Improving photoacoustic imaging in low signal-to-noise ratio by using spatial and polarity coherence

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ABSTRACT

To suppress the noise and sidelobe of photoacoustic images, a method is proposed combined with spatial coherence and polarity coherence. In this method, PA signals are delayed, multiplied, then performed polarity coherence operation, and finally summed. The polarity of delayed-and-multiplied signals rather than the amplitude is considered in polarity coherence operation. The polarity coherence factor is calculated based on the standard deviation of the polarity. Then, the factor as weights is applied to the coherent sum output after spatial auto-correlation to finally obtain the image. The simulated and experimental results prove that the noise level can be effectively suppressed due to the relatively low polarity coherence factor. Compared with the delay-and-sum method, the quantitative results in simulations show that the image contrast and full-width at half-maximum of the proposed method increase by about 227.0 % and 56.5 % when the signal-to-noise ratio of the raw signal is 0 dB, respectively. Besides achieving a better image contrast, this method obtains improvements in sidelobe attenuation and has a narrow main lobe.

1. Introduction

Photoacoustic imaging (PAI) is an emerging non-invasive biomedical imaging modality based on the photoacoustic effect [1]. In a PAI system, broad-band photoacoustic waves are generated by the tissue itself, resulting from the instantaneous thermoelastic expansion due to the absorption of electromagnetic radiation [2,3]. Images of optical absorption in the tissue can be reconstructed from PA waves detected by an ultrasound (US) transducer. Therefore, PAI combines rich optical contrast with good US spatial resolution in deep tissue [4–6]. PAI has demonstrated the potential in characterizing structural, functional, physiological, and molecular information for medical diagnosis [7–11].

The image quality of PAI highly relies on a reconstruction algorithm for solving the inverse problem of wave propagation. In the past decades, many algorithms have been explored for PA image reconstruction [12–15]. Back projection (BP) and delay-and-sum (DAS) methods are prevalent in PAI due to their simple implementation for providing elegant solutions to the inverse problem. However, their capability is insufficient in suppressing noise and sidelobe [16,17]. Benefiting from the different spatial coherence of the main lobe, sidelobe, and noise in different spatial locations, some spatial-coherence-based methods have been proposed to improve the PAI quality [18–22]. The delay-multiply-and-sum (DMAS) beamformer has revealed that it can use to suppress sidelobe and noise in PA images, by considering the spatial coherence of signals [19,20]. To further improve the resolution of DMAS, minimum-variance-based algorithms have achieved great resolution improvements as well as sidelobe reductions, at the expense of a higher computational burden [23]. Beamformer combined with the coherence factor weighting (CF) has been developed in US and PA fields to obtain high-quality images [24–26]. CF mainly depends on the ratio of the coherent sum to the incoherent sum in the amplitude of the delayed signals. It has been proved that CF can achieve better noise and sidelobe rejection. However, the amplitude information of PA signals is easy to be affected by the electromagnetic noise, quantization error of digital sampling, and variation of laser energy [22]. Consequently, the accuracy of CF could be disturbed by these system interferences.

For the reconstruction algorithm, it is essential to realign the phase of the received signals. When the phase diversity of signals is consistent, the polarities of signals are presented as the same, but the amplitudes may be different. Therefore, the polarity characteristics of signals carry

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important information on phase coherence [27]. A weighting factor, called the sign coherence factor (SCF), directly depends on the standard deviation of phase polarity between different signals [28]. Compared with CF, SCF is obtained by taking full use of the phase diversity of signals, which provides higher independence of object distribution [27]. Besides, the polarity can still be retained even when the amplitude of signals is distorted. Benefiting from these advantages, SCF exhibits better performance in suppressing the sidelobe, noise, and especially the grating lobe for US imaging [29,30].

In this study, a method for PA image reconstruction is proposed, which is based on signal delay, multiplication, polarity coherence, and summation (DMPCS). This method combines the spatial coherence of DMAS beamformer and phase polarity coherence of SCF to improve the image quality of PAI. The simulation and phantom experiments are conducted to evaluate the performance of the DMPCS method. The metrics of image contrast and full width at half maximum (FWHM) are used to quantify the image quality. Finally, in vivo experiments are used to examine the practicability of the proposed method.

2. DMPCS theory combined with spatial and polarity coherence

Let’s suppose a US transducer array with $N$ active elements is used to receive PA signals. Then detected PA signals $S(t)$ can be expressed as

$$S(t) = [s_1(t), \ldots, s_i(t), \ldots, s_N(t)],$$

where $s_i(t)$ is the PA signal at time $t$ obtained by the $i$-th element with $i = 1, \ldots, N$.

The pixel value at $(x, z)$ by performing DMPCS is given by

$$P_{\text{DMPCS}}(x, z) = P_{\text{FC}}(x, z) \times P_{\text{DMAS}}(x, z),$$

where $P_{\text{DMAS}}(x, z)$ is the amplitude multiplication between different channel signals. The amplitude multiplication between different channel signals. The

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$$P_{\text{DMPCS}}(x, z) = P_{\text{FC}}(x, z) \times P_{\text{DMAS}}(x, z),$$

where $P_{\text{DMAS}}(x, z)$ is described as [13].

$$P_{\text{DMAS}}(x, z) = \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{s}_i(t - \tau_i(x, z)) \tilde{s}_j(t - \tau_j(x, z)),$$

with

$$\tilde{s}_i(t - \tau_i(x, z)) = \text{sign}[s_i(t - \tau_i(x, z))] \sqrt{s_i(t - \tau_i(x, z))},$$

where $\tau_i(x, z) = \sqrt{(x-x_i)^2 + (z-z_i)^2} / c$, $c$ is the speed of sound in media. The coupling multiplied operation in Eq. (3) results in the central frequency $f_0$ being shifted to DC and 2nd harmonic frequency ($2f_0$) components [31]. A bandpass filter is applied to keep the frequency indeed.

In Eq. (2), the polarity coherence factor $F_{\text{PC}}(x, z)$ can be calculated as follows. First, a matrix $B$ is obtained by

$$B = [B_1(x, z), B_2(x, z), \ldots, B_{N-1}(x, z), B_N(x, z)],$$

with

$$B_i(x, z) = \left\{ \begin{array}{ll} \tilde{s}_i(t - \tau_i(x, z)) \sum_{j=1}^{N} \tilde{s}_j(t - \tau_j(x, z)) & , i = 1, \ldots, N-1 \vspace{0.5cm} \\ 0 & , i = N \end{array} \right.$$

Here, $B_i(x, z)$ represents the obtained new time-delayed signals considering the spatial correlation. $B_i(x, z)$ can be regarded as a type of small aperture DAS operation with the coefficient $\tilde{s}_i(t - \tau_i(x, z))$.

Second, the polarity of $B_i(x, z)$ is extracted. Let $b_i(x, z)$ $(i = 1, 2, \ldots, N)$ denote the sign bits of $B_i(x, z)$, that is,

$$b_i(x, z) = \left\{ \begin{array}{ll} 1, B_i(x, z) \geq 0 \\ -1, B_i(x, z) < 0 \end{array} \right.$$

Third, the variance $\sigma_{b_i}^2(x, z)$ of sign bit $b_i(x, z)$ can be calculated as

$$\sigma_{b_i}^2(x, z) = \frac{1}{N} \sum_{i=1}^{N} b_i^2(x, z) - \frac{1}{N^2} \left[ \sum_{i=1}^{N} b_i(x, z) \right]^2 = 1 - \left[ \frac{1}{N} \sum_{i=1}^{N} b_i(x, z) \right]^2.$$

Finally, the standard deviation is used to define the polarity coherence factor

$$F_{\text{PC}}(x, z) = 1 - \sigma_b(x, z)$$

The polarity coherence factor $F_{\text{PC}}$ is related to phase polarity dispersion rather than amplitude dispersion. When all time-delayed signals keep the same polarity, the factor $F_{\text{PC}}(x, z)$ can perfectly equal 1 despite slight fluctuation in amplitude at the indication of absorbers. Correspondingly, the $F_{\text{PC}}(x, z)$ is equal to 0 when the polarity is evenly divided. Therefore, when the factor $F_{\text{PC}}(x, z)$ is used for weighting, the noise with scattered phase polarity distribution can be effectively suppressed. Besides, the DMAS beamformer introduces spatial coherence by the amplitude multiplication between different channel signals. The multiplication enlarges the difference in amplitude of signals between noise and absorber. Thus, the proposed method which combines spatial coherence and polarity coherence may have further noise suppression at a low SNR level.

3. Methods and materials

3.1. Numerical simulation

Numerical simulations in 2D (lateral-axial direction) were first conducted to evaluate the performance of the proposed method. As shown in Fig. 1, the numerical scenario consists of eight absorbers with a diameter of 0.05 mm at four different depths. The two adjacent absorbers are separated by 2 mm in the lateral direction (x-direction) and 5 mm in the axial direction (z-direction), respectively. A transducer with 64 elements was used to detect PA signals. The pitch of the element is 0.32 mm. The center frequency of the transducer is 2.5 MHz. The K-wave tool was used to simulate PA excitation, propagation, and detection in a tissue with a speed of sound of 1500 m/s [32]. The first pair of absorbers is 10 mm away from the transducer. PA signals were recorded with a sampling frequency of 10 MHz.
3.2. Phantom experiment

The phantom experiments were performed to evaluate the proposed method in practice. A Q-switched Nd: YAG laser (OPOTEK, LLC, USA) generated the laser pulse with a pulse width of 4.5 ns and a pulse repetition rate of 10 Hz at 690 nm wavelength. The laser was collimated, divided into two beams, and redirected to the phantom from both sides of the transducer by two reflectors with tunable angles, as shown in Figs. 2(a) and (b). The measured energy of the laser deposited in the phantom is 5.5 mJ/cm² which is under a safe level of incident laser fluence of pulsed radiation [33].

PA signals were detected by a US linear-array transducer with 64 elements and a center frequency of 2.5 MHz. The transducer array parameters are consistent with the above simulation. The detected PA signals were amplified with a gain of 40 dB (AMP128, Photosound, Houston, TX, USA) [34] and recorded with a sampling frequency of 10 MHz (Vantage 64, Verasonics Inc., Kirkland, WA, USA). The data acquisition and processing were performed in MATLAB 2020b.

Two hairs, as absorbers, were embedded in the phantom which was made of agar, as shown in Fig. 2(c). This phantom was put under a water tank in Fig. 2(b). An opening imaging window at the bottom of the tank was sealed with a 50-μm-thick fluorinated ethylene propylene plastic film, which let laser and ultrasound through. The lateral distance between the hair is about 2 mm. The hairs are about 13 mm away from the transducer. The imaging plane is perpendicular to two hairs. PA signals at different noise conditions were obtained by reducing the energy of the laser.

3.3. In vivo experiment

Finally, an in vivo experiment was performed to demonstrate the practicability of the proposed DMPCS method for photoacoustic microscopy. For acoustic-resolution photoacoustic microscopy (AR-PAM) [35,36], its resolution is determined by the acoustic focus. To improve the image quality in the out-of-focus region, AR-PAM often employs a virtual-detector-based synthetic-aperture focusing technique (VD-SAFT) [31,37]. The acoustic focus is considered to be a virtual detector. The reconstruction in the in-vivo experiment is based on the conjunction of the proposed DMPCS and VD-SAFT idea.

In our experiment, the laser pulses were emitted with a pulse repetition rate of 10 kHz, a pulse width of 8 ns, and a wavelength of 532 nm. The laser beam was coupled into fibers and was fixed around the periphery of a focused US transducer (Olympus NDT, V319-SU-F) [36]. As shown in Fig. 3. A transducer with a center frequency of 15 MHz was used to detect PA signals. The fractional bandwidth is 60 %. The focal length of the transducer is 19 mm. The sampling frequency is 250 MHz. A noninvasive mouse brain experiment was conducted with scalp preservation. The mouse was anesthetized by using the breathing anesthetic with 3 % isoflurane gas. The mouse sample was scanned point-by-point with a step size of 0.03 mm in the x and y direction by using the motorized translational stage to drive the US transducer. This is equivalent to a planer array. The in vivo experiments were approved by the Institutional Review Board of Affiliated People’s Hospital of Jiangsu University.

4. Results and discussions

4.1. Numerical simulation

Fig. 4 illustrates the images reconstructed by various algorithms (DAS, DMAS, DMAS-CF, and DMPCS) at different SNR levels. In Fig. 4 (a), these images are reconstructed from signals without noise. It is observed that the image reconstructed by DAS has strong sidelobes. Furthermore, the mutual interference of sidelobes forms significant artifacts between two absorbers. The other three images reconstructed by DMAS, DMAS-CF, and DMPCS get improved. Especially, DMPCS almost removes all sidelobes and artifacts in the image. Figs. 4(b) and (c) give the images reconstructed from signals with Gaussian white noise. Noise severely degraded the quality of the image obtained by DAS, in terms of the blurry shape of absorbers and the strong background speckle. But DMAS, DMAS-CF, and DMPCS methods reduce the influence of noise on the image. Especially, the images obtained by the DMPCS method have less noise and a more point-like shape.

Two factors, the full width at half maximum (FWHM) and the image contrast are measured to quantify the image quality. FWHM is calculated from Fig. 5, which is the normalized lateral projection of the area selected in the white dashed box in Fig. 4(a). Both effects of the sidelobe and speckle can be reflected by the lateral projection profiles. Image contrast is obtained by calculating the ratio between the average power inside the absorber [the region in the dashed circle, as shown in Fig. 4 (b)] and the background speckle [the region in the dashed rectangle in Fig. 4(b)]. The image contrast is defined as

\[
\text{image contrast} = 10 \log_{10} \left( \frac{\bar{E}_\text{signal}}{\bar{E}_\text{background}} \right),
\]

where \(\bar{E}_\text{signal}\) and \(\bar{E}_\text{background}\) are the mean power inside the absorber and the background speckle region, respectively. \(p(x_j, z_j)\) is the amplitude at pixel \((x_j, z_j)\). \(m\) is the number of pixels in the region for computation.

Fig. 5 indicates that the mainlobe obtained from DMPCS is narrower than the other three methods. The FWHM calculated for DAS, DMAS, DMAS-CF, and DMPCS methods from Fig. 5(a) is 0.63 mm, 0.39 mm, 0.30 mm, and 0.27 mm, respectively. DMPCS improves the image FWHM by 57.1 %, 30.8 %, and 10.0 %. It means that the proposed DMPCS method may have a better lateral resolution.

The image contrast calculated for DAS, DMAS, DMAS-CF, and DMPCS methods from Fig. 5(b) is 16.95 dB, 29.88 dB, 52.10 dB, and 55.42 dB, respectively. The DMPCS method increases the image contrast by 227.0 %, 85.5 %, and 6.3 %. DMPCS exhibits better performance for sidelobe and speckle suppression compared to the other three methods.

Fig. 6 illustrates the FWHM and the image contrast as a function of the SNR of the detected PA signal. As the SNR decreases, the FWHM of the DMPCS gradually increases, but the overall value is still lower than that of DAS, DMAS, and DMAS-CF. It indicates that the DMPCS method
is robust to provide a better lateral resolution under stronger noise conditions. Similarly, the image contrast of the DMPCS is also better than that of the other three methods as the SNR decreases. It means that the noise suppression effect of DMPCS is more significant than DAS, DMAS, and DMAS-CF, especially at higher SNR.

Fig. 7 compares the variation of the FWHM and image contrast with depth under different SNR levels of mentioned algorithms. The FWHM and image contrast in Fig. 7 are the average metrics of two points at the same depth. As can be seen from the figure, as the depth deepens, the FWHM of DMPCS gradually increases, but it is still less than other methods. As the SNR of the raw signal decreases, the proposed DMPCS can still maintain a good lateral resolution at a deep depth. For image contrast, the increase in depth does not seriously affect the performance of the proposed DMPCS to obtain higher contrast. Although the image contrast obtained by DMPCS is close to that of DMAS-CF in the case of a lower SNR due to the randomness of noise, the advantages of the proposed algorithm are obvious at a higher SNR.

Simulation results indicate that DMPCS offers the narrower possible main lobe width, better sidelobe suppression, and higher background speckle reduction in comparison with the DAS, DMAS, and DMAS-CF methods. In addition, the proposed DMPCS retains good image quality when at a low SNR level or a deep-depth case.
4.2. Phantom experiment

Fig. 8 gives the reconstructed images under different SNR levels. In Fig. 8(a), the image severely suffers from interference by sidelobes. With the increase of noise in raw signals, the image in DAS has strong background speckle and the two hairs image becomes fused, as shown in Fig. 8(b). However, these image sidelobes, distortion, and speckles are reduced in the DMAS, DMAS-CF, and DMPCS methods.

Table 1 gives the FWHM of the right hair calculated from Fig. 8. Table 2 lists the image contrast, calculated from the region marked by the white dashed circle and rectangle in Fig. 8(a). As shown, the FWHM of the DMPCS is improved by 56.4 %, 35.9 %, and 8.5 % over the DAS, DMAS, and DMAS-CF when the SNR of the raw signal is 20 dB, respectively. The image contrast of DMPCS is increased by 146.6 %, 57.3 %, and 7.4 % over the other methods, respectively. The quantitative comparison indicates that a higher-quality image can be obtained by the proposed DMPCS method.

The phantom experiment demonstrates that the DMPCS method...
delivers significant background speckle suppression in practice. Furthermore, the image of DMPCS has a narrower main lobe and less sidelobe. This may be useful for distinguishing two objects that are very close together.

4.3. In vivo experiment

Figs. 9 (a) and (b) give the maximum projection image of the x-y cross-section before and after using the DMPCS method. Figs. 9(a) and (b) are obtained with the scalp intact. To verify the reliability of the imaging results, we trimmed the scalp and photographed the brain after data collection, as shown in Fig. 9(c). It can be seen from Fig. 9 that the location of the vascular imaging is consistent with the real situation. This indicates that PA images can be used to non-invasively characterize the mouse brain. Comparing Figs. 9(a) and (b), the projection image of

![Graphs showing FWHM and image contrast for different SNR levels.](image)

**Fig. 7.** The variation curve of (a), (b), (c) the FWHM and (d), (e), (f) the image contrast of simulated points at different depths in different SNR levels. The signals with (a), (d) no noise, (b), (e) an SNR of 0 dB, and (c), (f) –6 dB.

![Table 1](image)

Table 1
The FWHM of the right hair in Fig. 8 (mm).

| SNR of signals | DAS | DMAS | DMAS-CF | DMPCS |
|---------------|-----|------|---------|-------|
| 53 dB         | 1.78| 1.15 | 0.87    | 0.76  |
| 20 dB         | 1.72| 1.17 | 0.82    | 0.75  |

![Table 2](image)

Table 2
The image contrast of the hair phantom (dB).

| SNR of signals | DAS | DMAS | DMAS-CF | DMPCS |
|---------------|-----|------|---------|-------|
| 53 dB         | 21.61| 34.25| 50.07   | 49.59 |
| 20 dB         | 21.75| 34.09| 49.93   | 53.64 |

![Images showing reconstructed images](image)

**Fig. 8.** Reconstructed images for phantom from signals with an SNR of (a) 53 dB and (b) 20 dB.
DMPCS shows better noise suppression and higher image contrast. That is much more beneficial to clearly identify the blood vessels.

Fig. 10 compares the imaging results obtained by different methods under three SNR levels. All images represent the $x$-$z$ cross-section along the dashed line in Fig. 9. The first column of Fig. 10 is the images reconstructed from the original detected signals without artificial noise added. To compare the performance of these methods as the SNR decreased, white Gaussian noise was artificially added to the original detected signals. The second and third columns of Fig. 10 are the results reconstructed from signals after the SNR is decreased by 16 dB and 22 dB, respectively.

As shown, the images obtained from DAS show strong background speckles, due to the effect of noise, and multiple reflected waves for the skull, and sidelobe, but the DMAS, DMAS-CF, and DMPCS methods significantly improve the image quality. Especially, as SNR is low, the proposed DMPCS method can still provide a clean image with low speckle and good vessel images with a narrow width. This reveals the excellent background speckle suppression of DMPCS.

Table 3 gives the image contrast, which was measured from the area selected in the white dashed circle and rectangle of the B-scan image in Fig. 10(b). It shows that the DMPCS improves the image contrast by 73.8 %, 27.0 %, and 2.7 % compared with the other three methods when the SNR of the raw signal is decreased by 22 dB, respectively. The in vivo experiment confirms the utility of the proposed DMPCS method in AR-
Table 3
The image contrast of various methods at different SNR levels (dB).

| SNR of signals | DAS | DMAS | DMAS-CF | DMPCS |
|----------------|-----|------|---------|-------|
| Raw data       | 34.63| 47.74| 48.36   | 48.41 |
| 16 dB          | 22.20| 30.78| 36.56   | 38.23 |
| 22 dB          | 16.76| 22.94| 28.37   | 29.13 |

PAM.

4.4. Discussions

These results demonstrate that DMPCS has the potential to provide a better image quality in comparison to DAS, DMAS, and DMAS-CF. DMPCS can not only perform high-quality imaging of simple absorbers but also provide a high-contrast image for actual complex intracerebral vascular imaging. However, since DMPCS leads to a contrast enhancement, although noise and sidelobe can be effectively suppressed, the signals with weaker amplitudes may be ignored in the same colormap due to excessive suppression. For such a problem, the weighting factor can be adjusted exponentially according to the actual situation to alleviate the strong inhibitory effect.

Although the image quality degrades to a level comparable to that of DMAS-CF at a low SNR case, the performance of DMPCS is better than DMAS-CF at a high SNR level. This is because of the serious influence of signal distortion at low SNR. Moreover, the proposed DMPCS needs only one sign bit to compute the weighting factor. If the beamforming will be integrated into a digital signal processor chip to realize real-time imaging in the future, the DMPCS will be easier to deploy the hardware circuit and has smaller storage space than DMAS-CF.

5. Conclusions

In this study, we proposed a DMPCS method to reconstruct the photoacoustic image. The essence of this method relies mainly on the difference in spatial coherence and polarity coherence between the main lobe, sidelobe, and noise. In this method, a polarity coherence factor based on the polarity of signals is used to weight the DMAS beamformer to improve the image quality when at a low SNR level.

The simulated and experimental results prove that DMPCS can provide a better reduction in sidelobe, noise, and main lobe, and better image contrast improvement, in comparison to the other algorithms. This superiority of DMPCS is owing to the combination of spatial coherence and phase polarity coherence. The usage of spatial coherence of signals is useful to suppress the sidelobe and noise due to their low coherence at different spatial positions. Further application of polarity coherence on these spatially correlated signals can deeply suppress signals with scattered phase distribution. When at a low SNR level or at a deep depth, the better improvement of the image quality in DMPCS is still robust. Besides, only a sign bit of signals involved for coherence in DMPCS results in a straightforward hardware implementation. Therefore, the proposed DMPCS could be beneficial to improve the imaging quality of photoacoustic tomography and acoustic-resolution photoacoustic microscopy.

Declaration of Competing Interest

No conflict of interest exists in the submission of this manuscript.

Data Availability

Data will be made available on request.

Acknowledgments

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