Optimization of the Two-dimensional Sparse Matrix Ultrasonic Sensor by Improved Multi-object Monkey-King Genetic Algorithm

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Abstract

In order to reduce the full matrix capture and total focus method (FMC-TFM) imaging data in the ultrasonic phased array, and get higher data imaging efficiency and better imaging effect, the improved multi-object monkey-king genetic algorithm (MKGA) is used to optimize the design of the square probe in the two-dimensional sparse array. This algorithm is improved as follows: firstly, the crossover and mutation operators are improved so that the number of active elements remains unchanged in evolution; secondly, new population are generated by selecting and improving the monkey-king elites. The simulation results show that the improved multi-object MKGA can effectively increase the peak side lobe level (PSLL) by -4 dB~-9 dB and restrain the increase of the main lobe width.

Keywords

Ultrasonic sensor;sparse matrix;monkey-king genetic algorithm.

1. Introduction

In recent years, the detection technology based on the ultrasonic phased array has been widely used for testing and maintenance in the fields involved in petrochemical, aeronautical, navigational, nuclear power, and other industries. Originating from the medical and defense radar fields, it has been rapidly developed in the field of non-destructive testing (NDT). The phased array probe can be used for electronic focusing, deflection, and scanning by combining different elements to accommodate complex applications, and offer significant advantages over a single piezoelectric probe in the testing resolution, sensitivity, and the testing range.

The two-dimensional phased array probe in the ultrasonic phased array can deflect and focus the sound beam in transverse and lateral directions. With the support of high-performance hardware, three-dimensional ultrasonic data can be scanned, collected and imaged. For the two-dimensional probe in the ultrasonic phased array, the resolution can be effectively improved by enlarging the aperture of the array. However, if the aperture is enlarged by increasing the number of elements only, the system will become more complex, and result in more data to be processed at the back end. To avoid the impact from grating lobes, the space between elements must be not greater than $\lambda/2$ [1]. However, a small space between elements causes higher density of elements, severe mutual interference between elements, more difficulties and higher costs for fabrication of the probe.

The two-dimensional sparse array is designed to distribute elements through different spatial distribution in the two-dimensional probe array, reduce the density of elements, and minimize the amount of data to be processed, achieving excellent scanning performance, high-resolution testing, low mutual radiation between elements, easy processing, and low cost, etc. It keeps the effective aperture almost the same as that in the two-dimensional full array. It also enables the response of pulse echo in the two-dimensional array to have good integrated acoustic performance at a lower cost of the hardware.

The optimization design of the sparse array is actually to select the optimal process from different combinations of elements. The advantages and disadvantages of an array combination are generally evaluated by the acoustic performance in the response of pulse echo. That is, the characteristics of the main lobe and side lobe are integrated to design and optimize the objective function. It is generally expected to have a narrow main lobe width, and a low maximum side lobe. This is favorable to the transverse resolution, and reducing the artifact interference.

The full matrix capture and total focus method (FMC-TFM) imaging technology is a high-resolution imaging technology proposed by Holmes et al. from University of Bristol in the UK in 2005 [2]. It involves full-capture acquisition and full-focus imaging. FMC is to get the most complete imaging information for subsequent processing by getting the A-scan data sets for all transmitter-receiver pairs in the probe. However, it takes a long time to process a large amount of data in the Total focus computation. The existing hardware usually takes tens of seconds to a few minutes to process such data, failing to meet the requirements for rapid imaging in certain industrial detection applications. Moreover, for the detection applications with a large number of probe elements, this will greatly increase the cost of the hardware in the phased array detection system.Therefore, the two-dimensional sparse array, and the FMC-TFM need to consider the effects arising from the size, number and spacing of elements in the sound field to optimize the spatial distribution.

2. Related Work

Over the past years, some solutions were proposed for the comprehensive issues in the design of the sparse phased array in the world. Haupt pioneered to study the issues for optimizing the two- and three-dimensional antenna sparse matrix genetic algorithms through the genetic algorithm, and proposed the mathematical model [3]. Boeringer used the particle swarm optimization algorithm to study the sparse matrix [4]. Huo et al. optimized the two-dimensional random sparse array based on the statistical method, and achieved good results [5]. Yang et al. used the minimum redundancy array and genetic algorithm to design the scan range of 30° and resolution of 6.2° in the two-dimensional sparse array [1]. He et al. adopted a design method based on the integer coding genetic algorithm to reduce the side lobes and increase the ratio of the main and side lobes [6]. Chen conducted a thorough study on the two- and three-dimensional sparse antenna arrays in the sparse matrix [7]. Peng et al. put forward the one-dimensional ultrasonic sparse array algorithm and evaluation scheme [8]. In these studies, some are for optimization of the antenna phased arrays, some are for optimization of the one-dimensional linear arrays, and they have achieved good results. However, no study is integrated with TFM.

Based on the studies, this paper has carried out the following work for imaging in compliance with the two-dimensional sparse matrix and FMC-TFM algorithm optimized by the genetic algorithm.

① The multi-object collaborative optimization is conducted for the number, spatial distribution, and acoustic performance (the main lobe width and the side lobe level) of elements in the two-dimensional sparse matrix by the genetic algorithm. The multi-object adaptive operator is proposed to define the fitness function. This operator does not require the setting of parameters for multi-object optimization, and adaptively adjusts the space for setting parameters according to the evolution of the genetic algorithm. After optimization, in addition to a lower number of elements, it achieves the spatial distribution of elements with excellent acoustic performance.

② Improvements are made to optimize the two-dimensional sparse matrix genetic algorithm. Firstly, the matrix coding scheme and matrix crossover operator are improved according to the principle of the genetic algorithm proposed by De Jong. Compared with the binary coding scheme, the matrix coding scheme can be more in line with the characteristics of the plane array, and feature a fast search speed. Secondly, the elite retention scheme based on the monkey-king genetic algorithm (MKGA) is used instead of the natural selection operator to ensure the speed of convergence and the preservation of the best individuals, and increase the probability of jumping away from the local space in evolution.

③ The imaging from the two-dimensional sparse matrix is combined with that from the FMC-TFM imaging. The imaging quality subject to the two-dimensional full-array, two-dimensional uniform array, and optimized two-dimensional sparse array are evaluated by using indicators, such as the signal-to-noise ratio (SNR).

This paper is arranged as follows: Section 1 presents the introduction, which mainly introduces the two-dimensional sparse matrix, the FMC-TFM imaging; Section 2 presents related work; Section 3 describes the acoustic characteristics of the two-dimensional plane array, and presents the improved genetic algorithm; Section 4 presents the parameters and results of the experiments, including the comparisons for the side lobe levels, number of active elements, and signal-to-noise ratio; Section 5 presents the conclusion and outlook.

3. Analysis of the Design and Acoustic Performance for the Two-dimensional Sparse Matrix based on the Improved Genetic Algorithm

3.1 Analysis of the Acoustic Performance.

The optimization of the two-dimensional sparse matrix for the ultrasonic phased array probe is based on the optimization method of the thin phased array antenna in the phased array radar. As shown in reference [3], Haupt constructed a uniform feeding two-dimensional sparse array, with the aim of reducing the side lobe level in the asymmetric sparse linear array. The equally-spaced grids used in the design of the sparse array are shown in Fig. 1. The distribution of sound field is calculated with the spherical coordinate system. The letter θ is the angle between r and the positive direction of the z axis, and Φ is the angle between the projection of r on the xOy plane and the positive direction of the x axis. The coordinate cosine is $u = \sin\theta \cos\Phi$ and $v = \sin\theta \cos\Phi$. The transverse and lateral apertures of the array are Dx and Dy respectively. If the array has grids in the quantity derived from the equation $N_g = (2N + 1) \times (2M + 1)$ for elements, and all elements in the array are modeled by the point source, for the far field of R >> D, the approximation of the far field is applied, and the lobes of the sound pressure in the continuous sound field of the array in the hemispherical airspace with radius R can be expressed as follows:

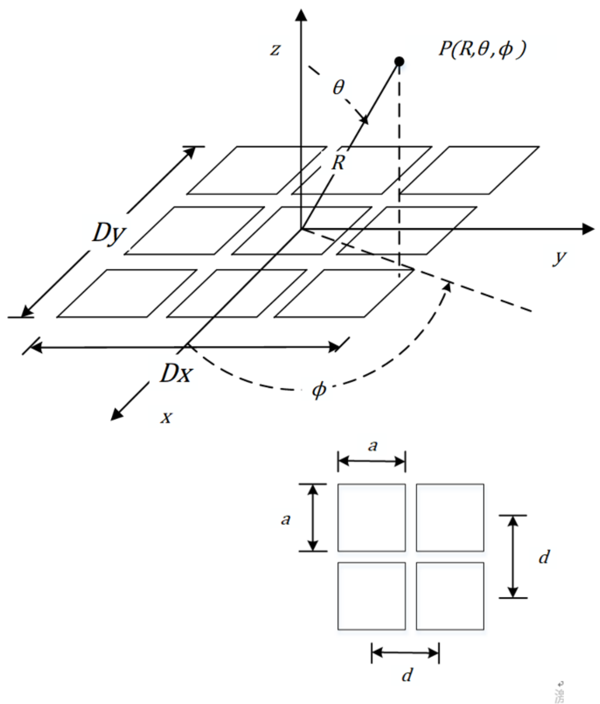


Fig. 1 Geometry and coordinate system of the two-dimensional phased array

$$D(\theta,\Phi)=\sum_{i=-N}^{N}\sum_{j=-M}^{M}\omega_{ij}e^{j\psi}=\sum_{i=-N}^{N}\sum_{j=-M}^{M}\omega_{ij}e^{jk\left[x_{ij}(\sin\theta\cos\phi-\sin\theta_0\cos\phi_0)+y_{ij}(\sin\theta\sin\phi-\sin\theta_0\sin\phi_0)\right]}$$
$$=\sum_{i=-N}^{N}\sum_{j=-M}^{M}\omega_{ij}e^{jk\left[x_{ij}(u-u_0)+y_{ij}(v-v_0)\right]} \tag{1}$$

Where, ω_{ij} is the weighting coefficient (0 or 1) of the (i,j)th array element, $k = 2\pi / \lambda$ is the number of waves, $(x_{ij}, y_{ij}, 0)$ is the coordinate of the (i,j)th element, the sound beam is deflected and focused at (R, θ_0, Φ_0), $u_0 = R \sin\theta_0 \cos\Phi_0$, $v_0 = R \sin\theta_0 \sin\Phi_0$.

In the study on the ultrasonic Peak Side Lobe Level (PSLL), only the real part of the lobes for the sound pressure is adopted, all elements are isotropic point sources, and then the beam with n elements can be expressed as follows:

$$E(u,v)=\sum_{i=-\mathrm{N}}^{\mathrm{N}}\sum_{j=-\mathrm{M}}^{\mathrm{M}}\omega_{ij}\mathrm{I_m}\cos\left\{\mathrm{k}\left[x_{ij}(u-u_0)+y_{ij}(v-v_0)\right]\right\} \tag{2}$$

Where, I_m is the amplitude of excitation.

The PSLL in the two-dimensional array is currently measured in two ways: one is the PSLL at Φ=0, and the other is the PSLL beyond the value of $u^2 + v^2 \leq 0.4$.

Definition 1: The PSLL in the two-dimensional array can be defined as the side lobe level in the case of $\Phi = 0$.

$$\mathrm{PSLL}=\max\left\{\left|\frac{E(u,v)}{\mathrm{FF_{max}}}\right|\right\} \tag{3}$$

$$s.t.(u-u_0)^2+(v-v_0)^2>0.4$$

FF_{max} is the peak main lobe, and the constraint denotes other lobes outside the area of the main lobes.

Definition 2: The average side lobe level (ASLL) is defined as the ratio of the main lobe width dropped by -6 dB to the range of all beams.

3.2 Population Initialization.

Population initialization in the genetic algorithm is designed on the basis of natural coding. In this paper, matrix coding, the most natural representation of a two-dimensional array, is used. The initialized population is a two-dimensional random array in which the number of constructs is popsize. According to the previous section, the two-dimensional array is 2M +1 in length and 2N + 1 in width, and the center of the array is the coordinate origin. The initial population generated in this way can meet the number of elements and the minimum space between elements, and express all feasible solutions in the solution space.

3.3 Crossover and Mutation Operators.

With regard to the crossover genetic operator used for optimization of the two-dimensional sparse plane array, we use the following crossover method: firstly, select an area randomly, e_{ij} ,$0 \leq i_1 \leq i_2 \leq 2M$, $0 \leq j_1 \leq j_2 \leq 2N$; secondly, select two individuals, and exchange the selected areas of these two individuals. The mutation operator is subject to a single-point mutation operator. We select one of the elements, and then perform the inverse operation.

3.4 Monkey-King Elite Operator.

Steady-state elite retention strategy: It puts the top 50% of the optimal fitness values in the old population into a new population, and keeps the current excellent evolutionary achievements. Then, it randomly generates *Popsize / 2* random population to avoid premature convergence, and increase the diversity of population and the probability of jumping away from the early maturity points.

3.5 Adaptive Multi-object Function Operator.

The more the number of elements, the higher the sound field energy emitted by the active elements, and the better the imaging effect if the interference between elements is eliminated. However, this will increase the amount of data collected later, and require high performance for the hardware. In order to optimize both the number of elements and the side lobe level in the sound field, the multi-object adaptive operator is used in this paper. The number of elements and the side lobe level in the sound field are constructed by the following formula:

$$F = \frac{f1}{f2} + \alpha \times f3 \tag{4}$$

Where, $f1$ is the minimum PSLL, $f2$ is the -50 dB main lobe width, $f3$ is the number of elements, and α is the multi-object coordination factor, with the aim of optimizing the two objective functions at the same magnitude. The adaptive multi-object function operator can provide a good solution for each target, and coordinate the relationship between the characteristics of sound field and the number of elements. Moreover, it is adaptive to an evolutionary algebra without adjusting the sparsity ratio. As a result, the two-dimensional plane array is optimized properly. The overall flow of the genetic algorithm is shown in Fig. 2.

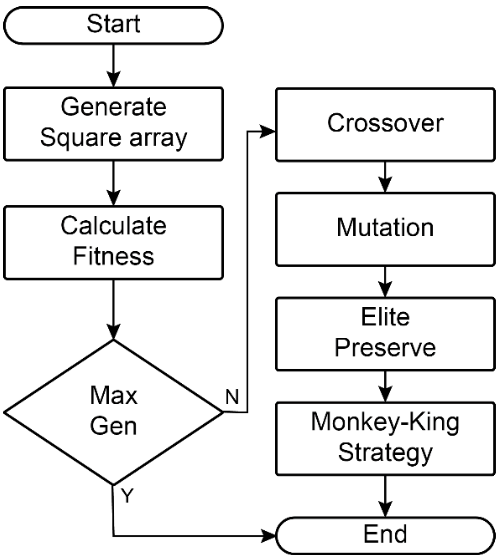


Fig. 2 Flow chart of the improved monkey-king genetic algorithm

4. Experiments

4.1 Simulation Parameters.

In this paper, the geometry of the two-dimensional square phased array is shown in Fig. 1. The full aperture size of the array is 16λ / 2× 16λ / 2, the center frequency of the array is 5 MHz, the wavelength is λ=0.375 mm, the test block is made of stainless steel, and the sound velocity is 5920 m/s. The space between elements is d = λ / 2, the size of an element is a=0.35λ, the number of elements is 16×16, the center frequency of elements is 5 MHz, and the bandwidth is 2.4 MHz. The array uses four periodic sinusoidal signals as the excitation signals through the Hanning window function. The distribution of sound field is calculated with the spherical coordinate system, and the response of pulse echo in the array is calculated in the hemisphere with radius R, as shown in Fig. 1. In this paper, the model of ultrasonic imaging is the pulse field model based on the spatial impulse response and its sound field simulation model proposed by Arendt [9, 10, 11] to analyze and calculate the response of pulse echo in the two-dimensional array. In all analyses, the emission focus lies in the hemisphere with R=40 mm from the center of the array, the deflection direction is (θ_0, Φ_0), and the same array is used for transmitting and receiving signals.

In this paper, a full array with the square aperture is selected as the reference array. It takes all elements as active elements, featuring good acoustic characteristics: narrow main lobe, vanishing grating lobes, and low side lobes.

4.2 Comparison between the Peak Side Lobe Levels (PSLL)

Table 1 shows the comparison between the optimized and unoptimized side lobe levels in the fully-sampled array with different sparsity ratios and different focus positions.

If the side lobe level is low, the artifact effect will be small. As shown in the table, for a full array, the PSLL gets higher as the focus deviates from the center; if the sparsity ratio is low, the PSLL will be high; the array optimized by the monkey-king genetic algorithm is reduced by at least -4 dB compared with the original randomly uniform array for the PSLL, and by up to -8 dB for the best optimization. Therefore, it can be concluded that: the higher the sparsity ratio, the lower the PSLL, and the lowest the PSLL in the full array; the more the deviation from the center, the lower the PSLL; after optimization by the MKGA, the side lobe level can be effectively reduced by -4 dB or more.

Table 1 Peak side lobe levels in different directions with different sparsity ratios

	Full Array	1/4 Sparsity		1/8 Sparsity		1/16 Sparsity	
(θ0, Φ0)	--	Unopt.	Opt.	Unopt.	Opt.	Unopt.	Opt.
(0°，0°)	-85 dB	-50 dB	-55 dB	-43 dB	-49 dB	-36 dB	-40 dB
(45°，0°)	-73 dB	-46 dB	-53 dB	-39 dB	-45 dB	-30 dB	-32 dB
(45°，45°)	-71 dB	-45 dB	-50 dB	-37 dB	-43 dB	-30 dB	-35 dB

4.3 Comparison between the Main Lobe Widths.

Table 2 shows the relationship between the main lobe width and the sparsity ratio and the focus position. The main lobe width can affect the resolution of the imaging. In the table, the angle of the -50 dB lobe width at the focus is taken as the measure. As shown in the table, the center of focus deviation has no effect on the main lobe width when the array is full; the sparsity ratio has little effect on the main lobe width; and the main lobe width is decreased by about 40% after optimization by the multi-object MKGA. Therefore, the multi-object MKGA can optimize the main lobe width and the PSLL to get satisfactory results.

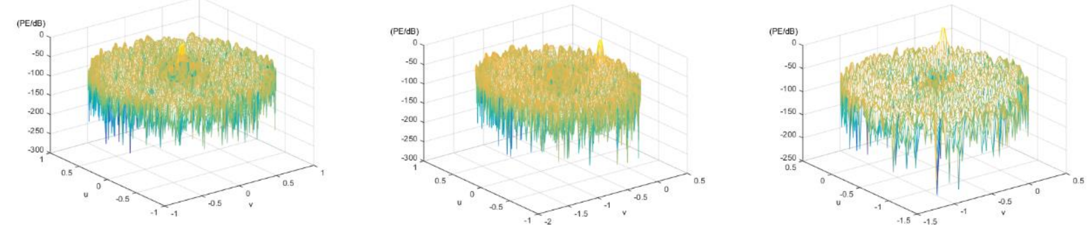
Table 2 Angles of the main lobe width with different sparsity ratios in different directions

	Full Array	1/4 Sparsity		1/8 Sparsity		1/16 Sparsity	
(θ0, Φ0)	--	Unoptimized	Optimized	Unoptimized	Optimized	Unoptimized	Optimized
(0°, 0°)	10°	14°	6°	10°	6°	14°	6°
(45°, 0°)	10°	10°	6°	10°	6°	10°	6°
(45°, 45°)	10°	10°	10°	10°	10°	10°	10°

4.4 Response of Pulse Echo in the Two-Dimensional Phased Array.

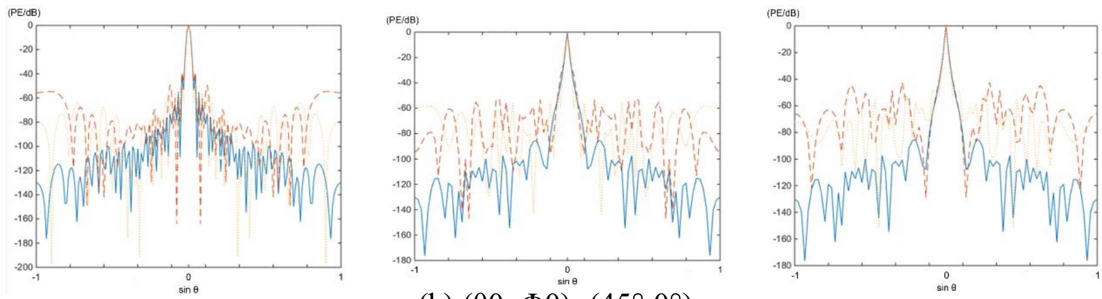
Fig. 3 shows the response of pulse echo in three different focus directions. As shown in the Fig., the response of pulse echo also varies with the focus direction.

Fig. 4 shows the response of pulse echo in the case of $\Phi = \Phi_0$ and a sparsity ratio of 1/4. As shown in the figure, the main lobe width for the response of pulse echo in the optimized sparse array is similar to that in the unoptimized randomly uniform distribution. However, there are still some effects of reducing the main lobe width.



(a) (θ0 ,Φ0)=(0°,0°) (b) (θ_0 ,Φ_0)=(45°,0°) (c) (θ_0 ,Φ_0)=(45°,45°)

Fig. 3 Response of pulse echo with a sparsity ratio of 1/4 in different focus directions .



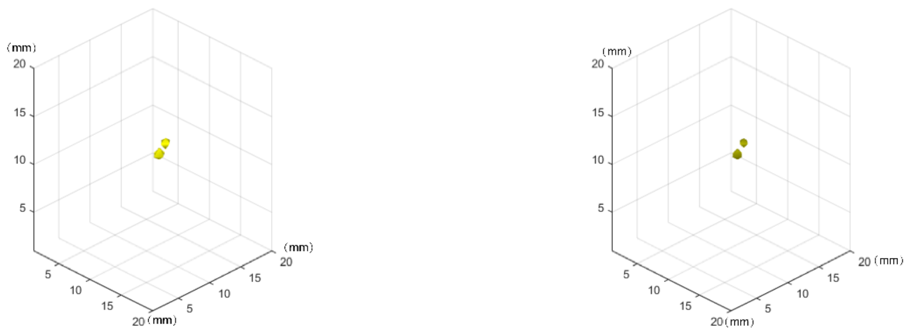
(a) (θ0 ,Φ0)=(0°,0°) (b) (θ0 ,Φ0)=(45°,0°) (c) (θ0 ,Φ0)=(45°,45°)

Fig. 4 Response of pulse echo in the case of Φ = Φ0 and a sparsity ratio of 1/4

4.5 Comparison between Imaging and Signal-to-Noise Ratio.

The study on imaging and signal-to-noise ratio (SNR) involves only 11 ×11 square two-dimensional arrays because of the limited memory capacity. Assume that there are two defects in the region of interest (ROI).

Before optimization, the maximum sound pressure of reflection after focusing is 4.6543e-24 v. It has been optimized to 4.7532e-24 v, and reflected in the image as the color depth of the isosurface. After optimization, the SNR is increased.



a) Imaging before optimization b) Imaging after optimization

Fig. 5 Imaging in the two-dimensional square array with TFM and a sparsity ratio of 1/4 (two defects)

5. Conclusion

This paper emphasizes the study on the optimization design from the monkey-king genetic algorithm (MKGA) for two-dimensional periodic sparse arrays, which makes the optimization more efficient. For the design method, the size and sparsity ratio are selected according to the resolution of imaging. Then, the advantages of the MKGA in fast convergence and easily jumping away from early maturity are used for optimization. In the process of optimization, the corresponding crossover and mutation operators are designed in line with the particularity of the ultrasonic plane array. After optimization, the distribution form of the two-dimensional square plane array is established. The experiment shows that the MKGA can decrease the peak side lobe width by -4 dB~-9 dB without increasing the main lobe width, and effectively restrain the increase of the main lobe width.

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