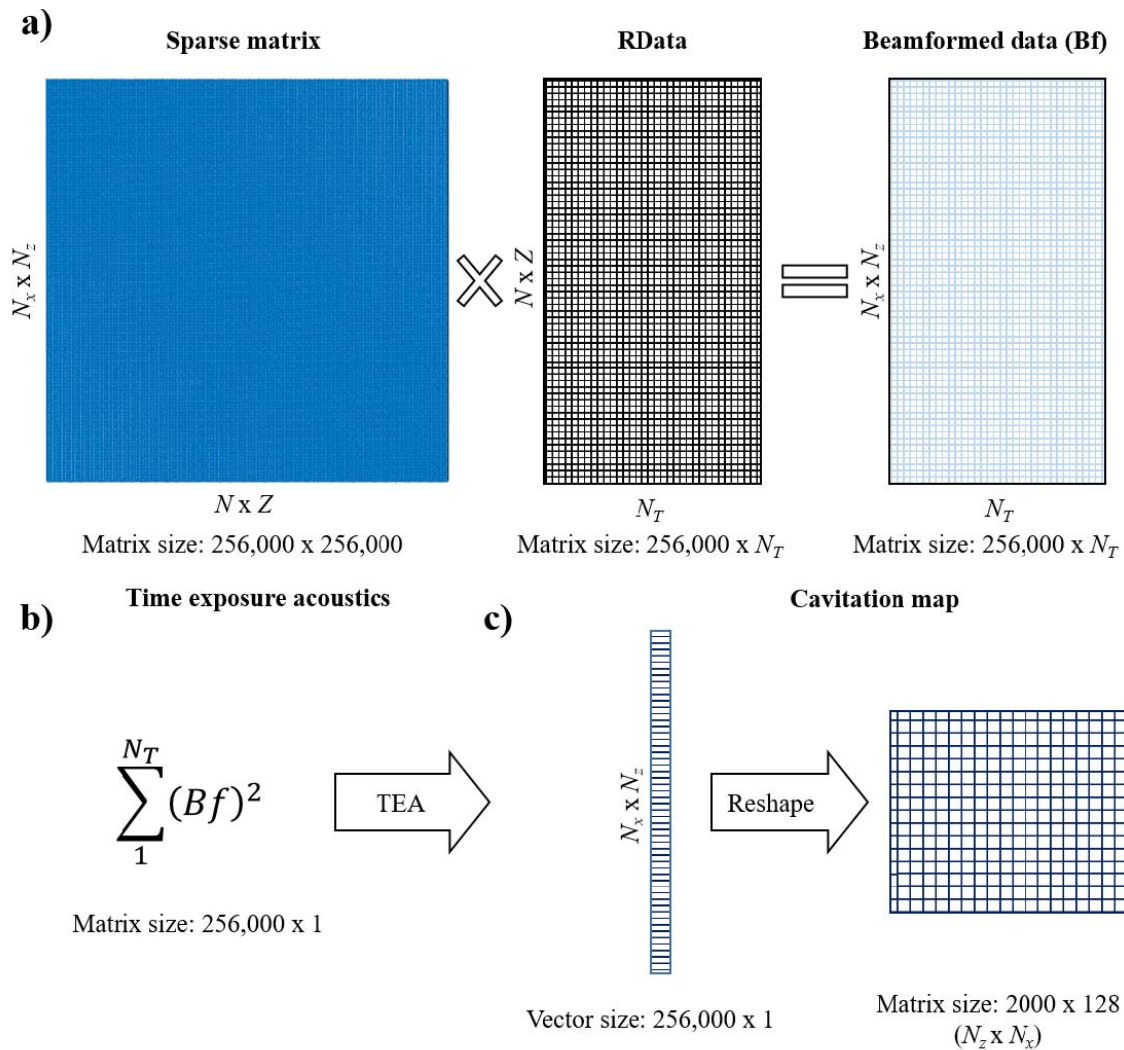


Fig. 2. TEA-PAM real-time algorithm using sparse matrix operation. (a) DAS beamforming algorithm using GPU-accelerated sparse matrix operation. (b) TEA operation. (c) Cavitation maps.

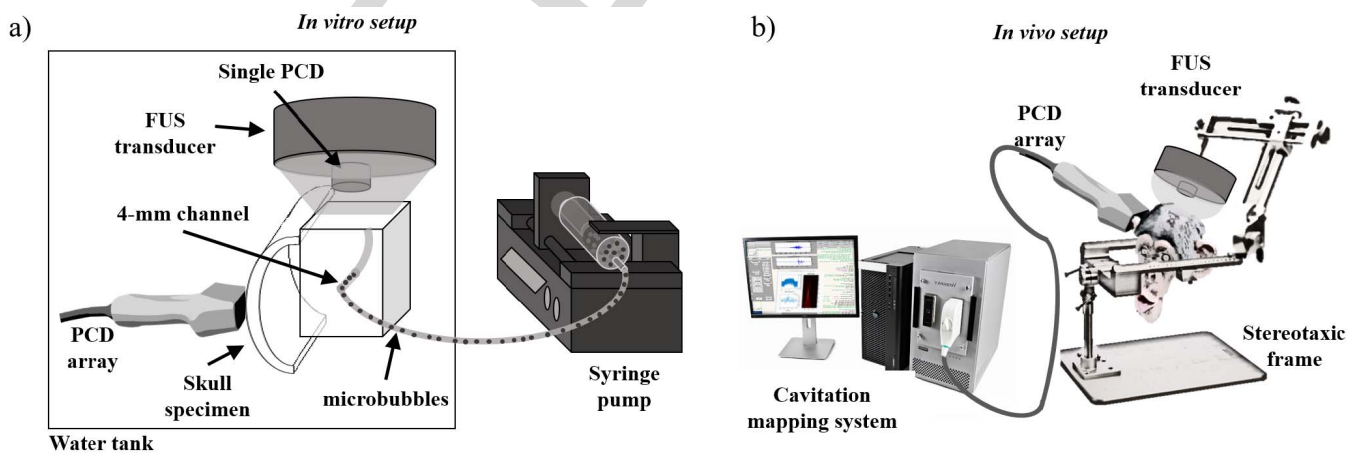


Fig. 3. Experimental setups for (a) *in vitro* skull and phantom and (b) *in vivo* BBB opening in NHP. In the *in vitro* experiment, the FUS transducer was placed on the top of the phantom and orthogonal to the PCD array. The skull was placed between the phantom and the PCD array for assessing the skull effects on the cavitation mapping. In the *in vivo* experiment, the FUS transducer was targeted to the region-of-interest based on the neuronavigation coordinates while the PCD array was placed against the temporal bone window toward the FUS focus.

291 stereotaxic frame for head fixation [Fig. 3(b)], with targets
 292 set at the caudate-putamen and hippocampus using a neu-
 293 ronavigation system (Brainsight Vet System, Rogue Research

Inc., Montreal, QC, Canada). The neuronavigation guidance
 was performed using anatomical T1-weighted magnetic res-
 onance (MR) brain images (3-D turbo field echo sequence,

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297 TR/TE = 11.1/5.1 ms, FA = 8°, and resolution = $0.7 \times$
 298 $0.7 \times 0.7 \text{ mm}^3$; Philips 3 Tesla scanner). The animals received
 299 in-house manufactured monodisperse microbubbles injected
 300 intravenously (2.5×10^8 bubbles/kg) and were sonicated for
 301 2 min (derated peak-negative pressure = 450 kPa, excitation
 302 frequency = 0.5 MHz, pulse length = 10 ms, and PRF =
 303 2 Hz). The reported pressures correspond to *in situ* values, fol-
 304 lowing transmission through an NHP or human skull, and were
 305 estimated prior to the experiment using a capsule hydrophone
 306 (HGL-0200, ± 3 dB frequency range: 0.25–40 MHz, electrode
 307 aperture: 200 mm; Onda Corp., Sunnyvale, CA, USA). The
 308 cavitation activity was monitored in real-time using the same
 309 PCD array and single PCD transducer described in the *in vitro*
 310 test. The PCD array was aligned with the focal region of the
 311 FUS transducer using neuronavigation-guidance through the
 312 skull temporal window (a thinner part of the skull serving as an
 313 acoustic window). The BBB opening and safety were assessed
 314 by MR images acquired 1 h after sonication. The BBB
 315 opening was confirmed by comparing T1-weighted contrast-
 316 enhanced images (Gd-DTPA-BMA, Omniscan, GE Health-
 317 care, Princeton, NJ, USA; 0.2 mL/kg) acquired before and
 318 following the sonication (3-D spoiled gradient echo sequence,
 319 TR/TE = 8.5/4.8 ms, FA = 8°, and resolution = $1 \times 1 \times$
 320 1 mm^3). Safety was evaluated with T2-weighted MR images
 321 for assessing potential edemas (TR/TE = 3000/80 ms, flip
 322 angle or FA = 90°, and resolution = $0.4 \times 0.4 \times 2 \text{ mm}^3$).

323 F. Quantification of Acoustic Cavitation Emission Using 324 the Single-Element PCD

325 Stable cavitation dose (SCD_h), stable cavitation dose with
 326 ultra-harmonics (SCD_u), and the inertial cavitation dose (ICD)
 327 were calculated following the same methodology of previ-
 328 ous studies [58], [59]. Harmonic components with frequency
 329 bandwidths of 20 kHz ($n \times f$, where $f = 0.5$ MHz
 330 and $n = 3, 4, 5, \dots, 10$) were extracted from the frequency
 331 spectrum obtained from the PCD signal in Volts. Similarly,
 332 ultra-harmonic components ($m/2 \times f$, where $f = 0.5$ MHz
 333 and $m = 5, 7, 9, \dots, 19$) were extracted using the same
 334 frequency bandwidth size. SCD_h was calculated by the root
 335 mean square (RMS) of the harmonic components, SCD_u,
 336 by the RMS of the ultra-harmonic components and ICD by
 337 the RMS of all other components not included in SCD_h and
 338 SCD_u, between 1.25 and 5.00 MHz.

339 G. Benchmarking

340 The first benchmarking test compared the computational
 341 time and sample processing rate of CPU and GPU
 342 implementations of the sparse and standard DAS matrix mul-
 343 tiplication using the NHP *in vivo* data set ($Z = 2000$ samples,
 344 $N = 128$ elements, $N_z = 2000$ axial pixels, and
 345 $N_x = 128$ lateral pixels). All GPU computations were per-
 346 formed using GPU-enabled MATLAB functions. Both GPU
 347 and CPU tests were performed using a number of samples
 348 N_T from 10 to 1500, except for the CPU standard DAS
 349 implementation that was limited to 500 samples as it reached
 350 unpractical computational times (several hours). The second
 351 benchmarking test compared the computational time with

$Z = 2000$ samples, $N = 128$ elements, and $N_T = 30$
 for different sizes of FOV, where the lateral map size N_x
 remained constant equal to 128 pixels, and the axial map size
 varied: $N_z = 50, 100, 200, 500, 1000$, and 2000 pixels. The
 testing routines included only the beamforming processing
 (Fig. 2) and did not include the sparse matrix construction
 (Fig. 1). Similarly, the memory allocation for the standard
 processing was disregarded to allow an adequate comparison
 of processing time only with both methods. The benchmarking
 was performed offline in a Dell Precision T7910 workstation
 (dual-processor Intel Xeon CPU E5-2650 v4 at 2.20 GHz,
 128 GB of RAM) equipped with a GPU (NVIDIA Quadro
 P6000, 24 GB memory, 3840 cores, driver: 392.56) running
 MS Windows 10 Pro 64-bits and MATLAB 2017b.

366 III. RESULTS

367 The effect of the integration time T_i on the GPU sparse-
 368 matrix algorithm computational time T_c (including both beam-
 369 forming time and integration time) and cavitation mapping
 370 quality was assessed off-line in phantoms with and without
 371 skull specimens. The computational time increased linearly
 372 with the integration time as the number of beamformed
 373 samples for each cavitation map increased with T_i [Fig. 4(a)].
 374 To achieve real-time monitoring the maximum computational
 375 time was limited by the time between pulses ($T_c < 1/\text{PRF}$),
 376 which in the case of NHP BBB opening sessions was defined
 377 as 0.5 s (for PRF = 2 Hz). A maximum T_i of 1.44 μs was
 378 found in order to achieve a real-time cavitation mapping with
 379 N_T equaling 30 samples. In addition to that, the maximal
 380 intensity in the mapping plateaued at approximately 62.5 μs
 381 (1300 samples). The maximum intensity for each integration
 382 time was defined as the pixel intensity with the highest value
 383 in each reconstructed passive map. The -6 dB cavitation
 384 region size defined in the map was quantified and found
 385 to increase with T_i with a transient formation of discrete
 386 spots of cavitation activity during the first 20 μs [Fig. 4(b)].
 387 Then, the cavitation region size decreased, possibly due to
 388 the destruction of resonant microbubbles at the periphery
 389 of the focus, reaching a steady-state spatial distribution at
 390 around 62.5 μs .

391 The cavitation detectability determined by system sensitivity
 392 was then tested in phantoms using 62.5- μs integration time
 393 for pressure levels ranging from 150 to 600 kPa (Fig. 5).
 394 Cavitation maps without the skull showed localized cavitation
 395 distributions at all pressure levels [Fig. 5(a)]. Acquisitions
 396 with skull samples presented a threshold for cavitation detec-
 397 tion at 300 and 450 kPa for NHP skull [Fig. 5(b)] and
 398 human skull [Fig. 5(c)], respectively. The cavitation activity
 399 was spatially distorted in the presence of both skulls, forming
 400 an elongated pattern as a result of the beamforming degrada-
 401 tion caused by the skull scattering. The pressure thresholds
 402 identified here are in the range used for BBB opening in NHP.

403 Following the *in vitro* experiments, the *in vivo* experiments
 404 were performed in NHP during the BBB opening sessions.
 405 The PCD array was placed on the temporal window aiming at
 406 the FUS targeted area, with the PAM plane covering a lateral
 407 cross section of the FUS focus [Fig. 6(a)]. The BBB opening

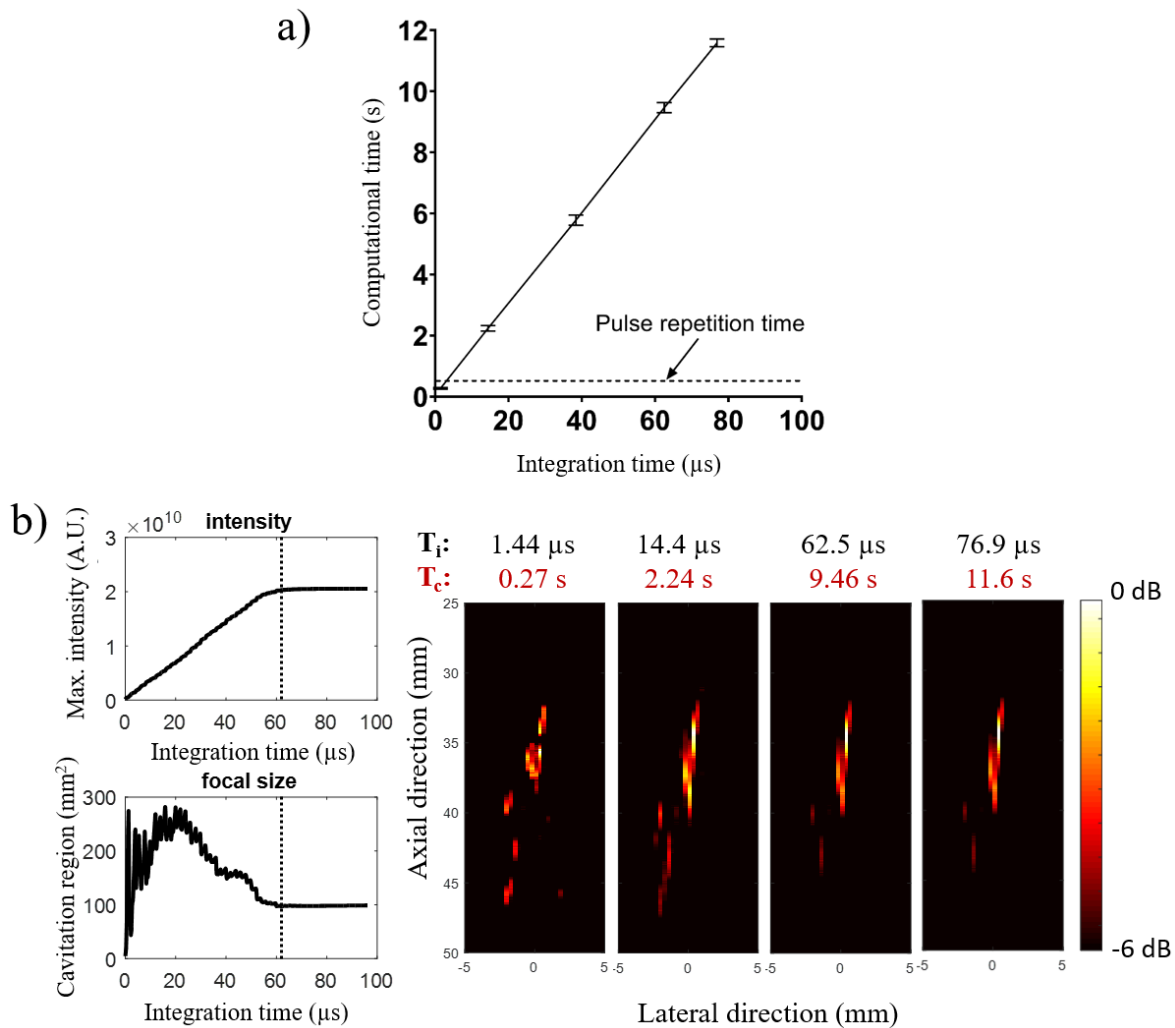


Fig. 4. Effect of integration time on computational time and cavitation mapping characteristics. (a) Computational time T_c increased linearly with the integration time T_i , which limited the integration time to a maximum of 1.44 μs for PRF = 2 Hz (0.5 s of pulse repetition period). (b) T_i also affected the mapping quality with lower values providing maps with discrete cavitation spots out of focus and values higher than 62.5 μs reaching a steady state of cavitation map. This representative case was performed at 450 kPa. Computational times T_c refers to the reconstruction of large acoustic maps (2000 axial pixels \times 128 lateral pixels).

and monitoring result at 450 kPa obtained from NHP 1 is shown in Fig. 6(a). The frequency spectra from the beam-formed signals at the location of maximum image intensity acquired during control and acquisitions with microbubbles are shown in Fig. 6(b). The cavitation levels obtained from the single-element PCD acquisition following spectral filtering showed a substantial increase of both stable and inertial cavitation once microbubbles perfused the brain [Fig. 6(c)]. The cavitation intensity [Fig. 6(d)] obtained from consecutive cavitation maps [Fig. 6(e)] was qualitatively consistent with the cavitation activity observed with the single-element PCD. The single-element PCD traces are presented with independent components cavitation (harmonic, ultra-harmonic, and inertial), whereas the cavitation activity detected by the PCD array shows the total activity without spectral filtering.

The results from the second test performed at 450 kPa in the NHP 2 are shown in Fig. 7. In this case, only stable cavitation was observed from data acquired with the single-element PCD

[Fig. 7(c)]. The majority of the observed stable cavitation was harmonic-based, with only a few pulses having ultra-harmonic dose higher than the baseline. The frequency spectra obtained with the PCD array at the location of maximum image intensity are shown in Fig. 7(b). As shown in the previous studies, the skull attenuation is highly variable across different skull locations and across animals due to bone thickness variation and different ratios of cortical to trabecular bone [22], [60]. The variation of the skull attenuation contributed to the differences in the signal components using the single-element and PCD array [Fig. 7(c) and (d)]. In addition, the single-element PCD presents a higher sensitivity and much broader frequency bandwidth. The single-element PCD had a higher sampling frequency (50 MHz versus 20.8 MHz) than the PCD array, thereby providing spectra at higher frequencies without aliasing. These differences highlight the importance of multiple cavitation detectors for safety redundancy. The cavitation maps in the logarithmic intensity scale (in decibel)

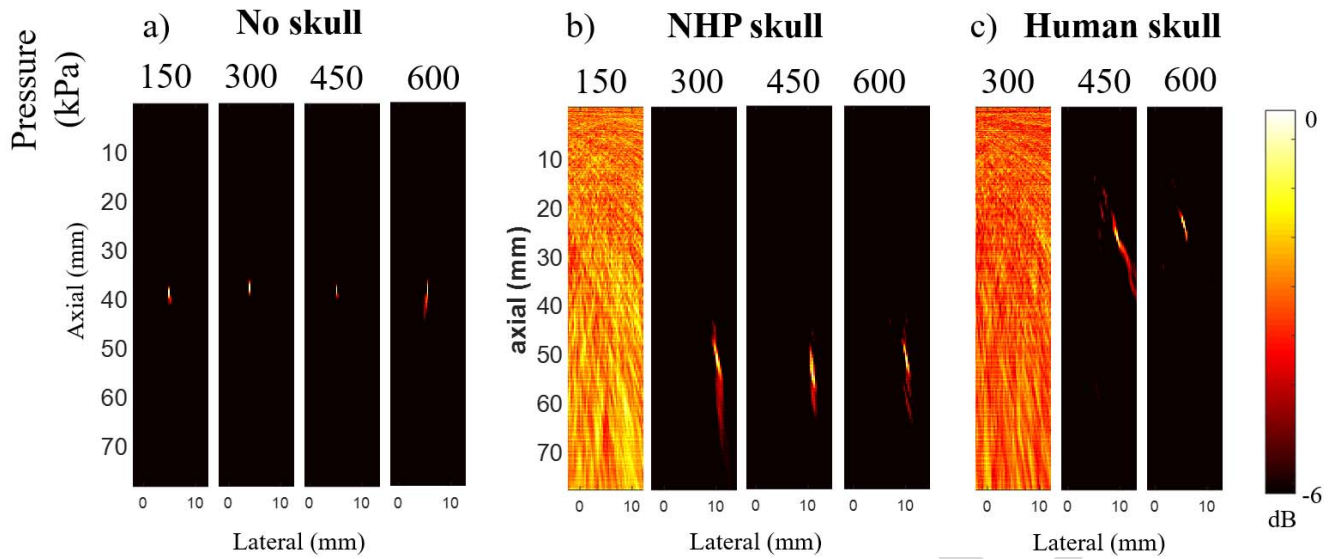


Fig. 5. Cavitation mapping sensitivity through primate skull. Cavitation maps using $62.5\text{-}\mu\text{s}$ integration time at variable pressure levels were acquired (a) without a skull, (b) with NHP skull, and (c) with human skull between the PCD array and the phantom.

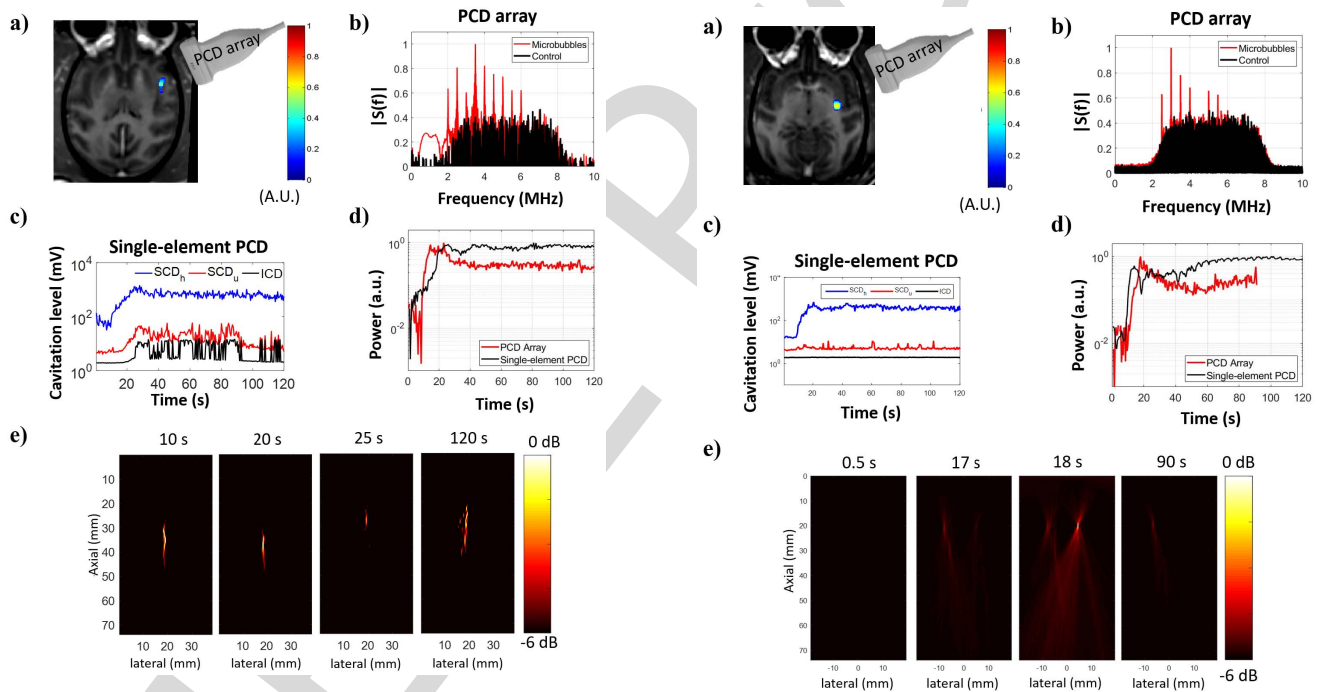


Fig. 6. Cavitation activity recorded during BBB opening in NHP 1. (a) BBB opening (in color) induced by sonication at 450 kPa revealed in contrast-enhanced T1-weighted MR image. (b) Frequency spectra obtained from the beamformed signal at the location of maximum image intensity. (c) Cavitation activity evaluated with a single-element PCD transducer (cavitation dose). (d) Normalized power detected with a PCD array positioned at the temporal window and a single-element PCD transducer co-aligned with the FUS transducer. Power was defined as the sum of squared beamformed data using $1.44\text{-}\mu\text{s}$ integration time for the PCD array and the entire signal duration for the single-element PCD transducer. (e) Spatial distribution of the cavitation activity shown in cavitation maps (-6 dB) for different samples.

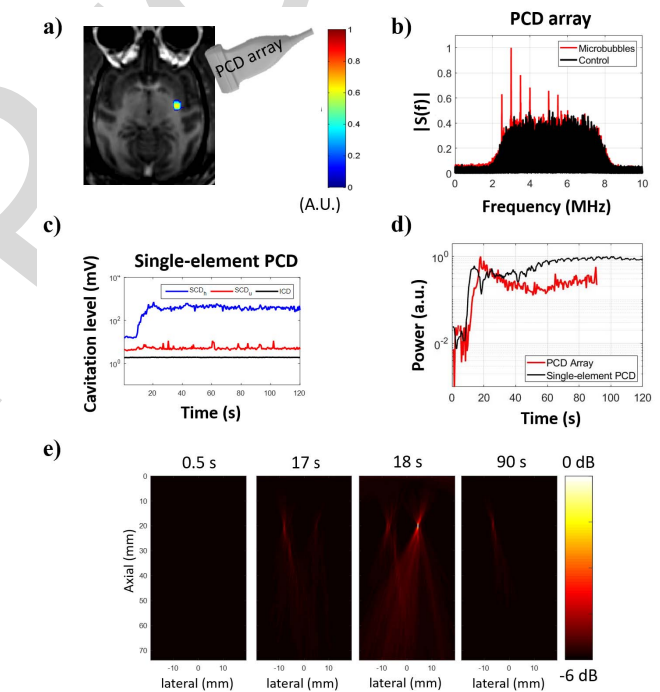


Fig. 7. Cavitation activity recorded during BBB opening in NHP 2. (a) BBB opening (in color) induced by sonication at 450 kPa revealed in contrast-enhanced T1-weighted MR image. (b) Frequency spectra obtained from the beamformed signal at the location of maximum image intensity. (c) Cavitation dose detected using a single-element PCD transducer indicating only stable cavitation throughout the sonication duration. (d) Normalized power detected with a PCD array positioned at the temporal window and a single-element PCD transducer co-aligned with the FUS transducer using $1.44\text{-}\mu\text{s}$ integration time. (e) Reconstructed cavitation maps (-6 dB) for different samples.

444 were used for monitoring both the spatial location and intensity
 445 of cavitation over time [Fig. 7(e)]. Interestingly, cavitation
 446 events were detected in two locations, possibly caused by

cavitation in the neighboring larger vessels or caused by the
 447 sidelobes of the FUS beam. 448

The benchmarking revealed that sparse matrix operation
 449 improved both GPU and CPU performance. The computational
 450

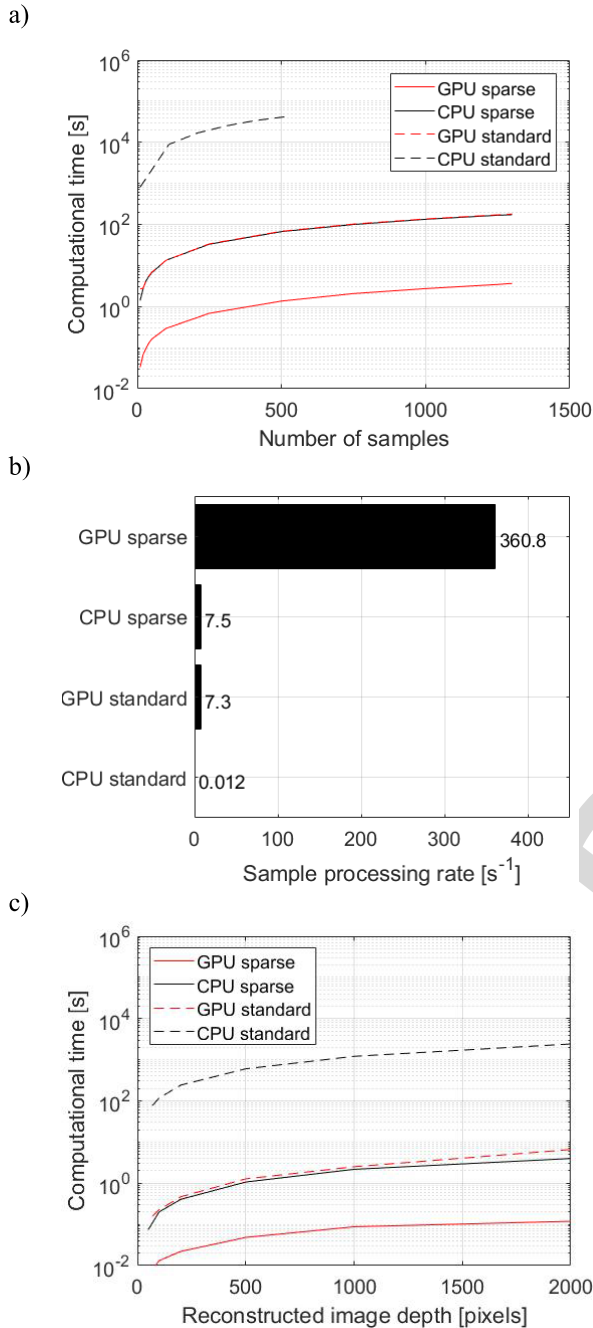


Fig. 8. Benchmarking for sparse matrix operation. (a) Computational time of CPU and GPU implementations for the sparse matrix multiplication and standard DAS using the NHP *in vivo* data set for integrated sample N_T varying from 10 to 1500 (Z : 2000 samples, N : 128 elements, N_x : 128 lateral pixels, and N_z : 2000 axial pixels). (b) Sample processing rate at the same conditions. (c) Computational time with $N_T = 30$ for different sizes of FOV, where the lateral map size N_x remained constant equal to 128 pixels and the axial map size varied: $N_z = 50, 100, 200, 500, 1000,$ and 2000 pixels. The benchmarking was performed offline in a Dell Precision T7910 workstation (dual processor Intel Xeon CPU E5-2650 v4 at 2.20 GHz, 128 GB of RAM) equipped with a GPU (NVIDIA Quadro P6000, 24 GB memory, 3840 cores, driver: 392.56) running MS Windows 10 Pro 64 bits and MATLAB 2017b.

time had a linear relation with the number of samples, and it is presented in the log scale as the CPU standard DAS implementation resulted in computational times four orders of magnitude higher than the GPU sparse implementation [Fig. 8(a)]. In GPU, the sparse matrix performed approxi-

mately 50 times faster than the standard DAS matrix, whereas, in CPU, the same comparison resulted in approximately 600 times difference. Interestingly, the CPU sparse and GPU standard DAS implementations presented similar results with sample processing rates of 7.3 and 7.5 s^{-1} , respectively [Fig. 8(b)]. On the other side, the GPU standard DAS implementation presented a much higher average sample processing rate of 360.8 s^{-1} . Similarly, for a fixed number of samples $N_T = 30$, the sparse matrix implementation reduced the computational time for variable FOV sizes [Fig. 8(c)]. The GPU sparse matrix implementation decreased the computational time by a minimum of 21.9 times (FOV: 50×128 pixels) in comparison with GPU standard matrix implementation and a maximum of 55.3 times (FOV: 2000×128 pixels) with an average of 28.5 times across different FOVs. The sparse matrix performed on CPU was an average of 617 times faster than the CPU standard implementation and 1.33 times faster than the GPU standard implementation. The processing times required per PAM pixel for FOV varying from 50 to 2000 pixels axially \times 128 pixels laterally using 30 samples were on average 0.03 ± 0.01 , 0.51 ± 0.01 , 0.67 ± 0.09 , and 311.71 ± 3.94 μs /pixel/sample for GPU sparse, CPU sparse, GPU standard, and CPU standard implementations, respectively. For both CPU and GPU implementations, the sparse matrix was loaded in the memory prior to the time testing routines. Similarly, for the standard DAS method, the time for memory allocation was disregarded. The loading time was 6.86 ± 0.13 s and the CPU-GPU transfer time was 0.79 ± 0.06 s.

IV. DISCUSSION

In this study, we demonstrated the implementation of sparse matrix beamforming and TEAs on a GPU for real-time transcranial cavitation mapping. The system was tested *in vitro* using human and NHP skull specimens, which allowed to investigate the computational time for real-time cavitation mapping, and *in vivo* during ultrasound-mediated BBB opening sessions in NHP, which allowed to test the setup and algorithm in a close to clinical setup condition.

The summation over the integration time used in the TEA algorithm enhanced the continuously scattered signal from microbubbles by suppressing the background noise, which affected the mapping quality and homogeneity of cavitation distribution [61], [62]. Noisier maps (discrete cavitation spots outside the transducer focus potentially associated with very transient bubble activity) were found *in vitro* for short integration times, while a steady cavitation distribution could be achieved with long integration time duration (>62.5 μs). Despite the higher SNR achieved with a high number of beamformed samples, the computational load and the number of frames were limited by the total integration time to lie within the pulse repetition period. For the PRF used in the test *in vivo* (2 Hz), 30 samples could be reconstructed for an integration time of 1.44 μs . The increased number of pixels in the axial direction (i.e., 2000) was chosen based on active imaging parameters; however, the pixel size of 37 μm is significantly smaller than the nominal passive acoustic mapping resolution at these imaging depths. The nominal axial resolution of PAM would be equal to 2.1 mm, assuming an

513 imaging depth of 40 mm, an aperture size of 38.4 mm, and a
 514 mean receive wavelength of 0.28 mm [63]. As demonstrated
 515 by the benchmarking, the sparse matrix density ($N_x \times N_z$ by
 516 $N \times Z$) and the RF data set density ($N \times Z$ by N_T) [Fig. 2(a)]
 517 can be modified, which ultimately changes the computational
 518 time at a rate of $0.03 \pm 0.01 \mu\text{s}/\text{pixel}/\text{sample}$. Therefore,
 519 a reduced number of pixels can accelerate the processing,
 520 which allows a longer integration time. Future work will
 521 involve cavitation maps with a larger axial pixel size, to accel-
 522 erate computation times and enable real-time mapping with
 523 the integration of longer data sets, while preserving spatial
 524 information. As previously reported by Acconcia *et al.* [64],
 525 the microseconds time scale can potentially provide insights
 526 into bubble dynamics, such as the rapid bubble cloud evolution
 527 and its stochastic nature, as opposed to long integration times.
 528 Furthermore, the majority of cavitation activity is constrained
 529 within the first hundreds of microseconds of an ms-long
 530 therapeutic pulse. Previous *in vitro* work has shown that 80%
 531 of the total cavitation energy is emitted within 200 μs (or
 532 0.2% of the total pulse length) during therapeutic ultrasound
 533 exposure [65], [66]. This is likely due to the destruction of
 534 resonant microbubbles at the beginning of the therapeutic
 535 pulses, with smaller nonresonant microbubbles emitting lower
 536 cavitation energy for the remainder of the pulse. Future studies
 537 will correlate time exposure with bubble dynamics observed
 538 with high speed videography [67]. The pressure thresholds
 539 for the cavitation detection through human and NHP parietal
 540 bone specimens using the PCD array were in the range of
 541 pressure employed in previous studies [25], [58], [59], [68].
 542 These results demonstrate the capability of the system to map
 543 spatial and temporal microbubble activity in real-time.

544 The benchmarking results revealed that the sparse matrix
 545 operation can decrease considerably the computational time
 546 in both CPU and GPU. For the computer configuration tested
 547 here, the CPU sparse implementation performed very similar
 548 to the GPU standard DAS implementation. Despite differences
 549 that other computer configurations may present (i.e., less pow-
 550 erful CPU processors with more powerful GPU), the sparse
 551 matrix operation is demonstrated to be a feasible solution for
 552 decreasing the computational time of operations with dense
 553 data sets, which enables either larger FOV or larger data sets
 554 relevant to therapeutic applications. An interesting character-
 555 istic of the sparse matrix operation is that it can be applied
 556 regardless of the number of processed samples, thus the
 557 integration time can be adapted easily to result in high image
 558 quality based on the trade-off of integration time and real-time
 559 visualization. It is important to note that similar operation is
 560 not practical with a fully sampled reconstruction matrix as for
 561 the data set used here matrix ($256\,000 \times 256\,000$), the fully
 562 sampled matrix would require 488.3 GB of computer memory
 563 as opposed to sparse representation that requires only 1.05 GB.
 564 On the other hand, the sparse matrix-based beamforming
 565 presents limitations such as the need to construct the sparse
 566 matrix [(3)–(5)] offline and several hours prior to its use.
 567 This method requires time-consuming iterative calculations
 568 and memory allocation to allow the element indentation. This
 569 is partially resolved as only a single matrix construction at
 570 the highest sampling is needed. Then, the matrix can be

571 downsampled to adjust to any reduced FOV or channel data
 572 size. Once the sparse matrix size is adjusted, the multiplication
 573 of the sparse matrix and channel data can be performed, which
 574 will result in the beamformed data. The allocation of the
 575 pre-constructed sparse matrix in the computer or GPU memory
 576 is performed only once and it takes a few seconds, which will
 577 depend on the computer performance and sparse matrix size.

578 Next, we demonstrated an *in vivo* test of our system
 579 during FUS-mediated BBB opening session in NHP. The
 580 skull presents high variability in the thickness, variable pro-
 581 portion of cortical, and trabecular bone distribution across
 582 skull regions, and, subsequently, high variability of the ultra-
 583 sound attenuation [60]. Therefore, it is important to monitor
 584 cavitation activity with as low attenuation as possible, espe-
 585 cially since high frequency emissions from microbubbles are
 586 more heavily attenuated through the skull. Cavitation mapping
 587 was, therefore, performed through the thin temporal bone,
 588 which presents lower attenuation than other skull bones.
 589 This experimental configuration was shown to be viable at
 590 mapping cavitation activity and demonstrated the feasibility
 591 of GPU-accelerated sparse matrix computing in a close to
 592 clinical setup. The system was qualitatively compared against
 593 single-element PCD acquisitions, which presented the same
 594 trend for the cavitation activity. PCD with both single-element
 595 and multielement transducers was performed to illustrate the
 596 qualitative similarities in the temporal evolution of the detected
 597 signals [Figs. 6(d) and 7(d)]. However, we have used the
 598 normalized values, because a direct quantitative comparison
 599 is not possible, due to different receiving center frequencies,
 600 sensitivity patterns, and sampling frequencies. In the foreseen
 601 clinical use, device limitations can be ameliorated by using
 602 multiple safety monitoring redundancies, which in this case
 603 both single-element and array transducers can detect indepen-
 604 dently potentially high-risk cavitation activity. Future imple-
 605 mentations will include simulations based on CT-scans [35],
 606 [37], [69] with the co-registration of MR images from the
 607 neuronavigator and simulated acoustic beam profiles.

608 Beamforming degradation caused by the diffraction pattern
 609 of the receiving array and interference caused by multiple
 610 bubbles emitting acoustic signals at the same time generated
 611 spatial distortions of cavitation activity, which resulted in
 612 an elongated pattern of cavitation activity. Differences in
 613 the beam shift can be explained due to differences in the
 614 skull curvatures of human and NHP specimens. As previously
 615 reported [32], [61], [69], potential focal shifts may be present,
 616 but were not studied here. Differences in the human and NHP
 617 specimen size forced different positioning of the imaging array
 618 in relation to the therapeutic transducer. Thus, the location
 619 of focus was not consistent across acquisitions. Nevertheless,
 620 the focal distortion is an example of problems encountered
 621 during treatment that shows the need of real-time spatial
 622 monitoring of cavitation.

623 Frequency-domain approaches can significantly accelerate
 624 processing even without a GPU, due to the spectral filtering
 625 of narrowband harmonics or ultraharmonics [35], [36]. How-
 626 ever, the quality and speed of such approaches depends on
 627 the pulse length. Shortening the pulse length leads to pro-
 628 gressively wider harmonic and ultra-harmonic peaks, thereby

629 increasing the integration bandwidth and computational load.
630 Furthermore, discrimination of different cavitation modes, e.g.,
631 inertial versus non-inertial cavitation, becomes increasingly
632 more difficult with shorter pulse lengths. Therefore, frequency-
633 domain algorithms need to be modified for different excitation
634 sequences, especially for the examined frequency windows.
635 Finally, to calculate the total acoustic energy emitted by the
636 exposed microbubbles, one needs to integrate throughout the
637 frequency domain, which negates the need for frequency-based
638 analysis.

639 On the other hand, time-domain approaches can be very
640 slow when examining long RF signals with a traditional CPU
641 approach [Fig. 8(a)]. Time-domain DAS is a simple process
642 inducing a relatively low computational load and provides
643 direct information about the total cavitation energy produced
644 within the focus, regardless of the pulse length or cavitation
645 mode. Cavitation energy has been previously correlated with
646 the induced bioeffect, such as the drug delivery efficiency [70].
647 The same algorithm can be applied without modification
648 using any excitation sequences, ranging from μ s-long pulse
649 sequences for BBB opening [71] to s-long sequences for HIFU
650 ablation [30]. Our study describes a method for accelerating
651 time-domain PAM for both CPU- and GPU-based systems
652 (Fig. 8) across a broad spectrum of ultrasound therapies.
653 Sparse-matrix multiplication provides a general method to
654 accelerate PAM processing at any pulse length [Fig. 8(a)] or
655 map size [Fig. 8(c)].

656 The sparse matrix implementation demonstrated here
657 employed a simple DAS algorithm that allowed for accel-
658 erated image acquisitions. However, as previously described
659 by Haworth *et al.* [36], the axial resolution using this algo-
660 rithm can be ten times worse than lateral resolution when
661 using small-aperture 1-D receiver arrays. When large-aperture
662 2-D receiver arrays are employed the axial dimension of
663 the point-spread function obtained via DAS beamforming is
664 approximately twice that of its lateral counterpart [61], [72],
665 [73]. As we demonstrated in NHP, this can be partially
666 overcome by changing the orientation of the passive array at
667 an acute angle using the temporal window so the mapping
668 can be provided with a compromise of resolution between the
669 axial and lateral orientations (worst case in coaxial orientation
670 with the therapy transducer). In addition, introduction of the
671 skull may have caused shifts in the position of cavitation
672 activity in reconstructed images. Yet, the algorithm tested in
673 this study demonstrates the capability of the GPU-accelerated
674 sparse matrix operation using large RF data sets. Despite
675 the higher spatial resolution achieved with more sophisticated
676 algorithms such as the robust Capon beamforming [74], [75],
677 its computational load is still challenging for GPU-processing.
678 We recognize that including a comparison against other cavi-
679 tation mapping algorithms would have been desirable; however,
680 limited key information and expertise in alternative methods
681 would yield misrepresentative conclusions. Coded excitation
682 can also be implemented to improve the confinement of
683 microbubble activity [76] and the decoding on receive could
684 enable higher SNR [77]. Additionally, implementation of a
685 closed-loop feedback control for cavitation mapping may be
686 beneficial for online treatment optimization [78]. This would

687 provide a more reliable control of the microbubble activity
688 from regions inside the brain while avoiding artifact from other
689 sources such as acoustic coupling media or regions outside the
690 brain [22]. In our future work, L7-4 will be replaced with a
691 lower frequency array, to facilitate cavitation mapping through
692 the human skull and reduce aberrations occurring at higher
693 frequencies.

694 Finally, the sparse matrix implementation in GPU is a
695 feasible method for accelerating image formation. This method
696 can enable enlarging the FOV that could potentially help
697 identify in real time off-target cavitation activity. In the context
698 of this study, real-time imaging was enabled only for extremely
699 short integration times (i.e., 1.44- μ s duration or 30 samples).
700 Future work will involve generation of maps with a reduced
701 number of pixels but larger pixel sizes in the axial direction,
702 in order to accelerate beamforming of longer data sets. Such
703 a reduction of the axial pixel number by—for example—50-
704 fold would lead to an equivalent increase of the permissible
705 integration time by 50-fold. Together with the neuronavigation
706 system [25], the therapeutic transducer could be realigned
707 at normal incidence angles [79] during sonication or the
708 sonication could be halted if substantial beam aberrations are
709 observed.

710 V. CONCLUSION

711 Passive acoustic mapping has a great potential in clinical
712 cavitation-based FUS applications especially for monitoring
713 and guiding the treatments. A detailed implementation of
714 sparse matrix beamforming on a GPU for cavitation mapping
715 is demonstrated here as a method to accelerate processing.
716 We demonstrate with *in vitro* and *in vivo* tests that the GPU-
717 based sparse matrix method can accelerate passive acoustic
718 mapping compared to standard GPU or CPU processing, and
719 allow real-time processing of large maps (e.g., 2000 axial
720 pixels \times 128 lateral pixels) with limited integration times
721 (e.g., 30 samples). This methodology was proven efficient for
722 both CPU and GPU implementations. Moreover, cavitation
723 mapping through the human skull bone showed the feasibility
724 to use this technique in clinical applications. Finally, the
725 real-time capability together with the neuronavigation system
726 enables the operator to correct or halt sonications in case
727 substantial aberrations are observed.

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