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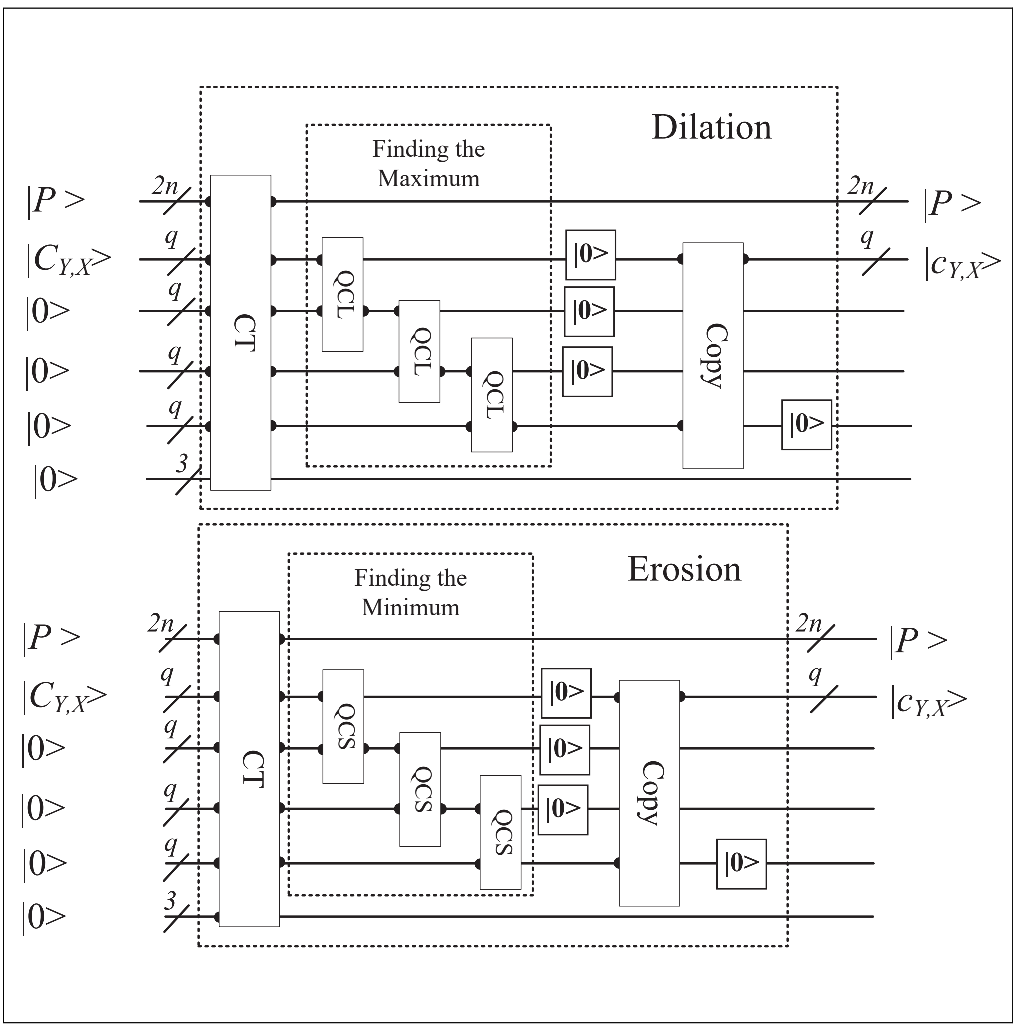

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Highlights

Propose a quantum SAR image denoising algorithm for removing the multiplicative noise

Design a quantum adder using fewer quantum resources to perform cyclic shift operations

Design some quantum units to construct the complete quantum circuit

Analyze the complexity of the quantum circuit and verified it on IBM Q

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A quantum synthetic aperture radar image denoising algorithm based on grayscale morphology

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SUMMARY

The quantum denoising technology efficiently removes noise from images; however, the existing algorithms are only effective for additive noise and cannot remove multiplicative noise, such as speckle noise in synthetic aperture radar (SAR) images. In this paper, based on the grayscale morphology method, a quantum SAR image denoising algorithm is proposed, which performs morphological operations on all pixels simultaneously to remove the noise in the SAR image. In addition, we design a feasible quantum adder to perform cyclic shift operations. Then, quantum circuits for dilation and erosion are designed, and the complete quantum circuit is then constructed. For a $2^n \times 2^n$ quantum SAR image with q grayscale levels, the complexity of our algorithm is O $(n+q)$. Compared with classical algorithms, it achieves exponential improvement and also has polynomial-level improvements than existing quantum algorithms. Finally, the feasibility of our algorithm is validated on IBM Q.

INTRODUCTION

With the increasing advancement of image acquisition equipment, the data of images also grows rapidly. Some special images, represented by synthetic aperture radar (SAR) images, have a large amount of data in themselves, which requires a great amount of computation when processing them, especially for some large-scale image processing tasks. Quantum computing makes full use of the superposition and entanglement of quantum mechanics, which makes its computation method have unique parallelism, thus speeding up the computation speed.[1,2] Image processing using quantum computing has become an important research direction to solve the real-time problem of classical image processing algorithms.

If one wants to utilize quantum mechanisms for image processing, one needs to store classical images into qubits, which is also the first task of quantum image processing research studies. At present, many scholars have studied the quantum image storage method and proposed various forms of storage models, which can be roughly divided into two categories: probability amplitude storage method and base state storage method. The probability amplitude storage method stores the color values of an image in the probability amplitude of qubits, and stores pixel positions in the base state. The representative of this method is the flexible representation of quantum image (FRQI).[3] Subsequently, the FRQI model was extended from grayscale images to red, green, and blue (RGB) images, and the the multi-channel RGB images representation of quantum images (MCQI)[4] model was proposed. In addition, quantum probability image encoding representation (QPIE)[5] is also another improved model of FRQI. This method uses a small number of qubits, but its drawback is that it is not convenient to quickly and accurately measure the color values in the probability amplitude of the quantum state. According to the assumptions of quantum mechanics, the probability amplitude of a quantum state cannot be accurately determined with a finite number of measurements. Although the method of storing images in base states uses more qubits, it can effectively solve the problem of measuring image information from quantum states. The representative of this method is the novel enhanced quantum representation (NEQR).[6] Due to the fact that this model can only store grayscale images of squares, an improved NEQR (INEQR)[7] was proposed. INEQR can store grayscale images of rectangles. Subsequently, in order to store color images, a generalized model of NEQR (GNEQR)[8] and a novel quantum representation of color digital images (NCQI)[9] were proposed. In these aforementioned storage models, NEQR is most suitable for storing grayscale images with the least amount of qubits and is better at directly manipulating the pixels of the image. Therefore, it has been chosen as the storage model for the image in this

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paper. Based on quantum image representation models, many quantum image processing algorithms have been proposed. Such as geometric transformation of quantum image,[10,11] quantum image steganography based on least significant bit (LSB),[12] feature extraction of quantum image,[8] quantum image scaling,[13] quantum image matching,[14] quantum image edge detection,[15–20] quantum image segmentation,[21–26] quantum image filtering,[27–30] quantum image recognition and classification,[31–34] etc.

In classic image processing algorithms, the interference of noise cannot be ignored. Therefore, image denoising is an important research direction in image preprocessing, and quantum image processing algorithms are also the same. In 2017, Yuan et al.[27] proposed a quantum image filtering method in the spatial domain, and they used quantum adders to implement correlation or convolution operations on images, thereby achieving filtering and avoiding the problem of quantum convolution being unachievable. However, this method must accurately know the specific value of the filter and is only applicable to filtering with integer coefficients. Subsequently, in 2018, they[28] improved the previously proposed filtering algorithm and designed a quantum multiplication technique that overcame the shortcomings of the previous version with unchanged complexity. In the same year, Li et al.[29] proposed a median filtering method in the spatial domain, which is a nonlinear method with better suppression effect on salt and pepper noise than the mean filtering method. In their work, a series of quantum computing units were designed to implement the algorithm, but the complexity was high and the demand for qubits was also high. In 2020, Essam et al.[30] proposed a new midpoint filtering method, which is a filter based order statistical filtering. They adopted modular design to design filtering quantum circuits and reduce the number of auxiliary qubits. However, the aforementioned filtering methods are only effective for additive noise and have poor effects on multiplicative noise in SAR images. In addition, the aforementioned algorithms will damage edge details in the image, which is not desirable in image denoising tasks.

In recent years, in order to achieve better image processing results, many scholars have applied mathematical morphology to quantum image processing. In 2015, Yuan et al.[35] first combined morphology with quantum image processing and proposed the quantum version of dilation and erosion, but its complexity is exponential, which is very high. In 2016, they[36] made improvements to quantum circuits of dilation and erosion, reducing their complexity to polynomial level, but they did not make an explicit algorithm for a particular task. In 2019, Fan et al.[37] applied morphology to gradient computation of images, which improved the complexity compared to classical gradient algorithms. In the same year, Li et al.[38] applied quantum morphology to image edge detection and image enhancement, and the complexity was also improved compared to classical algorithms. In 2022, Liu et al.[39] utilized grayscale morphology to segment images containing uneven illumination and proposed a quantum version of an image segmentation algorithm based on grayscale morphology. They also designed two new quantum circuits for dilation and erosion by using very few quantum gates and qubits, which makes quantum morphology algorithms possible in this noisy intermediate-scale quantum (NISQ) era. For the basic properties of morphology, we apply it to the noise reduction of SAR images containing multiplicative noise, which is a new quantum version of the research idea. And this method can effectively remove the noise in SAR images.

In general, the main contributions of this work are as follows.

(1) Based on grayscale morphology method, a quantum SAR image denoising algorithm is proposed, a quantum SAR image denoising algorithm is proposed, which can perform dilation or erosion operations on all pixels at the same time and quickly remove the noise in the SAR image.
(2) We design a quantum adder using fewer quantum resources to perform cyclic shift operations on SAR images. Then, quantum circuits of dilation, erosion and sort units are designed to implement corresponding functions in the quantum algorithm. A complete quantum circuit for quantum SAR image denoising algorithm was constructed based on the designed quantum units.
(3) The analysis of circuit complexity demonstrates the advantage of our algorithm, and experiment on IBM Q[40] verifies the practicability of our algorithm.

RESULTS

Circuit complexity analysis

The proposed algorithm (see the supplemental information) requires a total of $2n+q+3q+3$ qubits, and the quantum circuit is shown in Figure 1. Among them, $2n$ qubits are used to store pixel positions, and q qubits are used to store pixel color values. In addition, $3q$ qubits are used to store the color values of neighboring pixels. Finally, 3 additional qubits are needed as auxiliary qubits. Complexity analysis of quantum algorithms is usually measured in terms of the quantity of the basic quantum gates (single-qubit gate or dual-qubit gate) in a quantum circuit. The complexity of basic quantum gates, such as NOT gate, CNOT gate, and reset get, are all 1. A CSWAP gate has 3 qubits and its complexity is 3. From a study by Li et al.,[41] it can be seen that 5 basic qubit gates can form 1 Toffoli gate, therefore it has a complexity of 5. Quantum cost refers to the specific number of basic quantum logic gates used in a quantum operation, while time complexity is an indication of the complexity of the algorithm. For the quantum operation we designed, we need to use as few quantum logic gates as possible in this NISQ era. Therefore to be more precise, we need to use the quantum cost to evaluate the performance of the quantum operations. As for the whole algorithm, although its complexity also depends on the number of basic quantum logic gates, it realizes the algorithmic function by using a large number of quantum operations, which uses a relatively large number of quantum gates. Therefore, in order to comply with the algorithmic complexity evaluation method, we need to evaluate the complexity of the complete algorithm using the $O(\cdot)$ representation. This is also a common approach in related research work.[23–26] For a $2^n \times 2^n$ SAR image with q grayscale levels, we will discuss the complexity following the process of denoising algorithms.

First of all, we need to store the classical SAR image into qubits and we need to prepare it pixel by pixel. Classic image processing is aimed at digital images, only considering the algorithm process and not the process of image preparation. Similarly, the goal of our algorithm is to

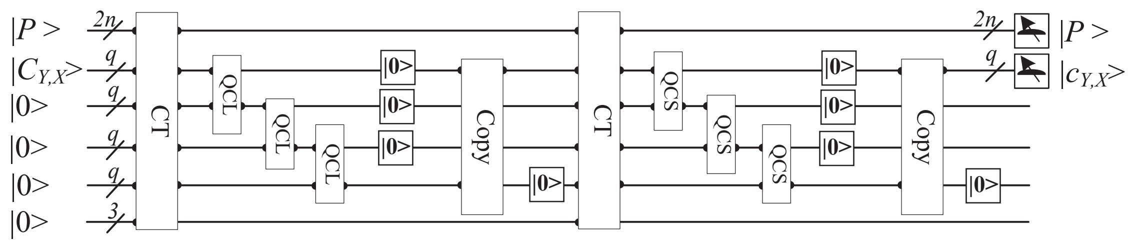

Figure 1. The quantum circuit implementation of the complete algorithm

process quantum images, so we will overlook the complexity of the process of preparing quantum images from classical images.[19,37,42] Hence the complexity of this step is 0.

In the proposed algorithm, we need to obtain the set of images using CT operations. In this step, we use the quantum adder designed in this paper for this purpose. Due to the use of very few quantum gates in our designed quantum adder, the complexity is only O(n). In this step, we need to construct the set of neighborhood pixels according to the structure element, so the complexity is O[2($n+n+n$)] = O(n). The complexity of our CT operation is greatly improved compared to the existing CT operation (its complexity is O(n^2)).[19,37,42]

The dilation operation is constituted by three quantum comparator larger (QCL) operations, four reset operations, and one copy operation. One QCL is composed of a QC operation, a Toffoli gate, and q CSWAP gate. Because the complexity of the quantum comparator we use is O (q), and QCL is achieved by adding a CSWAP gate to the output of QC, its complexity is also O (q). Then, 3 QCL operations, 4 reset operations, and 1 copy operation are needed. Therefore, the overall complexity of the quantum circuit for this dilation operation is O ($3q+4+q$) = O (q).

The process of erosion operation is similar to that of dilation operation, except that the QCL in the comparison operation is replaced by the quantum comparator smaller (QCS). Since their complexity is the same, both are O (q). Hence, the overall complexity of the erosion operation is also O (q).

Overall, the complexity of the quantum SAR image denoising algorithm is O ($n+q+q$) = O ($n+q$). The quantum cost and complexity of each module are shown in Table 1. Whereas the classical counterpart algorithm needs to process each pixel in the image one by one, hence, the complexity of the corresponding classical algorithm will not be less than O (2^{2n}). Compared with classical algorithm, our algorithm achieves exponential acceleration. In addition, the complexity and the number of qubits comparison of our algorithm with the existing quantum algorithms is demonstrated in Table 1, which shows the superiority of our proposed algorithm. The algorithm in a study by Yuan et al.[28] is a filtering method with weights in the spatial domain, which requires location shifting operations to obtain neighboring pixels, and the complexity of this shifting operation is O(n^2). The calculation of the weights also requires $(2k+1)(2k+1)$ multipliers to realize the convolution process, so its complete complexity is O (k^2n^2). In addition, the algorithm needs to add the pixels using addition operation (the complexity is O (k^2q^2)), so that the complexity of the complete algorithm is O ($k^2(n^2+q^2)$). In this algorithm, $2n+q$ qubits are required to store the original image, m qubits are required to store the weights during weight multiplication, and $m+q$ qubits are required to store the result of the multiplication. In addition, 1 qubit is also required to perform the addition operation, thus, a total of $2n+2q+2m+1$ qubits are required for this algorithm. The algorithm in a study by Li et al.[29] is a median filtering method in the spatial domain, which also requires cycle shift modules to obtain neighboring pixels, and the complexity is O (n^2). In addition, the comparator module, the swap module, the sort module, and the median calculation module has a complexity of O (n^2), O (q), O (q^2), and O (q^2), respectively. In summary, the complexity of the algorithm is O (n^2+q^2). In this algorithm, $2n+q$ qubits are required to store the original image. While performing the median computation, $8q$ qubits are required to store the neighboring pixels. Thus, a total of $2n+9q$ qubits are required for this algorithm. The algorithm in a study by Ali et al.[30] is a midpoint filtering method, which only requires the maximum and minimum values and then finds the median of these two numbers. It also requires the cycle shift modules to obtain the neighboring pixels and the complexity of this module is O (n^2). In addition, the comparator module's complexity is O (q), the swap module's complexity is O (q), the sort module's complexity is O (q), and the division by 2 module's complexity is O (q). Hence, the algorithm's complexity is O (n^2+q). In this algorithm, $2n+q$ qubits are required to store the original image. In addition, $9q$ qubits are required to store the neighboring pixels while performing the sorting calculation. Thus, a total of $2n+10q$ qubits are required for this algorithm. In summary, the complexity and the number of qubits of these algorithms mentioned above are both much higher than our proposed algorithm. This is because we have designed some quantum modules with low complexity, which is particularly significant in the NISQ era.

Table 1. Comparison of different quantum algorithms

Algorithms	Complexity	Number of qubits
Ref. [28]	O($k^2(n^2+q^2)$)	$2n+2q+2m+1$
Ref. [29]	O(n^2+q^2)	$2n+9q$
Ref. [30]	O(n^2+q)	$2n+10q$
Our algorithm	O($n+q$)	$2n+4q$

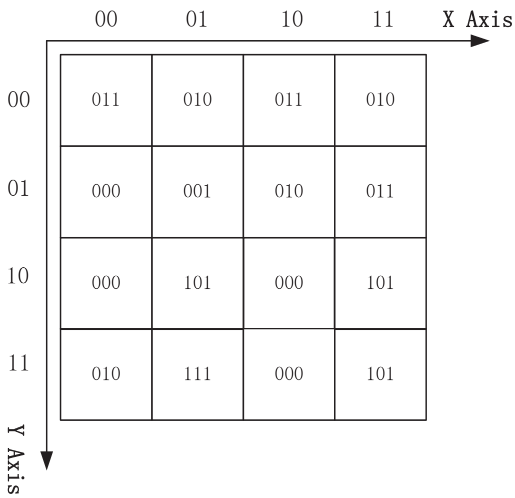

Figure 2. An example image of the original image

Experiment

The correctness of our proposed quantum algorithm can be verified by running the quantum circuit on the quantum platform. Because IBM Q provides some quantum computers and quantum simulators for users to use, we chose IBM Q as the experimental platform. Qiskit[43] toolkit (qiskit 0.46.0) can use the Python language (python 3.8) to build quantum circuit and run it on IBM Q. By measuring the qubits, one can get a histogram of the probability distribution and thus read out the image information in it. However, due to the scarcity of qubits, the number of qubits we can use is very small and totally insufficient to compute a SAR image for practical use. Therefore we use the quantum simulator "ibm-qasm-simulator" for verification, and the run-time of each task running on the simulator is limited to 10,000 s.

With reasonable use of qubits and without affecting the accuracy of the algorithm, we use a $2^2 \times 2^2$ SAR image with a grayscale range of $[0, (2^3) - 1]$ for the validation as shown in Figure 2. X and Y denote the pixel's position information, and the three-digit binary denotes the grayscale value.

Morphological filtering operations were performed on the above image using the quantum algorithm proposed in this paper. Due to the limited execution time of each circuit in the ibm-qasm-simulator, in order to reduce the running time of quantum circuits, we only measured the qubits that store color values and positions, and we performed 1,024 measurements.

Figure 3 shows the probability histogram measured in the quantum circuit of the SAR image processed by the algorithm, where the horizontal coordinate represents the sequence of measured qubits and the vertical coordinate represents the number of times each qubit sequence is measured. C is the pixel's color value of the result SAR image and P is the pixels' position. By reading the probability histogram, the schematic diagram of the processed SAR image is shown in Figure 4. The grayscale values are labeled in the figure in binary form. From the result image, it is clear that our proposed algorithm accurately implements the noise reduction process for SAR images.

DISCUSSION

Aiming at the problem that existing quantum filtering algorithms cannot effectively deal with multiplicative noise in SAR image, based on grayscale morphology method, a quantum SAR image denoising algorithm is proposed in this paper, which can use quantum mechanisms to perform dilation and erosion operations on all pixels in a single calculation and remove the noise in a SAR image. In addition, some useful quantum units are designed to construct complete quantum circuits. The complexity analysis of the circuit demonstrates the superiority of the algorithm. The feasibility of the algorithm is verified through the experiment on IBM Q.

Limitations of the study

When we perform morphological operations on SAR images, structure elements of different shapes and different sizes apply to different objects in the image. A single structure element may result in blurring or shape change of the object. Therefore, in order to improve the adaptability of the algorithm, our future research focus will be on quantum morphological algorithms with adaptive structure elements.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability

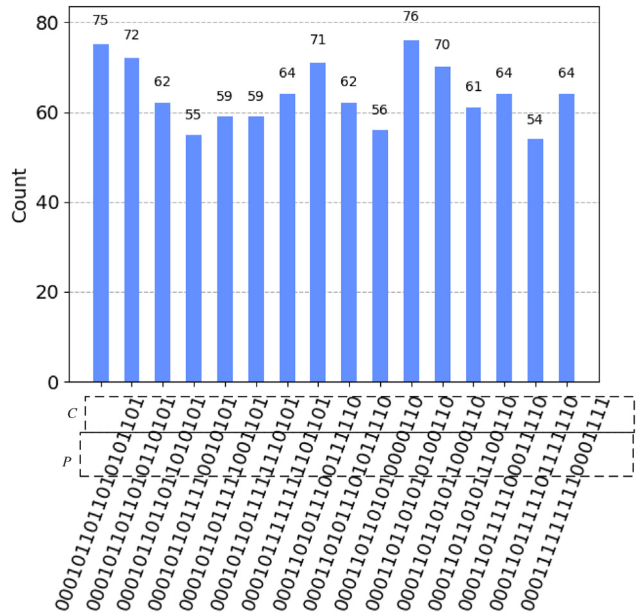

Figure 3. Probability histogram of the result image

- ○ Data and code availability
- EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS
- METHOD DETAILS
- QUANTIFICATION AND STATISTICAL ANALYSIS

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2024.109627.

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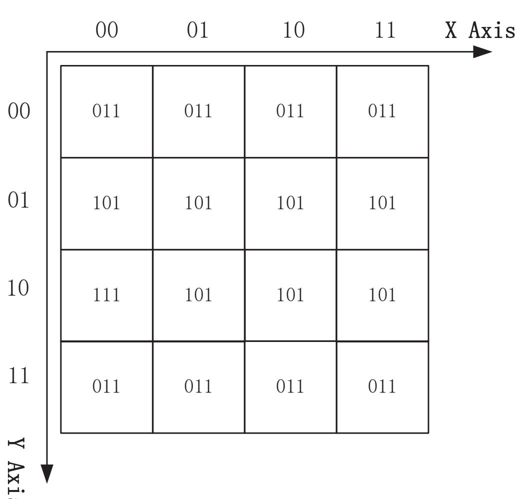

Figure 4. Processed SAR image read from probability histogram

AUTHOR CONTRIBUTIONS

L.W. and X.Y. designed this study. L.W., Y.L., and F.M. analyzed and drafted the manuscript. L.W., W.L., and Z.Z. completed numerical experiments. L.W. and T.L. revised the manuscript. All authors were involved in explaining the concept and results of the data. All authors have reviewed and approved the final version of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
IBM Q	ibm.com	https://www.research.ibm.com/ibm-q
Python	Python.org	https://docs.python.org/zh-cn/3/
Qiskit	qiskit.org	https://github.com/Qiskit/qiskit

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact Xutao Yu (yuxutao@seu.edu.cn).

Materials availability

This study did not generate new materials.

Data and code availability

- All data reported in this paper will be shared by the lead contact upon request.
- This paper does not report original code.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

Our study does not use experimental models typical in the life sciences.

METHOD DETAILS

The method details refer to the implementation of the quantum SAR image noise reduction algorithm using quantum circuits, it can be seen in the supplemental file named as "Method details".

QUANTIFICATION AND STATISTICAL ANALYSIS

The complexity of quantum algorithms is determined by the number of basic quantum gates used. The smaller the number of quantum gates, the lower the complexity of the algorithm. Therefore, our quantitative and statistical analysis strategy is to calculate the number of basic quantum gates in the quantum circuit of the algorithm and compare it with classical algorithms and existing quantum algorithms, as shown in Table 1. In addition, the circuit of the quantum algorithm needs to be verified. Therefore, we performed the validation on IBMQ and the validation results are shown in Figure 8- 8.