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Research advances of beamforming algorithms in medical ultrasound systems

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Highlights

- Algorithms such as adaptive beamforming and synthetic aperture technology have significantly improved the quality of ultrasound images.
- New algorithms, such as deep learning, can adapt to more complex signal environments at the expense of real-time performance.
- Combining different algorithms can overcome the limitations of a single algorithm, thereby improving image resolution, contrast, and noise resistance.

Abstract

Medical ultrasound imaging, as a non-invasive, safe, and reliable technology, plays an important role in clinical diagnosis and treatment. However, traditional ultrasound imaging techniques have limitations such as low resolution, poor penetration depth, and high noise levels. To address these issues, beamforming algorithms have become essential. This paper discusses the development and current research status of beamforming algorithms in the context of medical ultrasound systems, focusing on commonly used beamforming algorithms such as synthetic aperture imaging, adaptive beamforming (especially minimum variance distortionless response), and generalized sidelobe canceller technology. These algorithms optimize the emission and reception of ultrasound waves, overcoming the limitations of traditional techniques and improving image resolution, penetration depth, and noise suppression. They provide support for the advancement of medical ultrasound imaging technology and its clinical applications.

Keywords: Medical ultrasound imaging, beamforming algorithms, synthetic aperture, minimum variance, generalized sidelobe canceller

Introduction

Since its inception in the mid-20th century, medical ultrasound imaging technology has undergone continuous innovation and development, becoming an indispensable tool in modern medical diagnosis and treatment. Introduced in the 1950s, ultrasound technology primarily featured A-mode and B-mode ultrasound. A-mode ultrasound (Amplitude Mode) was mainly used to measure the distance of tissue interfaces, generating one-dimensional amplitude images, while B-mode ultrasound (Brightness Mode) produced two-dimensional grayscale images through brightness modulation, providing a more intuitive display of tissue structures. Although these early technologies had relatively low image quality and resolution, they marked the initial application and development of medical ultrasound imaging technology [1].

With advancements in electronic and computer technologies, real-time two-dimensional ultrasound (2D Ultrasound) gained popularity between the late 1960s to the 1970s. This technology, by utilizing mechanical or electronic scanning probes to generate and display real-time two-dimensional images of the human body, greatly improved the efficiency and diag-

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Table 1. Characteristics of ultrasound waves of different frequencies and their application

	Frequency (MHZ)	Characteristics	Applications
Low-frequency ultrasound	2-5	Capable of penetrating deeper tissues, suitable for observing deeper structures.	Liver, pancreas, heart, etc.
Mid-frequency ultrasound	5-12	Has higher resolution, suitable for observing structures at moderate depths.	Digestive tract, kidneys, bladder, etc.
High-frequency ultrasound	12-20	High-frequency ultrasound has higher resolution, suitable for observing superficial structures.	Breast, thyroid, ocular structures, etc.

nostic capabilities of ultrasound examinations [2]. It became widely applied in abdominal, cardiac, and obstetric examinations. Since then, medical ultrasound imaging technology has become a focal point of research. Technologies such as three-dimensional ultrasound, harmonic imaging, and endoscopic ultrasound have continued to evolve. These advancements have significantly improved the accuracy and efficiency of clinical diagnosis while expanding the application scope of ultrasound in disease diagnosis, treatment, and prognosis evaluation, solidifying its critical role in modern medicine.

To achieve high-quality ultrasound imaging, there is a growing demand for advanced ultrasound beamforming algorithms. The conventional Delay-and-Sum (DAS) Beamforming algorithm aligns the phases of signals from specific directions by applying delays and weights to signals received by each antenna, thereby enhancing signals from those directions. While this method is simple and computationally efficient, it has limited ability to suppress sidelobes and cannot effectively filter out interference signals from other directions [3]. The Dynamic Receive Focus algorithm, which fixes the transmission focus and overlays delayed ultrasound echo signals to obtain images, provides higher resolution and contrast near the transmission sound field focus, but results in overall lower quality ultrasound images [4]. The Synthetic Aperture (SA) beamforming algorithm, proposed by the team led by Professor Jensen at the Fast Ultrasound Imaging Center of the Technical University of Denmark, improves ultrasound image quality by sequentially excites individual array elements for wave transmission and allowing all array elements to receive the signals. This bidirectional focus of both transmission and reception, achieved through time-of-flight calculations, significantly enhances image clarity [5]. The Minimum Variance (MV) beamforming algorithm, proposed by Capon, constructs the weights of each channel in the phased array ultrasound endoscope from a signal processing perspective. It maintains an ideal signal while suppressing the total output signal energy, thereby improving image quality [6]. Nilsen's diagonal loading algorithm and subarray smoothing algorithm further enhance the robustness of the MV algorithm [7].

Domestic researchers have also conducted in-depth research on ultrasound imaging algorithms. Li et al. applied graphics processing unit parallel computing to the SA algorithm, solving the issues of computational complexity and large data demands, which improved imaging speed [8]. Su Ting et al. proposed the multi-line acquisition delay multiply and sum algorithm, which reduces the correlation between echo signals by combining and multiplying them using the MV approach [9]. Wang et al. proposed a MV algorithm that combines signal-to-noise ratio post-filtering and feature space fusion, leading to enhanced resolution and contrast compared to the traditional MV algorithm, with improved adaptability to noise [10].

Through domestic and international research, it is evident that classic beamforming algorithms such as DAS, MV, SA, and Generalized Sidelobe Canceller (GSC) remain essential in medical ultrasound imaging. This paper reviews the research progress on beamforming algorithms in the field of medical ultrasound. The second section introduces the basic principles and technical characteristics of ultrasound beamforming, including the generation, propagation, and reflection mechanisms of ultrasound waves. The third section briefly describes the literature retrieval process and summarizes the main content and conclusions of the reviewed literature. The fourth section introduces more classical beamforming algorithms and related technologies in existing research. The final section summarizes the main trends and challenges in current research on ultrasound endoscopic image processing and proposes future research directions.

The basic principle of endoscopic ultrasound

The acoustic principles and propagation characteristics of ultrasound are the foundation of ultrasound imaging. Ultrasound is a type of mechanical wave with a frequency higher than the

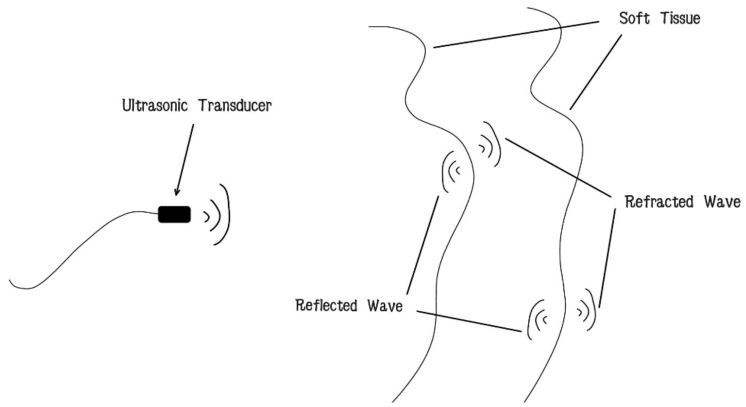

Figure 1. Reflection, refraction, and echo signal illustration.

human hearing range, typically above 20 kHz. The higher the frequency, the shorter the wavelength, enabling higher-resolution imaging. In medical ultrasound systems, the vibration frequency of sound sources generally ranges from 2 to 20 MHz. **Table 1** summarizes the various medical applications of these ultrasonic waves at different frequencies.

Ultrasound waves are emitted through an ultrasound probe or transducer, which contains one or more piezoelectric crystals that convert electrical energy into mechanical vibrations, producing the ultrasound waves. As these waves propagate through the body, they interact with different tissues, each of which has unique acoustic properties. At the boundaries between different soft tissues, the waves reflect and refract. When ultrasound waves encounter these tissue boundaries, part of the energy is reflected back, forming echoes. The piezoelectric crystals in the ultrasound probe convert the received echo signals into analog electrical signals, as illustrated in **Figure 1**.

These signals undergo a series of processing steps, including amplification, gain compensation, filtering, analog-to-digital conversion, and demodulation, before being sent to the display. During these steps, advanced image processing algorithms and techniques, such as noise reduction algorithms, image enhancement techniques, motion correction algorithms, and deep learning methods, are applied to improve the quality and accuracy of ultrasound images. The beamforming algorithms play a crucial role in the reception of reflected signals. During this process, the beamforming algorithm adjusts the transmission and reception time delays, as well as the phase and amplitude of multiple transducer elements in the ultrasound probe. By doing so, it optimizes the direction, focus, and shape of the ultrasound beam, thereby enhancing the resolution, contrast, and depth of the images.

Literature research

We conducted a literature search using keywords such as “medical ultrasound imaging” and “beamforming algorithms” across platforms like Google Scholar, Web of Science, and PubMed.

After thoroughly reviewing and categorizing a large number of papers, we selected over one hundred papers related to beamforming algorithms, including DAS, SA, MV, Regularization, and GSC. Among these, more than ninety papers were published within the last fifteen years. We summarized and classified nearly one hundred papers from 2009 onwards, selecting over thirty representative studies for in-depth discussion. **Table 2** summarizes the main content and research conclusions of these studies.

Synthetic aperture ultrasonography (SAUS)

SA technology was initially utilized for radar technology. SA Radar collects radar signals from a moving platform and utilizes signal processing techniques to simulate a large antenna aperture. SA Radar systems achieve high-resolution imaging by synthesizing a large aperture through motion. SA algorithms process the collected radar signals to generate high-resolution images. SA Radar finds extensive applications in various fields such as military, geological exploration, and environmental monitoring [41, 42].

Inspired by high-resolution imaging used in radar and optics, Professor Jørgen’s team at the Technical University of Denmark improved the SA algorithm and introduced it into medical ultrasound imaging. The specific steps of SA algorithm include data acquisition, motion compensation, data focusing, image processing, image enhancement, and post-processing. During the data acquisition stage, signal data are collected from different positions or directions. Subsequently, motion compensation is applied to correct for any platform or sensor movement during data collection. Next, the collected data is focused using signal processing techniques to concentrate signals from different positions or directions onto a single focal point. Finally, this focused data are used to generate high-resolution images, which can be further enhanced and post-processed to meet specific

Table 2. Summary of literature

Authors	Main content	Research conclusions
Chen et al. [11]	A SAF Method to Improve Signal-to-Noise Ratio and Resolution in Endoscopic Ultrasound.	Compared to traditional methods, this approach can improve the signal-to-noise ratio and resolution of ultrasound images by 9.38 dB and 51%, respectively.
Trots et al. [12]	STA Method Combined with Golay Coded Transmission.	While maintaining the resolution of ultrasound images, this method improves the signal-to-noise ratio and increases the imaging depth.
Chen et al. [13]	A Low-Complexity Global Motion Compensation Algorithm Based on the STA Method.	Compared to uncompensated images, the proposed motion compensation algorithm can improve the image CR and CNR by 13.73 dB and 2.04 dB, respectively.
Tasinkevych et al. [14]	Optimization of the MSTA ultrasound imaging method.	The optimal transmit aperture size provides balance between lateral resolution and penetration depth in the obtained two-dimensional ultrasound images, while maintaining a high frame rate.
Zhou et al. [15]	SASB Algorithm Based on Chirp Coded Excitation.	It achieves range-independent resolution while significantly reducing the size of front-end data, attaining imaging quality comparable to baseline 3D SASB.
Mirzaei et al. [16]	VSSA Imaging ultrasound imaging technology.	It overcomes the depth of field limitations of traditional source synthetic aperture imaging, offering significant advantages in high resolution, high A-line count, and penetration depth, and it can significantly improve the accuracy of lateral strain estimation.
Synnevag et al. [17]	An adaptive method with a Minimum Variance beamformer.	The Minimum Variance beamformer can compensate for resolution loss by using smaller transducers, wider transmission beams, or lower transmission frequencies.
Sreejeesh et al. [18]	Quadrature Rotation Decomposition-MVDR Beamforming Algorithm.	By solving the problem of high computational complexity of the MVDR algorithm, it has an advantage in terms of computation time and can be used for ultra-fast adaptive beamforming applications.
Holfort et al. [19]	A MV Method for Near-field Broadband Data Beamforming.	The Frequency Subband MV significantly improves the lateral resolution and contrast of imaging while reducing the number of transmissions, and it exhibits good tolerance to pointing vector errors.
Yan et al. [20]	MV based on Submatrix Space Coherence with the Sign Coherence Factor.	This method reduces sidelobe noise without increasing computational complexity and significantly improves the resolution and contrast of imaging in coherent plane-wave compounding.
Wang et al. [21]	CMSAW.	CMSAW introduces aperture coherence-based adaptive diagonal loading to enhance speckle preservation performance. CMSAW-MV improves resolution and suppresses sidelobes, incoherent clutter, and noise.
Aliabadi et al. [22]	OESMV.	This new signal-to-noise subspace identification method allows for flexible adjustment based on specific imaging needs to achieve optimal imaging results, significantly improving aspects such as image resolution, contrast, and grayscale levels.
Li et al. [23]	An eigen-based GSC.	This method can reduce sidelobe levels and improve contrast. It offers better lateral resolution and contrast compared to non-adaptive beamformers.
Li et al. [24]	A forward and backward generalized sidelobe canceller method for medical ultrasound imaging.	This method achieves good lateral resolution and contrast without the need for preprocessing algorithms. It can improve the imaging quality of medical ultrasound systems with lower computational overhead and higher reliability.
Yang et al. [25]	Cross Sub-aperture Averaging GSC.	Compared to DS, SA, and traditional GSC methods, GSC-CROSS improves lateral resolution by 76.9%, 68.8%, and 17.1% respectively.
Yang et al. [26]	A beamforming algorithm combining generalized sidelobe cancelation with feature space Wiener filtering.	Compared to DS and SA beamforming methods, this approach significantly improves the imaging quality of medical ultrasound systems in terms of lateral resolution and contrast.
Kumar et al. [27]	Deep learning-based algorithm to estimate inactive channel data in periodic sparse arrays.	The algorithm uses data from multiple active channels to estimate inactive channel data. This effectively reduces the element spacing in beamforming, thereby suppressing grating lobes, improving the image quality of sparse arrays.
Hyun et al. [28]	Neural network framework for beamforming ultrasound signals into speckle-reduced B-mode images.	This method demonstrates that networks trained in computer simulations can be generalized to actual in vivo imaging to produce images with significantly reduced speckle while preserving resolution.
Mamistvalov et al. [29]	Deep learning-based B-mode image reconstruction from temporally and spatially subsampled channel data.	The resolution is higher compared to previously proposed reconstruction methods from compressed data (such as NESTA), and comparable noise levels to DAS beamforming from fully sampled data.
Perdios et al. [30]	CNN-based image reconstruction combined with cross-correlation-based speckle tracking algorithm.	This method could unleash the full potential of ultrafast ultrasound, finding applications in areas such as ultrasensitive cardiovascular motion and flow analysis or shear wave elastography.

Authors	Main content	Research conclusions
Shin et al. [31]	MPAX based on Delay and Apodization Crosstalk.	The MPAX technique has been proven to be a highly effective method for suppressing reverberation clutter. This technique robustly suppresses near-field reverberation clutter, significantly enhancing the contrast of ultrasound images.
Nghia et al. [32]	A unified pixel-based beamforming algorithm adapting to the non-spherical waveform of the transmitted beam.	The unified pixel-based beamformer shows significant improvements in image quality compared to other delay-and-sum methods and demonstrates robust performance in limited in vivo studies.
Matrone et al. [33]	Short-Lag Focused F-DMAS formula to limit the signal lag time in the calculation of the coherence matrix used for beamformer formation.	The Short-Lag Focused F-DMAS formula controls the delay time of the signals involved in spatial coherence computation. This helps to maintain or enhance the performance of the F-DMAS algorithm while reducing computational complexity.
Dei et al. [34]	A CF weighting technique combined with ADMIRE.	The CF-weighted ADMIRE further improves image quality in certain aspects. The CF weighting used as a post-processing technique enhances contrast while reducing CNR and speckle SNR.
Rajamaki et al. [35]	Hybrid beamforming method using sparse arrays.	Combining sparse arrays with hybrid beamforming can significantly reduce the number of elements and front-end requirements to achieve the resolution of fully digital uniform arrays.
Ni et al. [36]	Simultaneous excitation of array elements with random sequences encoding, generating an unfocused ultrasound wavefront with random interference.	This method can enhance the detection of organ boundaries and aid in lesion localization in clinical applications such as abdominal and musculoskeletal imaging.
Goudarzi et al. [37]	A flexible beamforming framework using RED.	The RED algorithm provides the best image quality in terms of contrast metrics while preserving speckle statistics.
Asif et al. [38]	Sequential DAS method for focused transmission using fast-marching method.	This method helps overcome fat-induced signal distortion, thereby accurately imaging various pathologies in the liver and abdomen.
Guo et al. [39]	A pixel-based Delay Multiply and Sum beamforming with a Wiener filter.	Compared to traditional dynamic focusing, it has shown a significant improvement in lateral resolution. Compared to the conventional pixel-based algorithm, this method greatly enhances spatial resolution and contrast while maintaining the good characteristics of the beamformer.
Vayyeti et al. [40]	F-DowMAS nonlinear beamforming method.	By adaptively computing the optimal weights for each imaging point, F-DowMAS effectively enhances the resolution and contrast of the image while reducing noise and artifacts.

Note: SAF, Synthetic Aperture Focusing; STA, Synthetic Transmit Aperture; CR, contrast ratio; CNR, contrast-to-noise ratio; MSTA, Multi-Element Synthetic Transmit Aperture; SASB, Synthetic Aperture Sequential Beamforming; VSSA, Virtual Source Synthetic Aperture; MV, Minimum Variance; CMSAW, Covariance Matrix-based Adaptive Weighting; OESMV, Oblique Eigen-space Minimum Variance; GSC, Generalized Sidelobe Canceller; GSC-CROSS: Cross-Subarray Averaging GSC; DS, Delay-and-Sum; SA, Synthetic Aperture; CNN, Convolutional Neural Network; MPAX, Multi-Phase Apodization Crosstalk; F-DMAS, Filtered Delay Multiply and Sum; CF, coherence factor; ADMIRE, aperture domain model image reconstruction; RED, Regularization by Denoising; F-DowMAS, Filtered Delay Optimal Weighted Multiply and Sum.

requirements. The SA beamforming algorithm, illustrated in **Figure 2**, significantly improves imaging resolution and quality, holding important implications for medical diagnostics and other fields [5].

SAUS offers several advantages over traditional beamforming methods. Since it achieves fully dynamic focusing during both transmission and reception, SAUS offers higher spatial resolution. Additionally, since fewer components are needed to generate the waveform during each ultrasound pulse transmission, SAUS consumes less energy. These advantages have made SAUS a hot topic in beamforming algorithm research. Chen et al. proposed a SA Focusing (SAF) method to improve the signal-to-noise ratio (SNR) and resolution in ultrasound endoscopy. This technique leverages the rotational characteristics of the transducer probe, transmitting and receiving echoes at different times and positions during the rotational scan. By utilizing the coding and linear frequency modulation characteristics of the echoes, the algorithm develops axial and lateral matched filters to achieve compression in both directions [11]. Compared to traditional methods, SAF improves the SNR and resolution of ultrasound images by 9.38 dB and 51%, respectively. Therefore, it holds potential for future clinical and research applications. The Synthetic Transmit Aperture (STA) method provides fully dynamic focusing in both transmission and reception modes, offering the highest imaging quality. In the STA method, each array element sequentially emits pulses, while all elements receive echo signals. Data is acquired from multiple directions during transmission, and a complete image is reconstructed based on this data. The advantage of this method is that fully dynamic focusing can be applied during both transmission and reception, resulting in superior quality images. Trots and colleagues conducted theoretical and experimental studies on STA combined with Golay-coded

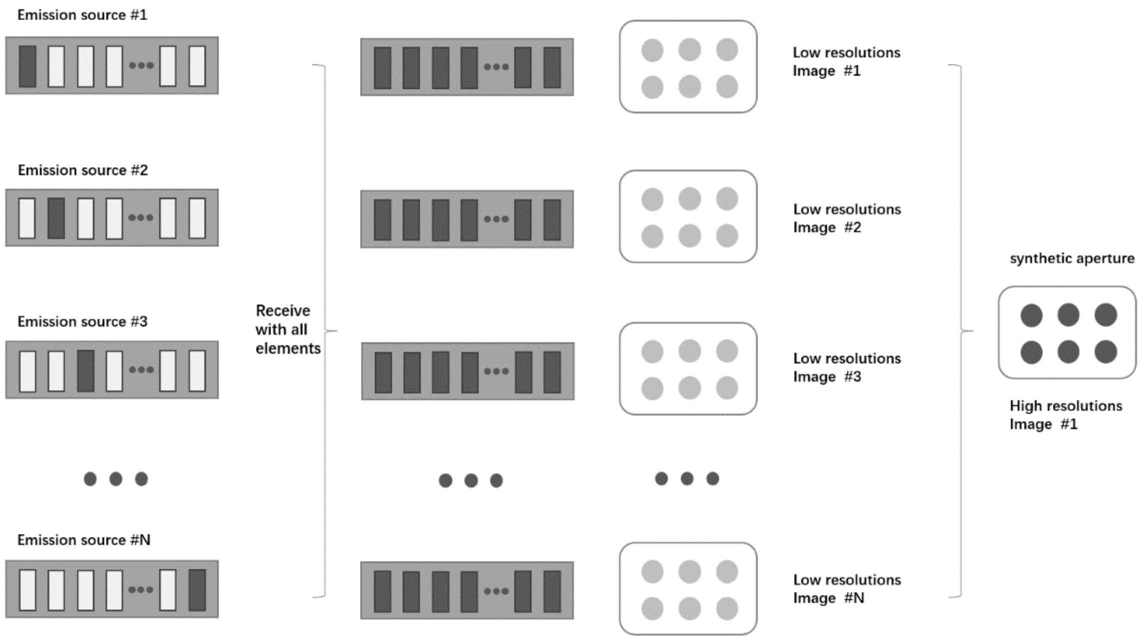

Figure 2. Development process of Synthetic Aperture beamforming algorithm.

transmission for medical ultrasound imaging [12]. The transmission of long waveforms with specific autocorrelation functions can increase the total energy of the transmission signal without increasing peak pressure. This enhances the SNR of the image and increases the display depth while maintaining ultrasound image resolution. Since high-resolution images in STA are formed by superimposing low-resolution images, they are susceptible to motion between transmissions. Chen et al. proposed a low-complexity global motion compensation algorithm, which uses common interest regions between different transmissions in STA imaging to form backward and forward beam vectors; By analyzing the relationship between specific beam vectors in STA imaging, this algorithm assesses the magnitude and direction of motion [13]. This motion compensation algorithm effectively reduces imaging blurring and distortion caused by motion, significantly improving the quality of the resulting high-resolution images. The low complexity of the algorithm makes it highly feasible and practical for real-world applications.

Compared to the traditional SA technology, the Multi-element Synthetic Transmit Aperture (MSTA) method effectively improves the frame rates of imaging systems while achieving a good balance between penetration depth and lateral resolution, making it one of the most promising methods in ultrasound imaging. Tasinkevych et al. optimized the MSTA method by identifying the ideal transmission aperture size that achieves the best balance between lateral resolution and penetration depth for 2D ultrasound images, all while maintaining a high frame rate [14].

Another advanced imaging method, SA Sequential Beamforming (SASB), merges the advantages of SA imaging with sequential beamforming, enhancing both the resolution and contrast of ultrasound images. It achieves resolution independent of distance while significantly reducing the size of the front-end data. Jian Zhou et al. proposed a 3D SASB volume rate enhancement method based on chirp-coded excitation, which improves the volume rate without compromising image quality. This method simultaneously uses four sub-apertures for both transmission and reception and employs a linear chirp as the excitation waveform to reduce interference. Cyst simulations using Field II indicate that this method achieves imaging quality comparable to baseline 3D SASB in both shallow and deep regions [15]. However, 3D ultrasound imaging generates a large amount of data at the front end, making it less unsuitable for high-volume portable medical applications. Virtual Source SA (VSSA) imaging technique offers an alternative approach. VSSA performs SA beamforming on focused transmit data, addressing the depth-of-field limitations of traditional SA imaging while maintaining the same lateral resolution. Mirzaei utilized VSSA for beamforming to achieve high resolution, a high number of A-lines, and penetration depth advantages similar to both SA and line-by-line imaging methods [16]. When compared to a commonly used lateral strain estimation method, VSSA method showed significant improvements. This

Table 3. Comparison of SA related algorithms in ultrasound imaging

Method	Advantages	Disadvantages	Effect comparison
SAF	Significantly improves signal-to-noise ratio and resolution.	Limited imaging depth and high data processing complexity.	Significant improvement in image quality but with increased complexity.
Golay Encoding in STA	Suppresses sidelobe amplitude and significantly improves signal-to-noise ratio.	Increases the computational burden of the system.	Significant improvement in image quality at the cost of increased complexity.
Motion Compensation Beamforming in STA	Improves both CR and SNR.	Affects the trade-off between imaging depth and resolution.	Slight improvement in image quality without additional complexity.
MSTA for Optimal Transmission Aperture	Significantly increases scattering amplitude with minimal lateral resolution loss.	Increases computational complexity of the system.	Significant improvement in image quality at the cost of higher complexity.
SASB With Chirp Encoding Excitation	Significantly increases volume rates without compromising image quality.	Requires high computing power and complex signal processing techniques.	Exceptional improvement in image quality, increased complexity and cost.
VSSA Imaging	Improves penetration depth while maintaining lateral resolution.	Increases computational complexity and implementation costs.	Moderate improvement in image quality with increased complexity.

Note: SA, Synthetic Aperture; SAF: Synthetic Aperture Focusing; STA, Synthetic Transmit Aperture; CR, contrast ratio; SNR, signal-to-noise ratio; MSTA, Multi-Element Synthetic Transmit; SASB, Synthetic Aperture Sequential Beamforming; VSSA, Virtual Source Synthetic Aperture.

technique not only enhances image clarity and detail presentation but also improves imaging of deep tissues, making it perform excellently in practical applications.

The studies mentioned above focus on SA imaging and introduce various algorithms and coding methods to optimize ultrasound imaging. The primary purpose is to improve image quality, signal-to-noise ratio, and adapt to different application scenarios. However, despite the advantages, SA technology involves complex signal processing algorithms and large data volumes, significantly increasing computational complexity compared to DAS method. The real-time performance of the system still faces challenges. **Table 3** summarizes the SA related technologies mentioned above.

MV beamforming

Adaptive beamforming algorithms are advanced beamforming techniques used to improve the quality of medical ultrasound imaging. Unlike traditional fixed beamforming methods, adaptive beamforming algorithms dynamically adjust beamforming weights based on the statistical properties of the received signals to optimize image resolution and contrast [43]. These algorithms determine the beamforming weight vectors by solving an optimization problem. The MV beamforming algorithm is one of the most commonly used adaptive beamforming algorithms. Its primary goal is to minimize the variance of the output signal by appropriately combining sensor signals in the array, thereby enhancing the desired signal in a specific direction while suppressing interference signals from other directions. Consequently, it reduces sidelobes and improves signal quality. **Figure 3** shows the architecture of the MV beamformer. Originally proposed by Capon in 1969, the MV beamforming is based on the Linear Minimum Mean Square Error theory. From a signal processing perspective, it constructs optimal weights for each channel in a phased array ultrasound endoscope to balance the desired signal against the interference signals. These weights are then applied to the sensor signals to form the output beam, thereby enhancing image quality [6]. MV beamforming performs well in low-noise environments and when the array accuracy is high. However, its performance may degrade when the directions of signal and noise are highly correlated. Therefore, in practical applications, MV beamforming typically requires consideration of the environmental conditions and signal characteristics. To improve performance, it is often combined with other beamforming methods, especially in challenging conditions where signal-to-noise ratios are low or interference is high.

In medical imaging, the simplest DAS beamformer is considered the lowest-performing due to its low resolution and relatively weak interference suppression capabilities. Compared to DAS beamformers, the MV beamforming algorithm offers better resolution at the cost of significantly increased computational complex-

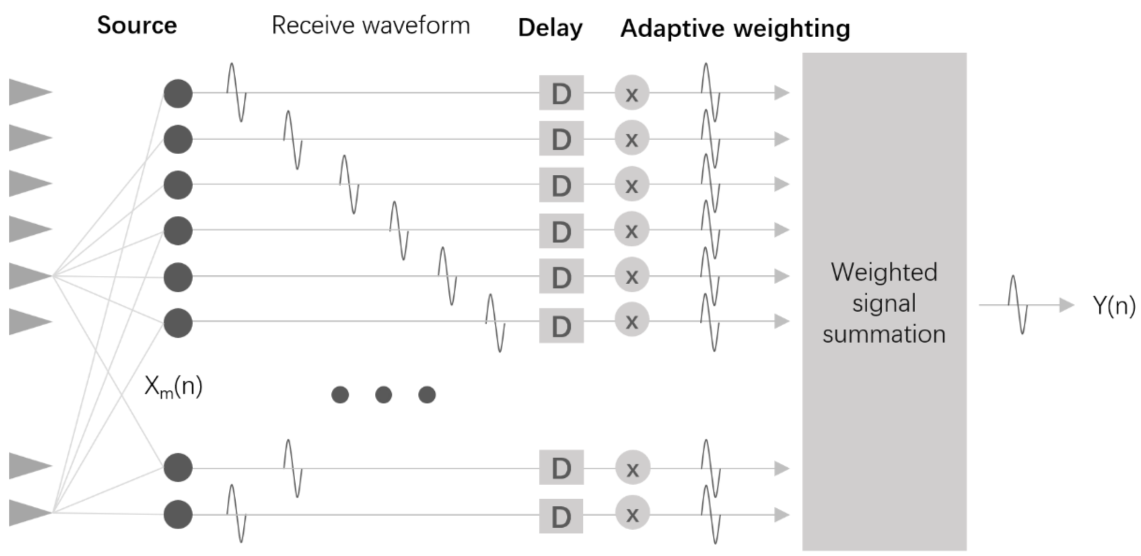

Figure 3. Minimum Variance beamformer architecture.

ity. Synnevag et al. demonstrated that using an adaptive method with a MV beamformer, characterized by low sidelobe levels and narrow beamwidth, not only improves resolution but also enhances imaging quality. By replacing the DAS beamformer with a MV beamformer at the receiving end, it is possible to reduce aperture size, increase frame rate, and improve penetration depth without sacrificing image quality [17]. The MV beamformer can also compensate for resolution loss when using smaller transducers, wider transmit beams, or lower transmit frequencies, making it a powerful tool for medical ultrasound imaging with broad application prospects and potential clinical value.

Sreejeesh proposed an enhanced MV Distortionless Response (MVDR) beamforming architecture, where the adaptive weight vector is calculated based on an improved Column-by-Column Given Rotation (CGR) method. Unlike traditional MVDR beamformers, the Quadrature Rotation Decomposition-MVDR beamformer is suitable for hardware implementation [18]. To improve real-time performance, a CGR-based parallel pipelined Quadrature Rotation Decomposition structure was adopted during the adaptive weight calculation phase, providing a highly efficient MVDR beamforming algorithm suitable for ultra-fast adaptive beamforming applications. Holfort et al. proposed an MV method for near-field beamforming of broadband data. This method is implemented in the frequency domain, providing a set of adaptive complex demodulation weights for each frequency sub-band. By combining the advantages of broadband signal processing and the MV beamforming algorithm, the aim is to significantly improve the resolution and contrast of ultrasound images. When processing frequency sub-bands, the broadband signal is divided into multiple sub-bands, with the MV beamforming algorithm applied to each sub-band, and the results then combined. This method utilizes the spectral information of broadband signals to enhance image quality [19]. Their validation using SA and plane wave transmission data—simulating 13-point targets and a circular cyst—demonstrated substantial improvements in lateral resolution, contrast, and tolerance to beam vector errors, while also reducing the number of transmissions required. Yan et al. combined MV based on submatrix spatial coherence with the Sign Coherence Factor. This method divides the receiving array into multiple submatrices and calculates the spatial coherence among them, effectively reducing coherent noise and improving image quality [20]. Additionally, this method can reduce sidelobe noise without increasing computational complexity. It significantly enhances the imaging resolution and contrast in coherent plane wave compounding imaging.

Despite the significantly improved image resolution, the performance of most MV beamforming algorithms in noise suppression is limited. Wang proposed a new pixel-adaptive weighting method based on Covariance Matrix-based Adaptive Beamforming to enhance the imaging performance of MV beamformers, namely Covariance Matrix-based Adaptive Weighting (CMSAW). The proposed CMSAW method estimates the corrected covariance matrix by adaptively applying spatial smoothing, rotational averaging, and diagonal reconstruction to compute the mean-to-standard deviation ratio [21]. CMSAW introduces adaptive diagonalization based

Table 4. Comparison of algorithms related to MV technology in ultrasound imaging

Method	Advantages	Disadvantages	Effect comparison
MV beamformer	Increases penetration depth, improves image quality.	The calculation process is complex and time-consuming, and sensitive to noise.	Improved image quality with wide application but increased CC.
Quadrature Rotation Decomposition-MVDR	High computational efficiency, suitable for ultra-fast adaptive beamforming applications.	Requires complex hardware design and optimization, with limited applicability.	Improved image quality, reduced CC, but high cost and limited applicability.
Broadband MV beamforming	Improves imaging quality and resolution.	High complexity, sensitive to broadband noise.	Significant improvement in image quality, but with increased CC.
Submatrix Spatial Coherence MV beamforming	Improves image contrast and clarity, reduces noise.	Highly dependent on the parameter selection and optimization.	Improved image quality with low noise, increased complexity.
Covariance Matrix-based Adaptive Weighting for MV beamforming	Strong adaptability and significant image quality improvements.	Complex adaptive weighting increases the computational complexity.	Improved image quality, but with high CC and poor real-time performance.
MV beamformer based on principal component analysis	Significantly improves image contrast and reduces data processing workload.	Algorithm complexity increases, making it sensitive to noise.	Improved image quality and reduced CC, but at high design costs.

Note: MV, Minimum Variance; MVDR, Minimum Variance Distortionless Response; CC, computational complexity.

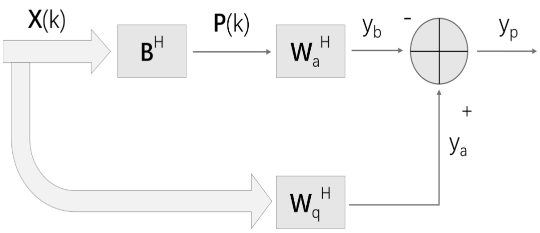

Figure 4. Structure of generalized sidelobe canceler.

on aperture coherence to enhance speckle preservation performance. CMSAW-MV can improve resolution and suppress sidelobes, incoherent clutter, and noise. With a computational complexity of O(N^2), CMSAW is suitable for real-time applications when utilizing a graphics processing unit. Eigen-space-based beamformers can remove most noises through the orthogonal projection of the signal subspace, offering better imaging contrast than traditional MV beamformers. Aliabadi proposed an innovative eigen-space beamformer called Oblique Eigen-Space MV (OESMV). This beamformer takes into account the correlation between signal and noise, by examining the SNR and using eigen-decomposition to distinguish between signal and noise subspaces [22]. The OESMV technique computes beamformer weights by projecting the MV weight vector along the noise subspace and onto the signal subspace using an oblique projection matrix. This approach allows for flexible adjustments according to specific imaging needs, yielding improved resolution, contrast, and grayscale quality.

Both the CMSAW and OESMV beamformers are extensions of MV beamforming, with the shared goal of improving contrast and resolution by minimizing output power. These methods maintain the adaptive qualities of MV beamforming but aim to reduce the computational complexity typically associated with MV techniques. However, the implementation of these algorithms requires specialized hardware and optimized algorithm design, which increases development costs and difficulty. Furthermore, these methods tend to perform poorly in noisy environments or scenarios with large datasets. **Table 4** summarizes the MV-related technologies mentioned above.

GSC

GSC is an advanced adaptive beamforming technique that effectively enhances the desired signal in the target direction while suppressing interference signals. It is widely used in fields such as radar, sonar, wireless communications, and medical ultrasound imaging, providing significant performance advantages [44-46]. GSC transforms the constrained problem of traditional adaptive beamforming algorithms into an unconstrained one by separating the linearly constrained space, thus overcoming the signal cancellation issue found in MV methods [47]. The structure of a GSC is illustrated in **Figure 4**. For adaptive beamforming, due to the high correlation of medical ultrasound echo signals, some processing algorithms must be introduced to eliminate this correlation. A commonly used method is the subarray averaging technique proposed by Evans et al. [48]. However, as the number of subarrays increases, the performance of GSC may converge toward that of a non-adaptive beamformer (like SA), reducing

Table 5. Comparison of algorithms related to GSC technology in ultrasound imaging

Method	Advantages	Disadvantages	Effect comparison
Eigenspace-Based Generalized Sidelobe Canceler Beamforming	Reduces computational complexity, enhances interference suppression capability.	Eigenvalue calculation is relatively complex and sensitive to noise.	Reduced computational complexity but with limited improvement in imaging quality.
Forward-backward Generalized Sidelobe Canceler Beamforming	Significantly improves spatial resolution and interference suppression.	The complexity of calculations increases, and the implementation of algorithms becomes more complex.	Improved image quality at the cost of higher computational complexity
Cross Sub-aperture Averaging Generalized Sidelobe Canceler Beamforming	Enhances imaging quality with greater robustness	Increased computational complexity, affecting real-time performance.	Improved image quality but with increased computational complexity.
Generalized Sidelobe Canceler Beamforming Combined with Eigenspace-Wiener Postfilter	Improves contrast and resolution of imaging, and effectively suppressed noise and scattering.	High computational workload, requiring additional hardware resources and optimization.	Significant improvement in image quality, but with increased computational complexity and cost.

Note: GSC, Generalized Sidelobe Canceller.

its adaptive advantage. While GSC can improve lateral resolution, this does not always lead to a corresponding increase in contrast. Therefore, how to obtain a reliable covariance matrix estimate that enhances lateral resolution while also improving image contrast has become a research hotspot [25].

The use of GSC significantly enhances the lateral resolution of medical ultrasound systems, but its ability to improve contrast is often unsatisfactory. Li et al. proposed a new eigen-based GSC for medical ultrasound imaging, which improves both lateral resolution and contrast [23]. In this method, the GSC weight vector is projected onto a vector subspace constructed from the eigen structure of the covariance matrix to obtain a new eigen-based GSC weight vector. By replacing the GSC weight vector with this new one, the sidelobe level is reduced, leading to improved contrast and lateral resolution. This method provides better lateral resolution and contrast compared to non-adaptive beamformers. Accurate estimation of the covariance matrix is crucial in adaptive ultrasound imaging as it fundamentally affects the performance of adaptive beamformers.

Li's team also developed a new forward and backward Generalized Sidelobe Canceller method for medical ultrasound imaging [24]. This method accurately estimates the covariance matrix using forward and backward subarray averaging. As a result, forward and backward Generalized Sidelobe Canceller achieves excellent lateral resolution and contrast, offering improved imaging quality for medical ultrasound systems. Additionally, this method is noted for its lower computational complexity and higher reliability, making it a practical solution for real-time ultrasound imaging applications.

Yang et al. proposed a new Cross-Subarray Averaging GSC (GSC-CROSS) method for medical ultrasound imaging, which uses a cross-covariance matrix instead of the traditional covariance matrix estimation [25]. In experiments using simulated echo data from scatterers and cyst-like targets, GSC-CROSS showed notable improvements in lateral resolution. Specifically, compared to DS, SA, and traditional GSC methods, GSC-CROSS improved lateral resolution by 76.9%, 68.8%, and 17.1%, respectively. The following year, Yang proposed a beamforming algorithm that combines GSC and eigen-space Wiener post-filtering. Based on the eigen-space decomposition of the covariance matrix of the received data, the components of the Wiener post-filter are calculated from the signal matrix and noise matrix. The adaptive weight vector of the GSC is further constrained by the eigen-space Wiener post-filter, making the output energy of the receiving array more closely match the desired signal compared to traditional GSC output [26]. In comparative evaluations, this method reduced the Full Width at Half Maximum by 85.5%, 80.5%, and 38.9% over DS, SA, and GSC beamforming, respectively, and improved the Contrast Ratio (CR) by 123.6%, 47.7%, and 84.4%, respectively.

Both GSC-CROSS and the combined GSC-eigenspace Wiener post-filter method significantly enhance the lateral resolution and contrast of medical ultrasound imaging systems. However, these improvements are often accompanied by an increase in computational complexity, which may affect real-time performance and implementation simplicity. **Table 5** summarizes the GSC related technologies and their respective performance enhancements, providing a comparative overview of the advancements discussed.

Algorithms related to machine learning and deep learning

Machine Learning (ML) and Deep Learning (DL) represent the latest advancements in the field of artificial intelligence. ML enables computers to learn from data and continuously improve their performance. ML methods include supervised learning, unsupervised learning, and reinforcement learning, with common algorithms such as linear regression, logistic regression, and decision trees [49]. DL, on the other hand, is a more advanced form of machine learning that uses multi-layer neural networks to simulate the human brain's structure, automatically learning complex feature representations from data to achieve higher levels of abstraction and learning capabilities. DL has achieved significant success in fields such as image recognition, speech recognition, and natural language processing [50]. These two technologies have widespread applications in various domains. In the medical field, ML and DL assist doctors in diagnosing diseases, predicting disease progression, and play crucial roles in drug development and clinical trials [51]. These technologies have contributed significantly to advancements in ultrasound beamforming, optimizing the beamforming process, improving image quality, and reducing noise and artifacts through complex data analysis and pattern recognition capabilities [52-58].

Sparse arrays reduce the number of active elements by increasing the spacing between elements, which grating lobe artifacts that degrade ultrasound image quality and reduce the contrast-to-noise ratio (CNR) in ultrasound imaging. Kumar et al. proposed a customized DL-based algorithm to estimate inactive channel data in periodic sparse arrays. This algorithm uses data from multiple active channels to estimate the inactive channels, effectively reducing element spacing in beamforming, thereby suppressing grating lobes [27]. The performance of this algorithm was validated with line targets in a water tank, multipurpose tissue-mimicking phantoms, and in vivo carotid artery data. Compared to pseudo-fully sampled arrays, grating lobe suppression improved by up to 15.25 dB, and CNR increased. The improvement in CNR in low-echo regions was more significant than in high-echo regions. The algorithm also maintained low root mean square error of phase unwrapping between fully sampled and pseudo-fully sampled arrays, makes it suitable for Doppler and elastography applications. Additionally, the speckle pattern was also preserved, making the estimated data suitable for quantitative ultrasound applications. This algorithm shows promise for improving sparse array performance and be applied in small ultrasound devices and two-dimensional arrays. Speckle noise, a common issue in traditional beamforming methods, often reduces the quality of ultrasound B-mode images. Hyun et al. proposed a framework using neural networks to reduce speckle noise during the beamforming process. A deep fully convolutional neural network (CNN) was trained to accept channel signals and output speckle-reduced echo estimates [28]. This method introduced a log-normalization loss function suitable for ultrasound imaging. Their studies showed that it is feasible to reconstruct ultrasound B-mode images using machine learning neural networks. Furthermore, the network, trained only on computer simulations, can be extended to real in vivo imaging, generating images with significantly reduced speckle noise while maintaining resolution.

Traditional medical ultrasound beamforming relies on high sampling rates that far exceed the actual Nyquist rate of the received signals, leading to large data storage and processing demands. This creates hardware and software challenges in the development of ultrasound devices and algorithms, ultimately affecting their performance. Recognizing the potential of deep learning in medical imaging, Mamistvalov et al. proposed a DL-based method for B-mode image reconstruction from temporally and spatially subsampled channel data [29]. Their approach begins by sub-sampling thedata below the Nyquist rate, aligning it in the frequency domain, and then converting it back to the time domain. The data were further subsampled spatially to acquire only a subset of the received signals. An encoder-decoder CNN was then trained using this partial data, with the MV beamformed signal generated from the original fully sampled data as the target. Their method produced high-quality B-mode images with superior resolution compared to previously proposed compressed data reconstruction techniques (e.g., NESTA) and DAS beamforming of fully sampled data. In terms of contrast-to-noise ratio, their results were comparable to MV beamforming with fully sampled data, achieving better and more efficient imaging than most current clinical practices. Ultrafast ultrasound imaging, capable of acquiring full-view images at thousands of frames per second, enables the analysis of rapidly changing physical phenomena in the human body. However, this im-

Table 6. Comparison of algorithms related to DL technology in ultrasound imaging

Method	Advantages	Disadvantages	Effect comparison
Gap-Filling Method for Suppressing Grating Lobes in Ultrasound Imaging Using DL	Effectively suppresses grid lobes, improves image quality and resolution.	Lack of generalization, requires a large amount of data sets and computing resources.	Significant improvement in image quality, but with high complexity and poor real-time performance.
Beamforming and Speckle Reduction Using Neural Networks	Enhances image contrast, automatically captures complex signal features during training.	High demand for computing resources, risk of overfitting with insufficient data.	Substantial improvement in image quality, but resource-intensive and limited real-time performance.
Deep-Learning Based Adaptive Ultrasound Imaging from Sub-Nyquist Channel Data	Reduces data acquisition and processing complexity while maintaining high-quality imaging results.	High implementation difficulty, requires extensive computing resources.	Improved image quality, but with high complexity and suboptimal real-time performance.
CNN-Based Ultrasound Image Reconstruction for Ultrafast Displacement Tracking	Improves speed and accuracy in dynamic imaging with ultrafast displacement tracking.	High cost of data acquisition and annotation, and limited generalization ability.	Enhanced image quality and fast imaging speed, but with poor generalization ability and the high cost.

Note: DL, Deep Learning; CNN, Convolutional Neural Network.

aging modality faces a trade-off between frame rate and image quality-higher frame rates can introduce motion artifacts while improving image quality typically requires more acquisitions, slowing the process. Perdios et al. addressed this challenge with a CNN-based method that reconstructs high-quality frames from single ultrafast acquisitions while using only two consecutive frames for two-dimensional displacement estimation. By integrating this CNN-based image reconstruction with a cross-correlation-based speckle tracking algorithm, they were able to estimate displacement even in areas affected by sidelobe and grating lobe artifacts, which traditional DAS methods struggle with [30]. Therefore, the proposed method may unlock the full potential of ultrafast ultrasound, finding applications in ultra-sensitive cardiovascular motion and flow analysis or shear wave elastography.

These studies illustrate the power of deep learning to enhance various aspects of ultrasound imaging, from beamforming and artifact suppression to speckle noise reduction and image reconstruction. Their advantages lie in the significant improvements in image quality and adaptability. However, challenges remain, such as high computational resource requirements, strong data dependence, and high implementation complexity. **Table 6** summarizes DL-related techniques mentioned above.

Other beamforming algorithms

Reverberation noise is a significant issue in ultrasound imaging, as it results from multiple reflections of sound waves between structural boundaries, resulting in image clutter and reduced contrast. To mitigate the impact of reverberation noise, Shin et al. proposed a novel beamforming technique called Multiphasic Adaptive Cross-Cancellation (MPAX), an improved version of the Delay and Apodization Crosstalk technique. While Delay and Apodization Crosstalk uses complementary square wave amplitude cancellations, MPAX improves upon this by employing multiple pairs of complementary sine phase cancellations, which more precisely control the amplitude and position of grating lobes. This results in an improved weighting matrix that effectively suppresses reverberation noise [31]. MPAX has demonstrated significant success in reducing near-field reverberation noise and improving ultrasound image contrast, making it a promising tool for generating high-contrast images and enabling more accurate clinical diagnoses. In another approach, Nghia et al. proposed a new unified pixel-level beamforming algorithm that better adapts to the non-spherical waveforms of transmitted beams, allowing the selection of the optimal signal for data synthesis from each transducer waveform at that location [32]. This method significantly improves image resolution and contrast by optimizing signal processing for each pixel, though it increases computational costs, requiring more resources and longer processing times. Nevertheless, the algorithm performed excellently in limited in vivo studies, demonstrating its reliability in handling real biological tissues. The results indicate that although further optimization and research are needed to reduce computational costs, this new beamforming algorithm has significant potential in clinical applications and could be widely used in medical diagnostics.

In Multi-Line Transmission, high frame rate ultrasound imaging is achieved by simultaneously transmitting multiple focused beams in different directions, thereby increasing imaging speed and efficiency. However, this method can lead to crosstalk between different beams, resulting in unwanted artifacts that affect image quality. The Filtered Delay Multiply and Sum (F-DMAS) beamforming algorithm has been proven to reduce such artifacts. This beamformer effectively reduces artifacts in the image and improves spatial resolution by using a nonlinear spatial coherence algorithm, resulting in clearer imaging. Matrone et al. proposed a "short-delay F-DMAS" formula to enhance the performance of the F-DMAS beamformer while managing computational complexity [33]. Specifically, by setting a maximum delay value to control the signal delay time involved in spatial coherence calculations, the "short-delay F-DMAS" formula maintains or improves the performance of the F-DMAS algorithm. Byram et al. introduced a model-based beamforming algorithm, known as Aperture Domain Model Image Reconstruction (ADMIRE) [59-62]. This algorithm uses a model of the reflected wavefronts of scatterers within the region of interest in the aperture domain signal, enabling the algorithm to identify scatterer locations and suppress clutter, particularly off-axis scattering and reverberation artifacts. By decomposing this signal into components of clutter and the desired signal, ADMIRE effectively suppresses clutter, including off-axis scattering and reverberation artifacts, resulting in clearer images. The algorithm preserves de-cluttered channel data, which can be further processed by other techniques to enhance image quality. Dei et al. developed a Coherence Factor (CF) weighting technique, finding that ADMIRE combined with CF weighting further improved image quality in certain aspects [34]. CF weighting, as a post-processing technique, enhances contrast while reducing CNR and speckle SNR. The results indicate that ADMIRE is robust against model mismatch caused by variations in sound speed, especially when the actual sound speed is slower than the assumed sound speed.

Hybrid beamforming significantly reduces the cost and power consumption of fully digital sensor arrays by decreasing the number of active front-end components. Sparse arrays can further reduce hardware costs. Rajamäki et al. proposed an algorithm for approximating fully digital beamforming solutions, extending to the more challenging hybrid and analog beamforming scenarios, using quantized phase shifters [35]. They determined the upper bounds for achieving fully digital solutions and derived closed-form expressions for beamforming weights in these cases. The research results indicate that combining sparse arrays and hybrid beamforming can significantly reduce the number of required elements and front-ends while achieving the resolution of a fully digital uniform array. Ni et al. introduced a new method where array elements are simultaneously excited by signals encoded with random sequences, generating non-focused ultrasound wavefronts with random interference [36]. As these wavefronts propagate through the medium, their energy is reflected back from the tissue, giving individual scatterers unique pulse responses. This method can significantly improve ultrasound imaging performance, especially in organ boundary detection and lesion localization. By using randomly encoded signals, the reflected waves from individual scatterers in the tissue have unique pulse responses, enabling more precise identification and localization of scatterers. This helps to more clearly distinguish different tissues, thereby enhancing the accuracy of organ boundary detection, particularly in cases involving complex tissue structures. Goudarzi et al. proposed a flexible framework for beamforming using the Alternating Direction Method of Multipliers, where each term is optimized separately. Their formulation includes the use of denoising algorithms within the beamforming process, specifically the Plug-and-Play and Regularization by Denoising (RED) [37]. The RED algorithm provides superior image quality in terms of contrast metrics while preserving speckle statistics.

Conventional ultrasound imaging typically employs DAS beamforming with dynamic receive focusing for image reconstruction, valued for its simplicity and robustness. However, DAS beamforming geometrically estimates delays assuming a constant speed of sound in the medium, typically 1540 m/s, without accounting for tissue heterogeneity. This approximation leads to cumulative delay estimation errors with increasing depth, reducing the resolution, contrast, and overall accuracy of ultrasound images. Asif et al. proposed a DAS method based on the fast-marching method for focused transmission, which utilizes an approximate speed of sound map to estimate refraction-corrected propagation delays for each pixel in the medium [38]. This method has been qualitatively and quantitatively validated at an imaging depth of approximately 11 cm, showing significant improvements in imaging errors caused by tissue heterogeneity, especially when speed of sound variations are induced by fat layers, making it valuable for complex abdominal and liver imaging applications. Guo et al. introduced a pixel-based Delay Multiply and Sum beamforming method combined with a Wiener filter to enhance ultrasound image quality [39]. Compared to traditional dynamic focusing, the unified pixel-based beamforming technique significantly improves lateral resolution. Besides, this method retains favorable characteristics of beamformers while significantly enhancing spatial resolution and contrast compared to the unified pixel-based algorithm. Its simplicity and excellent performance demonstrate its potential for clinical applications. Vayyeti et al. proposed a novel nonlinear beamforming method called Filtered Delay Optimal Weighted Multiply and Sum (F-DowMAS), which adapts optimal weights for each imaging point in traditional focused beam systems [40]. This method shows significant advantages in improving image quality, including better resolution and contrast, and reduced noise and artifacts. Compared to DAS and F-DMAS, F-DowMAS improves axial resolution by 57.04% and 46.95%, lateral resolution by 58.21% and 53.40%, CR by 67.35% and 39.25%, and CNR by 44.04% and 30.57%, respectively. This method provides a new direction in ultrasound imaging technology, showcasing the immense potential of nonlinear beamforming algorithms in enhancing diagnostic capabilities.

Discussions and challenges

SA technology and its improved beamforming algorithms offer significant advantages in enhancing resolution and improving the signal-to-noise ratio. However, these technologies require substantial processing power and memory resources. Additionally, SA techniques are highly sensitive to motion, making them prone to motion artifacts, which challenges their real-time application. MV algorithms, known for reducing coherent noise and significantly improving resolution and contrast, face similar challenges. GSC algorithms can reduce interference by canceling the phase and amplitude of undesired signals, showing robustness in multipath propagation and noisy environments. However, similar to SA and MV, they require significant computational resources and may introduce additional complexity in some cases. Machine learning and deep learning have revolutionized ultrasound beamforming by providing tools that can adapt to nonlinear relationships and complex signal environments. These methods excel at enhancing image resolution and contrast. However, the training and tuning processes of these models can be time-consuming and computationally intensive, making real-time applications nearly impossible. Composite beamforming algorithms offer the advantage of combining multiple beamforming techniques, thereby achieving higher image quality and performance. By integrating various algorithms, the limitations of individual techniques can be addressed, leading to improved resolution, contrast, and noise resistance. Additionally, composite algorithms can be flexibly adjusted for adaptation to different imaging needs and patient characteristics, allowing for more personalized imaging outcomes.

In recent years, the importance of ultrasound imaging in medicine has increased significantly. Medical ultrasound is a non-invasive and safe imaging technique that does not involve radiation or contrast agents, posing no risk of radiation damage to patients and being suitable for individuals of all ages. Ultrasound imaging is widely used in clinical diagnosis across almost all medical fields, including cardiology, hepatology, nephrology, endocrinology, gynecology, obstetrics, and orthopedics, for detecting and diagnosing various diseases and abnormalities. Additionally, ultrasound imaging offers advantages such as real-time capability, low cost, and portability, making it valuable in emergency medicine, surgical guidance, bedside diagnosis, and routine clinical practice. Ultrasound beamforming plays a crucial role in optimizing image resolution, contrast, and overall quality. This not only allows physicians to observe tissue structures and lesions more clearly but also aids in guiding interventional treatments, improving surgical outcomes. Therefore, the continuous advancement of ultrasound beamforming technology is vital for enhancing clinical diagnosis and medical standards. Future developments will depend on efficient algorithms, advanced noise suppression techniques, accurate speed-of-sound corrections, optimization of cost and energy consumption, and integration with multimodal imaging. These innovations will drive the widespread application of ultrasound beamforming technology in medical imaging, enhancing the accuracy and efficiency of clinical diagnosis.

Conclusion

In summary, ultrasound beamforming technology is one of the core components of medical ultrasound imaging, and its advancements directly impact image quality and diagnostic accuracy. Although existing beamforming techniques (such as SA, MV, and GSC) and deep learning-based methods have achieved significant progress in improving resolution, contrast, and noise resistance, their high computational resource requirements and complexity remain major obstacles to real-time applications. Composite algorithms, by integrating multiple techniques, offer effective solutions to these challenges. At the same time, medical ultrasound, due to its non-invasive, safe, and real-time nature, has become an indispensable tool for clinical diagnosis and treatment. In the future, through algorithm optimization, enhanced system efficiency, and integration with multimodal imaging, ultrasound beamforming technology will play an even greater role in medicine, providing patients with more precise, efficient, and personalized diagnostic and treatment experiences.

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