Abstract: The quality of the reconstructed photoacoustic image largely depends on the amount of photoacoustic (PA) boundary data available, which in turn is proportional to the number of detectors employed. In case of limited data (owing to less number of detectors due to cost/instrumentation constraints), the reconstructed PA images suffer from artifacts and are often noisy. In this work, for the first time, a deep learning based model was developed to super resolve and denoise the photoacoustic sinogram data. The proposed method was compared with existing nearest neighbor interpolation and wavelet based denoising techniques and was shown to outperform them both in numerical and in-vivo cases. The improvement obtained in Root Mean Square Error (RMSE) and Peak Signal to Noise Ratio (PSNR) for the reconstructed PA image using the sinogram data that was super-resolved and denoised using proposed neural network based method was as high as 41.70 % and 6.93 dB respectively compared to utilizing limited sinogram data.

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Fig. 1. The proposed Sinogram super-resolution and denoising convolutional neural network (SRCN) deep neural network architecture with seven convolutional layers. The sinogram which was upsampled by nearest neighbour interpolation is given as input (patches of $S_{IN}(512 \times 100)$) and the output is the residual map for the denoised sinogram (corresponding patches of $S_{R}(512 \times 100)$). Each convolution layer had 64 filters except the last, which had only one filter. Each convolution operation was followed by ReLU activation and batch normalization.

met by using interpolation based methods to super-resolve and denoise the photoacoustic sinogram. Alternatively, model based techniques were proposed to improve the quantitative accuracy for the PA images reconstructed for limited data cases. These algorithms are robust to noise and are computationally complex compared to analytical algorithms [6–11, 15–18]. The $k$-wave based interpolation [19], which is widely used, typically involves nearest neighbor/linear interpolation on the incomplete/limited data to obtain better image reconstruction. This interpolation main utility is to improve the reconstructed image obtained using time-reversal, i.e., outgoing wave from each discrete detector position in the time-reversal process interacts with other positions on the measurement surface at which a pressure value is also being enforced. This interaction can be improved by interpolation. Even if sufficient detectors are available for capturing the data for an acceptable reconstruction quality, the interpolation may not be able to mitigate the effect of noise present in the sinogram data.

In Ref. [20], a Convolutional Neural Network (CNN) was proposed for improving the PA reconstruction obtained using filtered backprojection algorithm. On optimization of data, in Ref. [21], the authors proposed a Recurrent Neural Network (RNN) that improves the quality of images and reduces scan time by exploiting temporal information. In similar line of work [22], a CNN was proposed to beamform the channel data to a PA image to improve the reconstruction. In [23], a CNN was proposed to fuse the characteristics of different images formed using analytical and model-based inversion methods to get an improved PA image reconstruction. The above mentioned methods mostly applied in the image space and there has been very little work that involved sinogram data. The proposed work here uses only the sinogram domain data and hence was not compared with the above techniques.

In general, deep learning has greatly influenced the domain of medical imaging, especially in terms of providing a fully data driven model in interpolation of missing data in sparse view sinograms of Positron Emission Tomography (PET) and was shown to perform better than other state of the art methods such as Linear and Directional Interpolation [24]. This was inspired by this progress, where a convolutional neural network (CNN) model has been proposed to interpolate and denoise the data to approximate the missing information in the photoacoustic sinogram. In [25], another network based on U-net architecture was proposed for super resolution of PET sinogram which was not attempted here as PET and PA data characteristics largely differ.
2. Image Reconstruction in Photoacoustic

PA image forward model reconstruction involves the computation of the pressure waves acquired by the ultrasonic transducers. The propagation of PA waves is given by the following equation [5]

$$\nabla^2 P(y, t) - \frac{1}{c^2} \frac{\partial^2 P(y, t)}{\partial t^2} = -\frac{\beta}{C_p} \frac{\partial H(y, t)}{\partial t},$$  \hspace{1cm} (1)

The notations are defined as:

- \(H(z, t)\): the energy deposited per unit time per unit volume
- \(P(y, t)\): the pressure at time and position as \(t\) and \(y\) respectively
- \(\beta\): thermal expansion coefficient
- \(c\): the sound speed
- \(C_p\): specific heat capacity

2.1. \(k\)-Wave Time Reversal Method

Time Reversal can be performed using K-wave toolbox [19] and it is a single step image reconstruction method. Let \(T\) be the maximum duration for which the PA wave travels inside the imaging domain [26]. It assumes that the solution vanishes outside this time stamp \(T\). The initial conditions were assumed to be zero, and the model solves it backward in time to give the initial pressure distribution at time '\(t\)'=0. Time reversal is capable of providing a model based resolution depending on the amount of available data (owing to the number of detectors) as well as the bandwidth of the ultrasonic detectors [10,26]. In cases, the boundary data acquired by the transducers is limited, the interpolated data (obtained using \(k\)-wave toolbox) is utilized for estimating the initial pressure distribution [19]. This technique can be applied for reconstruction of the initial pressure distribution for full bandwidth data as well as limited bandwidth data.

2.2. Automated Wavelet Denoising of Recorded Photoacoustic Data

Various techniques are available for denoising [27] the data before doing the PA reconstruction. One of the technique is performing wavelet denoising using maximum overlap DWT (MODWT) [28]. The main advantages of MODWT (non-orthogonal transform) are:

- The zero padding is not required as the sample size is not defined only for powers of 2.
- It applies a filter having zero phase which results in lining the original signal with the features.

A complete overview of maximum overlap DWT (MODWT) can be obtained in Ref. [28] and for applications in PA imaging please see Ref. [27]. In this work, MODWT was utilized to implement the wavelet smoothing and denoise the interpolated PA noisy signals. The threshold is set automatically using the universal threshold criteria [29].

2.3. Sinogram super-resolution and denoising convolutional neural network (SRCN) (Proposed)

Convolutional Neural Networks (CNNs) are gaining lot of importance as they are being utilized in various tasks in image processing and reconstruction [30,31]. CNNs comprise of activation layers, pooling layers, convolutional layers and batch normalization layers. In this work, we utilized a seven layer CNN with convolutional layers, activation and batch normalization layers. Each convolutional layer convolves 3*3 size kernels while moving one pixel at a time. Each
convolutional layer has 64 filters except the last layer which has only one channel. The structure of CNN used is given in Fig. 1. The loss function used for training of the proposed SRCN network was Mean-squared error (MSE). For better performance, residual learning technique [32] is used to train the network. Residual training involves training the network to predict the difference between the input and the ground truth. This has been shown to give better convergence as compared to training with ground truth as target. The MSE can be written as

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} ||\hat{y}_i - \phi(x_i)||^2
\]  

(2)

where \(\hat{y}_i\) denotes the expected residual of the network while \(\phi(x_i)\) denotes the output of the CNN.

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For training the deep learning model, the sinogram\(S\) with 100 detectors was utilized and the steps that generated the patches can be summarized by the following pseudo-code.

**Step-1:** \(S_F = Noise \ Free \ Sinogram \ with \ 100 \ detectors \) (512 \times 100) generated using \(k - wave\) on high dimensional grid.

**Step-2:** \(S_F\ (512 \times 100) \rightarrow S_{FN} \ (512 \times 100)\)

\(add \ Gaussian \ Noise\) (SNR 20/40/60 dB)

**Step-3:** \(S_{FN}\ (512 \times 100) \rightarrow S_{HN}\ (512 \times 50)\)

\(sub-\text{sample by factor of two Nearest Neighbor Interpolation}\)

**Step-4:** \(S_{HN}\ (512 \times 50) \rightarrow S_{IN}\ (512 \times 100)\)

**Step-5:** \(Residual: S_R(512 \times 100) = S_{IN}(512 \times 100) - S_F(512 \times 100)\)
Fig. 3. Comparison of reconstructed PA images of numerical Derenzo phantom using sinogram data obtained using different methods discussed in this work with SNR of sinogram being listed against each row (20, 40, and 60 dB). The target derenzo phantom is shown in (m), while the reconstruction obtained using 100 detectors without noise is shown in (n) to serve as ground truth in calculating RMSE and PSNR. The reconstructed PA image using sinogram data of (a-c) 50 detectors (d-f) 100 detectors nearest neighbour interpolated (g-i) 100 detectors interpolated and denoised using MODWT method (h-l) 100 detectors super resolved and denoised using proposed CNN based method. The figures of merit, RMSE and PSNR, for the reconstructed results were given in (o) ad (p) respectively with (n) serving as ground truth.

The CNN gets trained on patches of $S_{IN}$ as input and $S_R$ as expected output. The proposed SRCN architecture is given in Fig. 1.

The dataset consists of 4600 images extracted from the databases CHASE [33], DRIVE [34], and STARE [35], to result in 4600 sinograms for training and validation of proposed model. Fifty random patches of size $32 \times 32$ were extracted from each of these sinograms, resulting in 230,000 sinogram patches. Out of these, 200,000 patches were used for training and the remaining 30,000 were used for validating the network. The network (given in Fig. 1) consists of seven convolutional layers with each layer followed by a rectified linear unit (ReLU) and batch normalization. The network architecture is similar to the one used in Ref. [24], with reduced number of layers (20 to 7). The total number of trainable parameters were 186,497 while the number of non-trainable parameters were 640 (total number of parameters in the network to 187,137). The rationale behind such reduction is that the problem of PAT sinogram super-resolution has lesser complexity owing to sinogram representing a smooth function (ray sum), which can be easily learnable with reduced number of layers. The initialization was performed using random normal distribution having standard deviation as 0.001 and mean as 0.0 for all kernel weights and all biases were initialized with zeros. The loss function and the optimizer used were mean square error and Adam for training [36]. The learning rate was set to be $2 \times 10^{-8}$ while the first momentum and the second momentum were set to be 0.9, and 0.999 respectively. All computations, including training, were performed on computer having Dual Intel Skylake Xeon 4116 (24 cores) with a clock speed of 2.10 GHz with 64GB RAM consisting of two NVIDIA Tesla P100 12GB GPU cards. The batch size was chosen to be 100 and the model was trained for approximately 11.5 days. Around 11,000 epochs were ran in this duration as each epoch run time was about 91 seconds. Keras [37] using Tensorflow [38] as the backend
Fig. 4. Comparison of reconstructed PA images of in vivo rat brain sinogram data obtained using different methods discussed in this work. The reconstructed rat brain PA image using original 100 detectors data is shown (a) to serve as ground truth that is achievable. Reconstruction result using 50 detectors data is shown (b). The reconstructed result using 100 detectors sinogram data obtained using nearest neighbor interpolated is given in (c), MODWT method in (d), the proposed CNN method result is shown in (e). RMSE and PSNR (in dB) for these results are shown in (f) and (g), respectively with (a) being taken as ground truth.

was used for writing the code for testing and training the network. Once the CNN model was trained, the model was utilized in following manner with \( T \) representing the Testing sinogram:

\[
T_{HN} = \text{Noisy Sinogram with 50 detectors data} \\
T_{HN} (512\times50) \xrightarrow{\text{Nearest Neighbour Interpolation}} T_{IN} (512\times100) \\
T_{IN} (512\times100) \xrightarrow{\text{CNN}} T_R (512\times100) \\
T_F (512\times100) = T_{IN} (512\times100) - T_R (512\times100)
\]

Here \( T_F \) represents the predicted noiseless interpolated sinogram by the trained CNN, which becomes the input to the PA image reconstruction algorithm (in here, time-reversal).

3. Figures of Merit

For comparing the efficiency of the proposed methods, the following figures of merit were used for numerical simulations and experimental datasets.

3.1. Root Mean Square Error (RMSE)

It is an absolute metric to compare the reconstruction quality and is defined as [39,40] :

\[
RMSE(x^{\text{target}}, x^{\text{recon}}) = \sqrt{\frac{\sum (x^{\text{target}} - x^{\text{recon}})^2}{M}}
\]

(3)

Here, the reconstructed pressure distribution is denoted as \( x^{\text{recon}} \) while the target pressure distribution as \( x^{\text{target}} \), and the total number of pixels by \( M \). The lower the value of RMSE, the better is the reconstructed image quality.
3.2. Peak Signal to Noise Ratio (PSNR)

It is defined as [14]:

$$PSNR = 10 \log_{10} \left( \frac{(PeakValue)^2}{MSE} \right)$$

(4)

Here, Peak Value denotes the maximum possible value in the image and MSE denotes the Mean Square Error. The higher the value of PSNR, the better the reconstructed image quality.

4. Numerical and Experimental Studies

The imaging domain that was utilized in this work had dimension of 501×501. Each pixel is 0.1 mm wide and thus the size of the imaging domain is 50.1 mm × 50.1 mm. Hundred detectors are placed equidistantly on a circle of radius of 22 mm in the initial experimental setup. A high dimensional grid of size 401 × 401 was used to generate the sinogram data. To avoid inverse crime a lower dimension grid having size 201 × 201 was used to perform the reconstruction imitating the real experimental scenario. The numerical phantoms have a dimension of 201 × 201, thus having a size of 20.1 mm × 20.1 mm. The generated data from the high dimensional grid was added with white Gaussian noise to result in signal-to-noise ratio (SNR) levels of 20, 40, and 60 dB. An open source MATLAB toolbox k-wave [19] was used for generating the data in MATLAB. The number of time samples were 512 and the sampling frequency was chosen as 20 MHz. The acoustic detectors that were used had 2.25 MHz as the center frequency with bandwidth of 70%.

Numerical blood vessel and Derenzo phantoms were utilized in here to compare the reconstruction accuracy of the proposed SRCN method and compare it with other techniques. These phantoms were unipolar in nature having ‘1’ for the object of interest and ‘0’ for the background with an initial pressure rise distribution of 1 kPa. An in-vivo experimental data from rat brain was also utilized to validate the proposed SRCN deep neural network architecture. The data acquisition setup details and the experimental setup details are available in Ref. [41]. Note that all the animal experiments conducted here as part of the work followed the regulations and guidelines accepted by the institutional Animal Care and Use committee of Nanyang Technological University, Singapore (Animal Protocol Number ARF-SBS/NIE-A0263).

5. Results and Discussion

The image reconstruction obtained using the proposed CNN based interpolated sinogram data (\(T_F\)) was compared with the reconstruction obtained using original fifty detectors (\(T_{HN}\)) and the reconstruction obtained using the nearest neighbour interpolated sinogram for hundred detectors (\(T_{IN}\)). To prove the efficacy of CNN based interpolation and denoising, an automated denoising of the recorded photoacoustic data using Maximum Overlap Discrete Wavelet Transform (MODWT) [27] was also utilized and the reconstructed results were compared with the proposed SRCN deep neural network architecture. The denoising threshold was automatically chosen using universal threshold criteria. The reconstructed results were compared quantitatively using RMSE and PSNR with ground truth being reconstructed result obtained using original 100 detectors data (\(S_F\)).

The reconstruction PA images using the sinogram obtained using the methods discussed till now, including proposed CNN, were presented in Fig. 2 for the blood vessel phantom for SNR of sinogram being 20, 40, and 60 dB (arranged row wise respectively). The target phantom is shown in Fig. 2(m) and ground truth reconstruction using 100 detectors data (noise free) is shown in Fig. 2(n). The results obtained using 50 detectors sinogram data are shown in the first column (a-c). Reconstruction results for the interpolated sinogram for 100 detectors are shown in second column (d-f). The reconstructed PA images obtained using denoised sinogram data obtained via
MODWT method are shown in the third column (g-i). The reconstructed PA images using the proposed CNN based interpolated denoising method were presented in fourth column (j-l). The reconstructed images using sinogram obtained via the proposed deep learning based method was capable of mitigating aliasing artifacts and improvement in visibility of edges. The reconstructed PA image background is less noisy for the result obtained using proposed method. The RMSE and PSNR (in dB scale) of reconstruction results are shown in Figs. 2(o) and 2(p) respectively. The improvement (decrease) in RMSE obtained for 20 dB case (first row) was 29.14% while for 40 (Second row) and 60 (third row) dB cases, the improvement it achieved was 41.16%, and 41.70% respectively compared to results obtained to using only 50 detectors data. Similarly the improvement in PSNR obtained for 20, 40, and 60 dB cases was 3.68, 4.21, and 4.26 dB respectively. The same trend was also observed for the case of numerical Derenzo phantom (Fig. 3). In this case, the small radius circles were indistinguishable due to the aliasing artifacts in all results except proposed CNN based method. The improvement for the sinogram data having SNR of 20 dB in terms of RMSE and PSNR was 5.87% and 3.14 dB respectively. For sinogram SNR being 40 dB, the improvement was 6.25% and 2.95 dB respectively and for sinogram SNR being 60 dB, 6.28% and 2.95 dB improvement in RMSE and PSNR was observed respectively using proposed method in comparison to other standard methods (near neighbour interpolated and MODWT based denoised methods).

An in-vivo rat brain sinogram data was also utilized in this work to show the superiority of the proposed SRCN deep neural network architecture in pre-clinical imaging. The reconstruction result using original hundred detectors sinogram data is shown in Fig. 4(a), which serves as ground truth. The reconstruction using fifty detectors data is shown in Fig. 4(b) and the reconstruction obtained using the data after interpolation is shown in Fig. 4(c). The reconstructed PA image obtained using denoised sinogram data utilizing MODWT method was shown in Fig. 4(d). The reconstructed PA image using sinogram data of 100 detectors that were denoised and super resolved using the proposed deep learning based method was shown in Fig. 4(e). From these results, it is clear that the proposed CNN based method was able to provide super-resolved and denoised sinogram that enabled good quality PA images with reduction in artifacts and background noise. The RMSE and PSNR improvements were shown in Fig. 4(f) and 4(g) respectively. The PSNR improvement obtained in the proposed method as compared to the fifty detectors data was 6.93 dB. Since the in-vivo data was not acquired in the same fashion as the other numerical phantoms data, there are some structures missing in the denoised improved output, but the overall PSNR improved with reduction in artifacts with the proposed method. Since interpolation depends on the sampling of the data, the change in configuration leads to different set of data collected by the ultrasonic transducers. If the same configuration is used for training as well as testing as was shown for the numerical test phantoms, no loss of structures are observed with improvement in image quality. Even though this work shown only super-resolving and denoising of sinogram data from 50 detectors to 100 detectors with 512 time samples (making it limited data case), the proposed approach is in general applicable to super-resolving the sinogram of any dimension. Python and MATLAB codes for dataset creation, model construction, training and testing network were provided as an open source [42] to help users to replicate the proposed approach. Note that the training time could be further reduced with usage of multi-GPU framework (current set-up utilized only two GPUs).

6. Conclusion

The proposed sinogram super-resolution and denoising method that is deep learning based clearly shows significant improvement (PSNR improvement as high as 6.93 dB) in the reconstructed PA image. The absence of noise in super-resolved sinogram results in reduced artifacts and better reconstructed image quality. The results presented here were unseen by the proposed deep learning network and demonstrate that the proposed network was capable of providing a
generalizable model for super-resolving and denoising the sinogram. As deep learning is making strides in medical imaging, the proposed work clearly demonstrates the utility of the same in terms of improving limited experimental data in terms of super-resolving and denoising. The proposed approach was fully data driven and authoritatively shown to improve the reconstructed PA image quality using both numerical and \textit{in-vivo} cases.

**Disclosures**

The authors declare that there are no conflicts of interest related to this article.

**References**

1. J. Xia and L. V. Wang, “Small-animal whole-body photoacoustic tomography: a review,” IEEE Transaction Biomed. Eng. 61, 1380–1389 (2014).
2. L. V. Wang and S. Hu, “Photoacoustic tomography: in vivo imaging from organelles to organs,” science 335, 1458–1462 (2012).
3. M. Pramanik, G. Ku, C. Li, and L. V. Wang, “Design and evaluation of a novel breast cancer detection system combining both thermoacoustic (ta) and photoacoustic (pa) tomography,” Med. Phys. 35, 2218–2223 (2008).
4. P. K. Upputuri and M. Pramanik, “Recent advances toward preclinical and clinical translation of photoacoustic tomography: a review,” J. Biomed. Opt. 22, 041006 (2016).
5. Y. Zhou, J. Yao, and L. V. Wang, “Tutorial on photoacoustic tomography,” J. Biomed. Opt. 21, 061007 (2016).
6. K. Wang, R. Su, A. A. Oraevsky, and M. A. Anastasio, “Investigation of iterative image reconstruction in three-dimensional optoacoustic tomography,” Phys. Medicine & Biol. 57, 5399 (2012).
7. K. Wang, S. A. Ermilov, R. Su, H.-P. Brecht, A. A. Oraevsky, and M. A. Anastasio, “An imaging model incorporating ultrasonic transducer properties for three-dimensional optoacoustic tomography,” IEEE Transactions on Med. Imaging 30, 203–214 (2011).
8. A. Rosenthal, V. Ntziachristos, and D. Razansky, “Acoustic inversion in optoacoustic tomography: A review,” Curr. Med. Imaging Rev. 9, 318–336 (2013).
9. N. Awasthi, S. K. Kalva, M. Pramanik, and P. K. Yalavarthy, “Vector extrapolation methods for accelerating iterative reconstruction methods in limited-data photoacoustic tomography,” J. Biomed. Opt. 23, 071204 (2018).
10. C. Huang, K. Wang, L. Nie, L. V. Wang, and M. A. Anastasio, “Full-wave iterative image reconstruction in photoacoustic tomography with acoustically inhomogeneous media,” IEEE Transactions on Med. Imaging 32, 1097–1110 (2013).
11. N. Awasthi, S. K. Kalva, M. Pramanik, and P. K. Yalavarthy, “Image-guided filtering for improving photoacoustic tomographic image reconstruction,” J. Biomed. Opt. 23, 091413 (2018).
12. Y. Xu, L. V. Wang, G. Ambartsoumian, and P. Kuchment, “Reconstructions in limited-view thermoacoustic tomography,” Med. Phys. 31, 724–733 (2004).
13. S. R. Arridge, M. M. Betcke, B. T. Cox, F. Lucka, and B. E. Treeby, “On the adjoint operator in photoacoustic tomography,” Inverse Probl. 32, 115012 (2016).
14. S. Arridge, P. Beard, M. Betcke, B. Cox, N. Huynh, F. Lucka, O. Ogunlade, and E. Zhang, “Accelerated high-resolution photoacoustic tomography via compressed sensing,” Phys. Medicine Biol. 61, 8908 (2016).
15. A. Buehler, A. Rosenthal, T. Jetzfellner, A. Dima, D. Razansky, and V. Ntziachristos, “Model-based optoacoustic inversions with incomplete projection data,” Med. Phys. 38, 1694–1704 (2011).
16. X. L. Dean-Ben, V. Ntziachristos, and D. Razansky, “Acceleration of optoacoustic model-based reconstruction using angular image discretization,” IEEE Transactions on Med. Imaging 31, 1154–1162 (2012).
17. X. L. Dean-Ben, A. Buehler, V. Ntziachristos, and D. Razansky, “Accurate model-based reconstruction algorithm for three-dimensional optoacoustic tomography,” IEEE Transactions on Med. Imaging 31, 1922–1928 (2012).
18. G. Paltauf, J. Viator, S. Prahl, and S. Jacques, “Iterative reconstruction algorithm for optoacoustic imaging,” J. Acoust. Soc. Am. 112, 1536–1544 (2002).
19. B. E. Treeby and B. T. Cox, “k-wave: Matlab toolbox for the simulation and reconstruction of photoacoustic wave fields,” J. Biomed. Opt. 15, 021314 (2010).
20. S. Antholzer, M. Haltmeier, and J. Schwab, “Deep learning for photoacoustic tomography from sparse data,” Inverse Probl. Sci. Eng. pp. 1–19 (2018).
21. E. M. A. Anas, H. K. Zhang, J. Kang, and E. Boctor, “Enabling fast and high quality led photoacoustic imaging: a recurrent neural networks based approach,” Biomed. Opt. Express 9, 3852–3866 (2018).
22. E. M. A. Anas, H. K. Zhang, C. Audigier, and E. M. Boctor, “Robust photoacoustic beamforming using dense convolutional neural networks,” in Simulation, Image Processing, and Ultrasound Systems for Assisted Diagnosis and Navigation, (Springer, 2018), pp. 3–11.
23. N. Awasthi, K. R. Prabhakar, S. K. Kalva, M. Pramanik, R. V. Babu, and P. K. Yalavarthy, “Pa-fuse: deep supervised approach for the fusion of photoacoustic images with distinct reconstruction characteristics,” Biomed. Opt. Express 10, 2227–2243 (2019).
24. H. Lee, J. Lee, H. Kim, B. Cho, and S. Cho, “Deep-neural-network based sinogram synthesis for sparse-view ct image reconstruction,” IEEE Transactions on Radiat. Plasma Med. Sci. (2018).
25. H. Lee, J. Lee, and S. Cho, “View-interpolation of sparsely sampled sinogram using convolutional neural network,” in Medical Imaging 2017: Image Processing, vol. 10133 (International Society for Optics and Photonics, 2017), p. 1013328.
26. Y. Hristova, P. Kuchment, and L. Nguyen, “Reconstruction and time reversal in thermoacoustic tomography in acoustically homogeneous and inhomogeneous media,” Inverse Probl. 24, 055006 (2008).
27. S. H. Holan and J. A. Viator, “Automated wavelet denoising of photoacoustic signals for circulating melanoma cell detection and burn image reconstruction,” Phys. Medicine & Biol. 53, N227 (2008).
28. D. B. Percival and A. T. Walden, Wavelet methods for time series analysis, vol. 4 (Cambridge university press, 2006).
29. D. L. Donoho and J. M. Johnstone, “Ideal spatial adaptation by wavelet shrinkage,” biometrika 81, 425–455 (1994).
30. R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, (2014), pp. 580–587.
31. A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in Neural Information Processing Systems, (2012), pp. 1097–1105.
32. J. Kim, J. Kwon Lee, and K. Mu Lee, “Accurate image super-resolution using very deep convolutional networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, (2016), pp. 1646–1654.
33. M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka, C. G. Owen, and S. A. Barman, “An ensemble classification-based approach applied to retinal blood vessel segmentation,” IEEE Transactions on Biomed. Eng. 59, 2538–2548 (2012).
34. J. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. Van Ginneken, “Ridge-based vessel segmentation in color images of the retina,” IEEE Transactions on Med. Imaging 23, 501–509 (2004).
35. A. Hoover, V. Kouznetsova, and M. Goldbaum, “Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response,” IEEE Transactions on Med. Imaging 19, 203–210 (2000).
36. D. Kingma and J. A. Ba, “A method for stochastic optimization. arxiv 2014,” arXiv preprint arXiv:1412.6980 .
37. F. Chollet et al., “Keras: Deep learning library for theano and tensorflow,” URL: https://keras.io/ (2015).
38. M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin et al., “Tensorflow: Large-scale machine learning on heterogeneous distributed systems,” arXiv preprint arXiv:1603.04467 (2016).
39. N. Gandhi, M. Allard, S. Kim, P. Kazanzides, and M. A. L. Bell, “Photoacoustic-based approach to surgical guidance performed with and without a da vinci robot,” J. Biomed. Opt. 22, 121606 (2017).
40. P. P. Pai, A. De, and S. Banerjee, “Accuracy enhancement for noninvasive glucose estimation using dual-wavelength photoacoustic measurements and kernel-based calibration,” IEEE Transactions on Instrumentation Meas. 67, 126–136 (2018).
41. Y. Jiang, P. K. Upputuri, C. Xie, Y. Lyu, L. Zhang, Q. Xiong, M. Pramanik, and K. Pu, “Broadband absorbing semiconducting polymer nanoparticles for photoacoustic imaging in second near-infrared window,” Nano Lett. 17, 4964–4969 (2017).
42. N. Awasthi, R. Pardasani, S. K. Kalva, M. Pramanik, and P. K. Yalavarthy, “Sinogram super-resolution and denoising deep-neural-network (srdsn) for limited data photoacoustic tomography,” URL: https://sites.google.com/site/sercmig/home/patsrdn (2019).