RA-ACS_net Network: A Quantum Optical Reconstruction Method for Ultra-high Resolution Bioimaging

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***Abstract*—Ultra-high resolution bioimaging based on quantum optics offers high sensitivity at relatively low cost, yet conventional reconstruction algorithms face challenges of excessive sampling time, long computation, and artifacts that limit imaging quality. To overcome these issues, this study proposes a novel quantum optical bioimaging reconstruction method termed RA-ACS_net, which integrates a ripple algorithm with a hybrid attention mechanism network. The ripple algorithm provides global optimization for network parameter adjustment, while the attention mechanism enhances feature extraction and information fusion. Furthermore, a differentiated loss function (ALoss) is designed to preserve fine structural details and improve visual fidelity compared with conventional MSE loss. A large-scale dataset of quantum optics-based bioimages is employed for training and validation. Experimental results demonstrate that RA-ACS_net achieves superior reconstruction performance, with significantly higher PSNR and SSIM across both low and high sampling ratios, when compared to iterative algorithms (TVAL3) and existing deep learning models (DR2-Net, DPA-Net). The proposed approach exhibits robustness under sparse data conditions, reduces blocking artifacts, and accelerates convergence, thereby addressing critical limitations of current methods. This study highlights the potential of combining quantum optics with advanced deep learning optimization strategies to establish a practical and efficient framework for ultra-high resolution bioimaging.**

Keyword*—Ultra-high resolution bioimaging; quantum optics; computer vision; ripple algorithm; attention mechanism

I. Introduction

Bioimaging techniques are the cornerstone of modern biological and medical research, enabling us to observe and understand the structure and function of living systems at the molecular, cellular and tissue levels [1]. However, traditional imaging techniques, such as fluorescence microscopy and electron microscopy, are limited by diffraction limits and imaging speeds, making it difficult to meet the demand for high-resolution and highly dynamic imaging of biological systems [2]. In recent years, the rapid development of quantum optics and computer vision technology has provided the possibility to break through these limitations [3]. Quantum optics, especially single-photon detection technology and quantum entanglement, provides a means for bioimaging to go beyond the traditional diffraction limit; while computer vision technology, on the other hand, shows great potential in processing and analysing massive biological image data [4]. Therefore, it is very meaningful to study the integration method between ultra-high resolution bio-imaging, quantum optics and computer vision techniques, especially the use of deep learning techniques to generate models for ultra-high resolution bio-imaging image reconstruction [5].

With the application and development of quantum optics and computer vision technology in the field of bio-imaging, the research on quantum optics and computer vision technology for ultra-high resolution bio-imaging has also attracted the attention of experts and scholars in the field [6]. Currently, the research on the application and integration of quantum optics and computer vision technology in the field of bio-imaging mainly includes the application of quantum optics in bio-imaging, bio-imaging reconstruction based on machine vision, and bio-imaging image feature extraction and recognition [7]. This study focuses on the ultra-high resolution bio-imaging reconstruction problem by fusing quantum optics, and analyses a large number of literature. Currently, there are three main methods for sampling and reconstruction of quantum optics bio-imaging systems: 1) Under-sampling using a random measurement matrix or an orthogonal fixed matrix first, and then using iterative algorithms to reconstruct the images. Chong and Pramanik [8] use Gaussian measurement matrices to undersample the bioimaging, and orthogonal matching tracking method is used to reconstruct the image; Wanas et al, [9] use the full-variance generalised Lagrangian alternating direction algorithm as an iterative algorithm to reconstruct the bioimaging; 2) using Gaussian random measurement matrices or orthogonal fixation matrices for under-sampling, but using the deep learning-based reconstruction network to reconstruct the image. Yao et al. [10] proposed DR2-Net based on ReconNet, which solves the problem of degradation of reconstructed image accuracy due to the excessive depth of the network; Sun et al. [11] proposed a dual-path attentional network DPA-Net for compressed perceptual image reconstruction, which consists of a structural path, a texture path, and a texture-attentional module; and 3) using a deep learning network that integrates sampling and reconstruction. A sampling and reconstruction integrated residual codec network SRIED_Net was proposed in the literature [12] and used in a quantum optical bio-imaging system, where the results showed that the network reconstructs quickly and obtains better reconstruction performance. The current network reconstructs the image resulting in blocking of the reconstructed image, which reduces the reconstruction accuracy of quantum optics-based high-resolution bioimaging.

Aiming at the problems of the current high-resolution bio-imaging reconstruction network based on quantum optics, this study proposes a ripple algorithm to optimise the attention mechanism network for quantum optics high-resolution bio-imaging reconstruction method. Firstly, the problem of quantum optics application for ultra-high resolution bio-imaging, secondly, combining the ripple algorithm [13] and attention mechanism [14], the RA-ACS_net reconstruction network is proposed, and finally, the effectiveness and efficiency of the RA-ACS_net reconstruction network are verified by using high-resolution bio-imaging data based on quantum optics.

The main novelty of this study lies in the integration of the ripple algorithm with a hybrid attention mechanism network to address the limitations of existing quantum optical bioimaging reconstruction methods. Unlike traditional iterative algorithms and standard deep learning frameworks that often suffer from long reconstruction times, blocking artifacts, and limited robustness, the proposed RA-ACS_net model introduces an optimized parameter adjustment process guided by ripple-based global search. In addition, a novel differentiated loss function, ALoss, is designed to preserve structural details and enhance perceptual quality beyond the performance of conventional MSE. Experimental results on quantum optical bioimaging datasets demonstrate that the RA-ACS_net network significantly outperforms state-of-the-art models under both low and high sampling ratios, achieving higher PSNR and SSIM values. This methodological advancement not only improves reconstruction accuracy and robustness but also offers a practical pathway for bridging quantum optics and advanced computer vision in ultra-high resolution bioimaging.

The full study is structured as follows: firstly, the application of quantum optics in bio-imaging is analysed in detail in Section II, including single photon detection technology, quantum entanglement imaging and its practical application in biological systems. The design and realisation of the quantum optical bio-imaging system is presented, focusing on the core devices of the system and their working principles. In Section III, the RA-ACS_net reconfiguration network is proposed, and the reconfiguration network is optimised by combining the ripple algorithm and the attention mechanism. The bio-imaging reconstruction approach is presented in Section IV. Section V verifies the performance enhancement of the method proposed in this study in quantum optical bio-imaging through experimental comparison, and finally, Section VI summarises the research results of this study and provides an outlook on the future research direction.

II. Quantum Optics for Ultra-High Resolution Bioimaging Analysis

A. Quantum Optics in Biological Imaging

1) Single-photon detection technology: Single-photon detection technology takes advantage of the quantum properties of photons and is able to detect a single photon as a unit, thus achieving high-precision imaging under very low light intensity conditions [15], as shown in Fig. 1. In biological imaging, this technique is particularly suitable for fluorescently labelled single-molecule imaging, which can obtain high-resolution structural information while maintaining cellular activity.

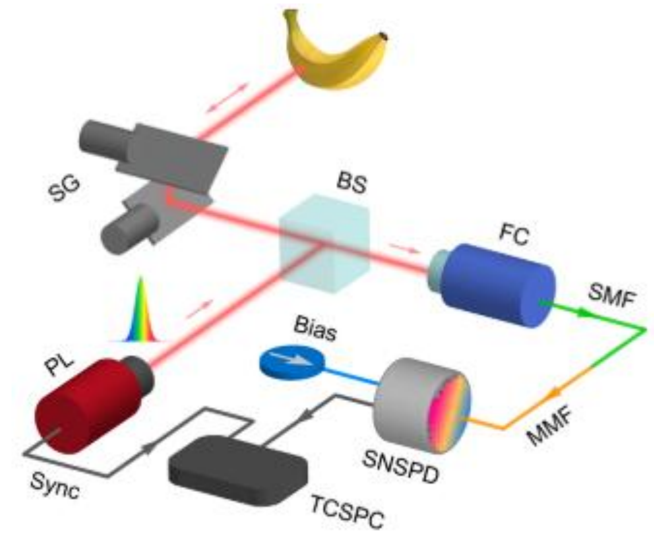


Fig. 1. Single-photon detection technology.

2) Quantum entanglement and imaging: Quantum entanglement [16] is a fundamental concept in quantum optics, where two or more particles are interdependent on each other in their quantum states, and even if there is a great distance between them, measurements on one of the particles will instantly affect the state of the other, and the schematic diagram of the principle of quantum entanglement is shown in Fig. 2.

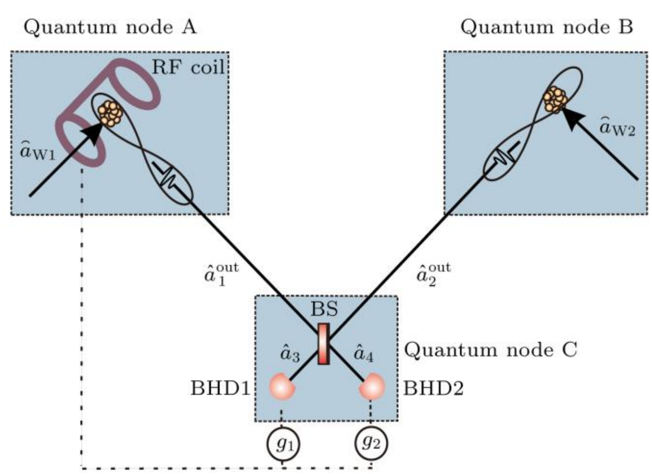


Fig. 2. Quantum entanglement.

Using the properties of quantum entanglement, a super-resolution quantum imaging system can be designed (Fig. 3) to achieve high-resolution imaging beyond the diffraction limit.

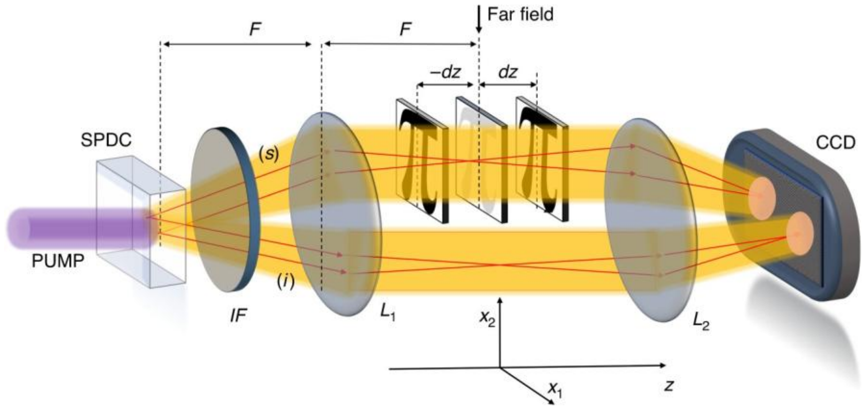


Fig. 3. Quantum imaging system.

3) Quantum optics in bioimaging: Quantum optical techniques show great potential in the field of bio-imaging due to their unique quantum coherence and entanglement effects. These techniques can significantly improve the resolution and sensitivity of imaging beyond the limits of conventional optical physics. Quantum imaging techniques using entangled photon pairs and single-photon detection can enable the observation of virus-sized cellular tissue structures as well as nanoscale defects in insulator materials, with specific applications analysed, as shown in Fig. 4.

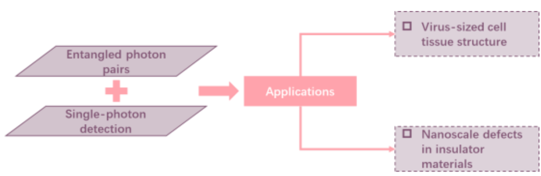


Fig. 4. Application of quantum optics in bio-imaging.

B. Quantum Optical Bio-Imaging System

Quantum optical bio-imaging systems utilise quantum coherence and entanglement effects to improve the resolution and sensitivity of imaging beyond the limits of conventional optical physics [17]. The research object of this study is the quantum optical single-pixel imaging system, which is shown in Fig. 5.

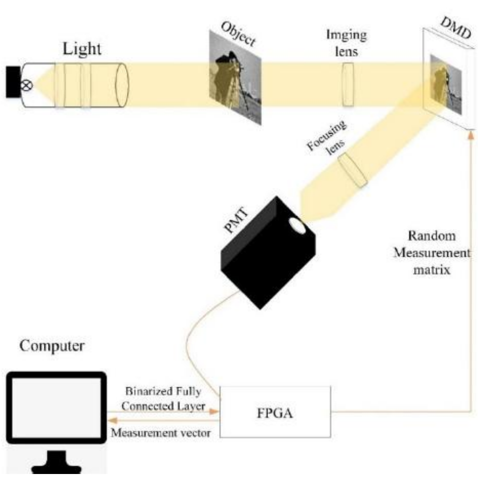


Fig. 5. Quantum optical single-pixel imaging system.

This study builds a quantum optical bio-imaging system whose core devices mainly contain a parallel single-photon source, a digital micromirror device DMD, and a single-photon detector PMT.

1) Parallel single photon source: In order to reduce the impact of light source scattering on the imaging results, this study designs a parallel single-photon source that can output a very weak parallel light, with a specific structure principle, as shown in Fig. 6.

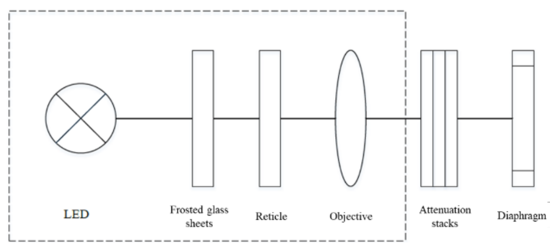


Fig. 6. Structure of parallel single-photon source.

2) Digital micromirror device DMD: Photonic single-pixel imaging schemes mainly implement spatial light modulation technology through spatial light modulators [18]. The electrically addressed spatial light modulator DMD used in this study has the advantages of high brightness, high reliability, simplified working circuit and high contrast, and its specific structure is shown in Fig. 7. The parameter settings of the DMD development board used in the experimental system of this study are shown in Table I.

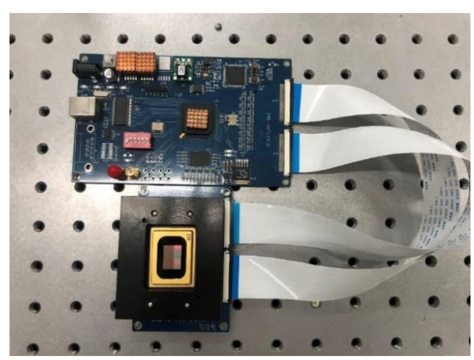


Fig. 7. Structure of DMD development board.

TABLE I DMD OPERATING PARAMETERS

Sports event	Setting parameters
resolution (of a photo)	1024×768
Micromirror size	13.68μm×13.68μm
Flip angle	±12°
frame rate	3000Hz
degree of contrast	2000:1
operating band	350nm~2700nm
synchronisation	Internal synchronisation, external synchronisation
random access memory (RAM)	DDR2

3) Single-photon detector PMT: The photon-counting single-pixel imaging system utilises a detector with a single-photon response to achieve the quantification of modulated light intensity. In this study, PMT is chosen as a single-photon detector, which is mainly composed of a photocathode, a collection anode and an electron multiplier pole, and its internal structure is shown in Fig. 8:

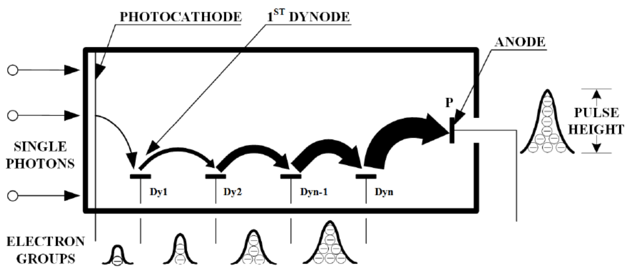


Fig. 8. PMT schematic.

C. Quantum Optical Bioimaging Reconstruction

In quantum optical bio-imaging systems, the traditional iterative reconstruction algorithms, although capable of accurately reconstructing the target image, have high time complexity, especially for large resolution images, where the reconstruction time is exponentially multiplied. In order to improve the efficiency of image reconstruction, ReconNet, as a neural network for reconstructing compressed perceptual images, was introduced into the quantum optical bioimaging reconstruction problem [19].

The structure of the ReconNet network is shown in Fig. 9. ReconNet consists of an upsampling module and an image enhancement module. The upsampling module contains one fully connected layer, and the image enhancement module contains six convolutional layers, each of which is post-positioned with a ReLU activation function to perform a nonlinear transformation.

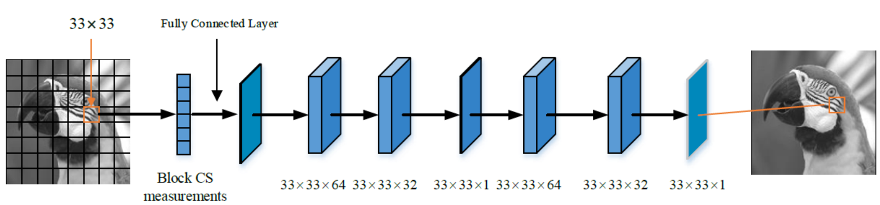


Fig. 9. ReconNet structure.

III. RA-ACS_NET RECONFIGURATION NETWORK

In order to improve the accuracy and efficiency of ultra-high resolution bio-imaging reconstruction based on quantum optics, this study uses the ripple algorithm to optimise the attention mechanism network and construct the RA-ACS_net reconstruction network.

A. Network of Attention Mechanisms

In order to reduce the computational burden of the reconstruction network and make full use of the image summary to give important information, this study adopts the attention mechanism [20] to construct the image reconstruction network and improve the image reconstruction effect. Attention mechanism network is divided into Hard Attention mechanism (Hard Attention) and Soft Attention mechanism (Soft Attention). According to the classification of attention mechanism structure and function, the attention mechanism network can be divided into Channel Attention Mechanism, Spatial Attention Mechanism and Hybrid Attention Mechanism, and the specific structure schematic is shown in Fig. 10.

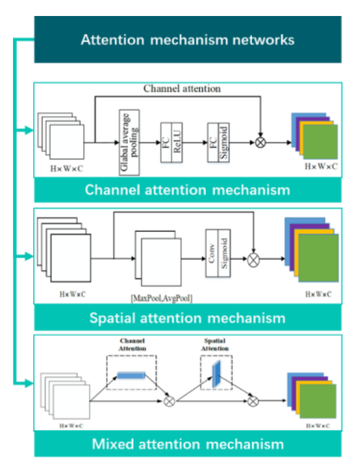


Fig. 10. Classification of attention mechanisms.

Inspired by the hybrid attention mechanism, this study adopts an attention mechanism network based on residual neural network, i.e., ACS_net, and the specific network structure is shown in Fig. 11. As can be seen from Fig. 11, ACS_net contains a picking sub-network and a deep reconstruction sub-network.

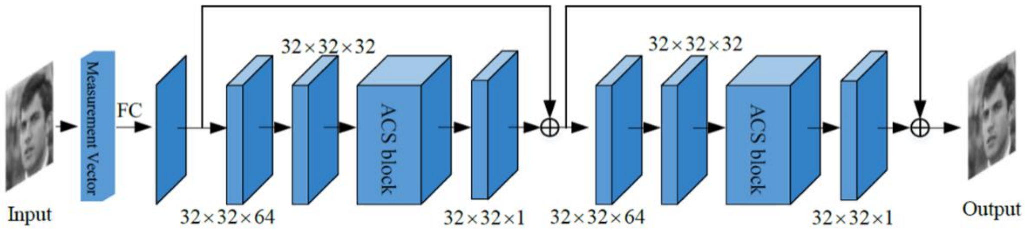


Fig. 11. ACS_net structure.

In the sampling network part, considering the screening of the input image information to ensure the completeness of the input information, ACS_net adopts the full connection layer to sample the original image to ensure the completeness.

In the deep reconstruction subnetwork part, ACS_net employs two residual blocks [21] to achieve the combination of lower-order features with higher-order features through jump connections. Each residual block contains a hybrid attention mechanism module (ACS_block) [22] and three convolutional layers. The structure of ACS_block is shown in Fig. 12, in which two convolutional layers are front-loaded, and then Batch Normalizaition is performed on these two convolutional layers, followed by a nonlinear transformation of the input feature maps through the activation function ReLU; finally, the input features are processed using the convolutional layers and the image reconstruction results are obtained.

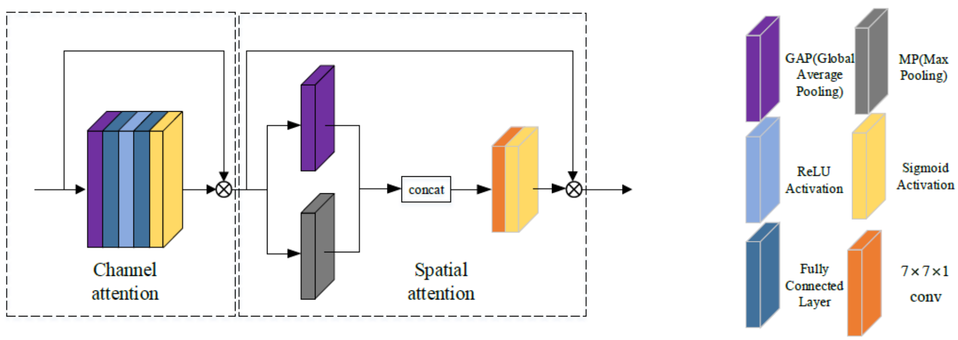


Fig. 12. Structure of the attention mechanism module.

In order to improve the overall performance of the model, this study designs a new loss function, namely ALoss (Attention Loss), which is calculated as follows, Eq. (1):

$$ALoss = \alpha \times \frac{1}{N}\sum_{i=1}^{N}\left\|x_i' - x_i\right\|^2 + \beta \times \frac{1}{N}\sum_{j=1}^{N}\left\|x_j'' - x_j\right\|^2 \tag{1}$$

where, x_i and x_j are the pixel values of the important and non-important regions of the original image block, x_i' and x_j'' are the pixel values of the important and non-important regions of the image recovered by the neural network, α and β are the scaling coefficients of the loss function, and N is the number of pixel points in the focal and non-focal regions of the image.

B. Ripple Algorithm

Ripple Algorithm (RA) is an optimization algorithm that simulates the phenomenon of ripple propagation in nature [13]. The RA algorithm has two features:

- The centroid adopts the ripple region search based on the current fitness and the global optimal fitness, which has stronger global search capability.
- The centroid searches relatively independently with the current optimal solution, and converges to the global optimal solution in a passive manner.

According to the characteristics of the ripple algorithm, this study performs a multi-layer ripple random point taking search with each centre point and calculates the random point adaptation value. The RA algorithm mainly includes two aspects of the search capability, i.e., exploration and exploitation, and the specific search schematic is shown in Fig. 13.

The multi-layer ripples are calculated by taking random points, as follows in Eq. (2):

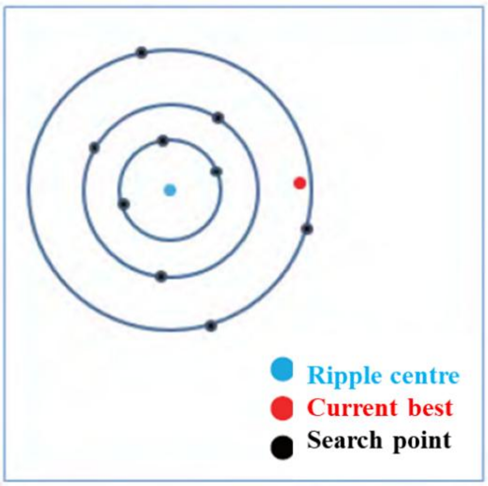
$$X_i^{km} = X_i + r \times R_i^k \tag{2}$$

where, X_i^{km} denotes the mth random search point in the kth layer of the ith centroid, X_i is the ith centroid, R_i^k is the radius of the kth layer of the ith centroid, and r is an n-dimensional random unit vector.

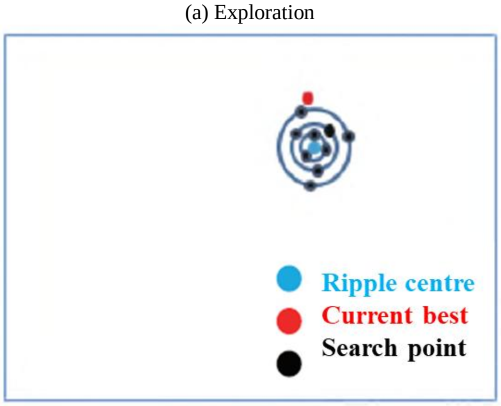
The ripple radius of each centre point is based on the gap between the current fitness and the global optimal fitness, the larger the gap, the larger the ripple radius and the wider the search area, and the smaller the gap, the smaller the ripple radius and the smaller the search area. The equation for calculating the ripple radius is as follows in Eq. (3):

$$R_i^1 = \log_\alpha \left(\frac{\sigma_i}{\sigma_{\max}} \right) \times \beta \tag{3}$$

where, α is the base of the logarithmic function and $\alpha \in (0,1)$; $\sigma_{\max}$ denotes the global maximum fitness value.



(a) Exploration



(b) Development

Fig. 13. RA algorithm search.

Comparing each centroid with its corresponding random point in the ripple layer, the point with the best fitness value is retained to form a new centroid cluster. Each centroid searches for the optimal point relatively independently rather than actively approaching the current optimal point, and the centroid cluster eventually converges to the optimal point as the iteration proceeds with the shrinkage function decreasing. The centre point update is calculated as follows in Eq. (4):

$$X_i^{t+1} = opt\left(X_i^t, X_i^{11}, \cdots, X_i^{km}, \cdots, X_i^{3M} \right) \tag{4}$$

where, X_i^{t+1} is the ith centroid of the centroid cluster in generation t+1, X_i^t is the ith centroid of the centroid cluster in generation t, X_i^{km} is the mth search point in layer k corresponding to the ith centroid, and M is the number of randomly taken points for each layer of ripples.

C. RA-ACS_Net Network Model

In order to improve the efficiency of ACS_net network reconfiguration, this study adopts the RA algorithm to optimise the ACS_net network parameters. The RA algorithm takes the ACS_net network parameters as the optimisation variables, MSE as the optimisation fitness function, and adopts the iterative process of the RA algorithm as the optimisation strategy, and the specific model construction is shown in Fig. 14.

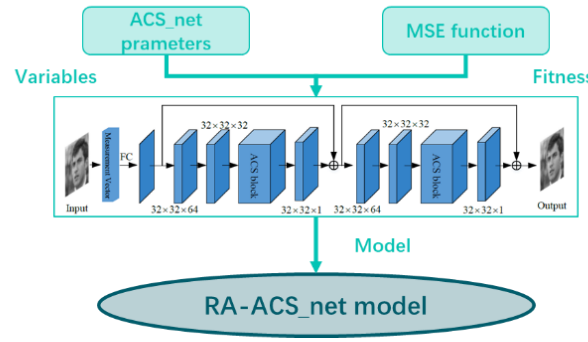


Fig. 14. RA-ACS_net network model construction diagram.

IV. Bio-Imaging Reconstruction Approach

In order to improve the efficiency and accuracy of the fusion quantum optics ultra-high resolution bio-imaging reconstruction method [23], this study proposes a fusion quantum optics ultra-high resolution bio-imaging reconstruction method based on RA-ACS_net. The method combines quantum optics, constructs an ultra-high resolution bio-imaging system, optimises the ACS_net network parameters using the ripple algorithm, and constructs a bio-imaging reconstruction method based on the RA-ACS_net network model. The specific method flow is shown in Fig. 15.

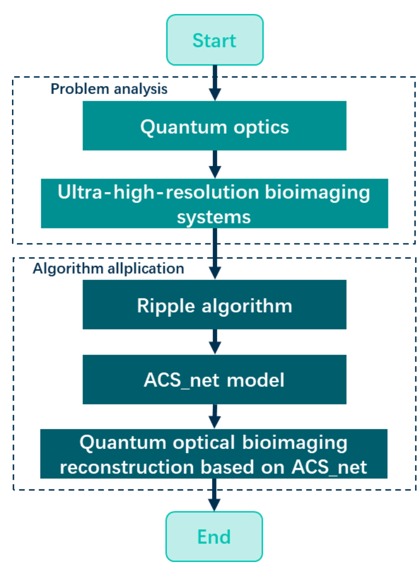


Fig. 15. Application of RA-ACS_net model in quantum optical bio-imaging.

V. Analysis of Results

In order to verify the efficiency of the RA-ACS_net reconstruction network proposed in this study, this study collects 19872 quantum optics-based bio-imaging images as the training set, and 128 bio-imaging images as the dataset for the training set to verify the performance of the network. For comparative analysis, this study firstly investigates the performance of different attention mechanism networks based on the RA algorithm in bio-imaging image reconstruction algorithms, secondly investigates the effect of different loss functions on reconstruction networks, and finally verifies the performance of the attention mechanism in quantum optics-based bio-imaging.

A. Comparative Experiments on Networks with Different Attention Mechanisms

In order to evaluate the effect of the attention mechanism on the reconstruction network models proposed in this study, controlled experiments are designed in this section to compare the reconstruction performance of the four reconstruction network models. The comparison algorithms used in the different attention mechanism network comparison experiments are shown in Table II. The results of the experiments of different attention mechanism network modules are shown in Fig. 16.

TABLE II PARAMETER SETTINGS OF THE ALGORITHM

Arithmetic	Algorithm setup
RA-CS_net	Removal of the Attention Mechanism module and optimisation of the CS_net parameter using the RA algorithm
RA-ACS_net_V1	Contains only the Channel Attention Mechanism module, which uses the RA algorithm to optimise the ACS_net_V1 parameter
RA-ACS_net_V2	Contains only the Spatial Attention Mechanism module, which uses the RA algorithm to optimise the ACS_net_V2 parameter
RA-ACS_net	Contains a hybrid attention mechanism module with RA algorithm to optimise ACS_net parameters

Fig. 16 shows the performance comparison of the four models at different Measuring Ratio (MR). It can be clearly seen that as the Measuring Ratio increases, the PSNR of all the models gradually increases. This is in line with the principle of Compressed Sensing (CS): the higher the Measuring Ratio, the more raw data we acquire, the better the quality of the reconstructed image, and the PSNR rises.

The RA-CS_net model performs the worst over the entire range of measurement ratios, especially at low measurement ratios (e.g., 0.1), where its PSNR is only about 25 dB, which is significantly lower than the other models. Even though the PSNR of this model increases as the measurement ratio increases, it is smaller and eventually the PSNR is still below 30 dB at a measurement ratio of 0.5. This indicates that the RA-CS_net model is weak in reconstructing the image with limited information, probably because the architecture of the model loses a lot of information when dealing with high compression rates.

By comparing RA-ACS_net_V1 with RA-ACS_net_V2, we find that both versions of the improved model outperform RA-CS_net over the entire range of measurement ratios, especially at a measurement ratio of 0.1, where the PSNR already reaches about 28 dB. As the measurement ratio increases, their PSNR improves rapidly, and finally at a measurement ratio of 0.5, both of them reach a PSNR of about 32 dB, which significantly outperforms that of RA-CS_net, indicating that the ACS (Adaptive Compressed Sensing) architectures have a significant improvement in the image reconstruction task, and they can better recover the original image, especially at medium to high measurement ratios.

RA-ACS_net: the model has the most impressive performance, especially at higher measurement ratios (e.g. 0.4-0.5), where it achieves a PSNR of more than 34 dB and close to 35 dB. This suggests that RA-ACS_net is able to utilise more measurements more efficiently, further improving the quality of the reconstruction.

The different magnitudes of PSNR enhancement with measurement ratio for different models are also reflected in Fig. 16. RA-CS_net has a relatively flat enhancement, indicating that it is not efficient in utilising the additional data. RA-ACS_net_V1 and RA-ACS_net_V2 have faster enhancement rates, especially at measurement ratios from 0.1 to 0.3, and their PSNRs are rapidly enhanced, which indicates that these improved models have a greater increase in data utilisation.RA-ACS_net boosts the most, and its PSNR continues to increase at higher measurement ratios (0.3 to 0.5), indicating that it performs best in high measurement ratio scenarios.

At low measurement ratios (0.1), the differences between the models are more obvious, especially RA-CS_net is much lower than the other three models. This indicates that the traditional RA-CS architecture has been difficult to recover images effectively when the amount of data is extremely limited, whereas the ACS-based model is able to extract more useful information from a small amount of data by means of self-adaptation, which significantly improves the reconstruction quality.

When the measurement ratio reaches 0.5, RA-ACS_net performs the best, with a PSNR close to 35 dB, while RA-CS_net still stays at less than 30 dB.This suggests that, although the reconstruction quality of all the models improves at high measurement ratios, the architecture of RA-ACS_net is able to make better use of the additional measurements and show better reconstruction results. This may be due to the stronger feature extraction and information fusion capabilities of the model.

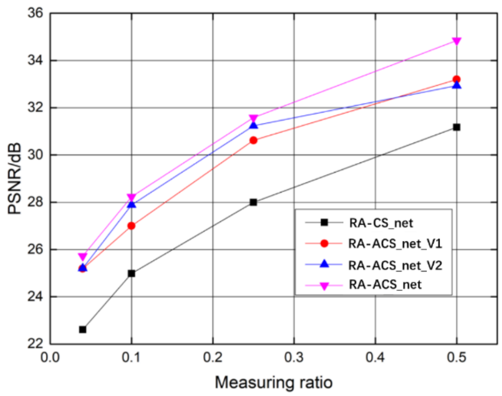


Fig. 16. Peak signal-to-noise ratio of reconstructed networks with different attention mechanism modules.

B. Comparison Experiment of Different Loss Functions

In order to evaluate the impact of the differentiated loss function ALoss designed in this study on the performance of the reconstructed network, a set of controlled experiments is designed in this section for validation, i.e., the comparison experiments between RA-ACS_net+MSE and RA-ACS_net+ALoss. The specific results are shown in Table III and Table IV.

From Table III, it can be seen that in terms of PSNR, the peak signal-to-noise ratio of the reconstructed network using the ALoss differentiated loss function is higher than the MSE loss function. From Table IV, it can be seen that the SSIM value of the reconstructed network using the ALoss differentiated loss function is higher than that of RA-ACS_net+MSE. It can be seen that the use of the ALoss function proposed in this study can greatly improve the performance of the reconstructed network RA-ACS_net_V2. The ALoss loss function improves the PSNR, as well as significantly improves the SSIM, which indicates that the loss function not only effectively improves the visual quality of the image but also better maintains the structural features of the image during the reconstruction process. MSE, although it also performs well, has limited performance enhancement when the measurement ratio is high, and especially performs significantly worse than ALoss in PSNR.

At low measurement ratios (MR=0.04), the performances of the two loss functions are relatively close, but the advantage of ALoss is gradually revealed when the measurement ratio increases, especially at high measurement ratios (MR=0.5), its image recovery is significantly better than that of MSE. If the application scenarios require a better reconstruction effect at high measurement ratios, the ALoss loss function is recommended. MSE can also be an option if the basic performance at low measurement ratios is pursued, but it is not as good as ALoss in terms of comprehensive performance.

The ALoss loss function outperforms MSE at all measurement ratios, especially at high measurement ratios, where it significantly improves the quality of the image reconstruction and exhibits greater applicability and effectiveness. Future studies can further explore the improvement of this loss function to enhance its performance under low measurement ratio conditions.

TABLE III PSNR (DB) RESULTS FOR DIFFERENT LOSS FUNCTION DESIGN METHODS

Aarithmetic	MR=0.04	MR=0.1	MR=0.25	MR=0.5
RA-ACS_net+MSE	22.788	25.050	28.230	30.617
RA-ACS_net+ALoss	22.986	25.467	28.632	31.950

TABLE IV SSIM RESULTS FOR DIFFERENT LOSS FUNCTION DESIGN METHODS

Arithmetic	*MR=0.04*	*MR=0.1*	*MR=0.25*	*MR=0.5*
RA-ACS_net+MSE	0.713	0.814	0.896	0.927
RA-ACS_net+ALoss	0.713	0.833	0.914	0.950

C. Quantum Optical Bio-imaging System Experiments

In order to verify the validity of the RA-ACS_net application, the reconstruction performance of RA-ACS_net in quantum optical imaging is analysed in this section, and the specific results are shown in Fig. 17.

Fig. 17 gives the results of the comparison of the PSNR metrics of the reconstructed images of RA-ACS_net and the traditional iterative algorithm TAVL3 at different measurement rates (MR=0.04, 0.1, 0.25, 0.5). From Fig. 17, it can be seen that the reconstruction performance of both RA-ACS_net and TAVL3 is improved as the measurement ratio increases; the PSNR metrics of RA-ACS_net are improved by 3.265 dB~6.71 dB compared with TAVL3. It can be seen that RA-ACS_net is well-suited to be applied for reconstructing images in a photo-quantum optics bio-imaging system. The TVAL3 algorithm gradually improves the PSNR when the measurement ratio increases, but the overall performance is relatively flat, and finally, the PSNR is about 23 dB at a measurement ratio of 0.5. The Proposed algorithm improves the PSNR significantly faster, outperforms TVAL3 in all measurement ratio conditions, and the PSNR is close to 30 dB at a measurement ratio of 0.5.

At a lower measurement ratio (0.1), the PSNR of TVAL3 is about 20 dB, while that of the Proposed algorithm is about 24 dB, showing a significant improvement in the reconstruction quality of the newly Proposed algorithm at low measurement ratios. This difference suggests that the Proposed algorithm is more effective than TVAL3 in dealing with sparse data, and may be structurally designed to be more adept at extracting information from limited data. As the measurement ratio reaches 0.5, the PSNR of the Proposed algorithm reaches 30 dB, showing a strong reconstruction capability, while the PSNR of the TVAL3 algorithm is only 23 dB, which is still significantly lower than that of the Proposed algorithm. This indicates that the Proposed algorithm is able to make better use of the information and improve the accuracy of image reconstruction when more data are acquired.

The PSNR of the TVAL3 algorithm grows at a slower rate, especially in the range of measurement ratios from 0.2 to 0.5, and the PSNR of the Proposed algorithm is more linear with measurement ratio and grows at a higher rate, especially in the range of measurement ratios from 0.1 to 0.5.

The Proposed algorithm shows better image reconstruction capability than TVAL3 both at low and high measurement ratios, and is suitable for scenes that require high quality reconstruction. The performance of TVAL3, on the other hand, improves more slowly and has greater limitations especially at low measurement ratios. In future research, we can continue to explore how to further optimize the Proposed algorithm to further improve the performance at higher measurement ratios.

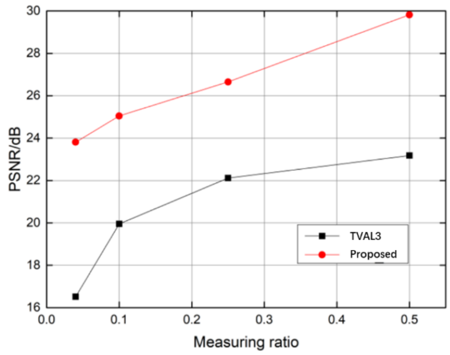


Fig. 17. Peak signal-to-noise ratio of reconstructed experimental maps with different algorithms.

VI. Conclusion and Outlook

Aiming at the problems such as the poor effect of image reconstruction methods in quantum optics bio-imaging systems, this study proposes a fusion quantum optics ultra-high resolution bio-imaging reconstruction method based on RA-ACS_net by combining the ripple algorithm and attention mechanism network. The method analyses the application of quantum optics technology in ultra-high resolution bio-imaging system and designs a quantum optics bio-imaging system, and at the same time explores and analyses the image reconstruction problem of quantum optics bio-imaging system, combines the attention mechanism network and the ripple algorithm, and puts forward the optimization of the ACS_net network model parameter method of the ripple algorithm, and constructs a bio-imaging reconstruction method based on the RA-ACS_net model. A bio-imaging reconstruction method based on the RA-ACS_net model is constructed. Comparative analysis of the proposed method using quantum optics-based bio-imaging image data shows that the RA-ACS_net method proposed in this study has a high peak signal-to-noise ratio for image reconstruction, and the image reconstruction effect is better. The subsequent work can consider denoising the image with noise reduction methods to improve the signal-to-noise ratio of the reconstructed image.

In the course of the study, we found that there are still several problems that have not been effectively addressed:

- Although the network proposed in this study has improved in the reconstruction effect, in practical applications, there is a certain noise interference in the quantum optical imaging process, especially in the low photon counting conditions, the noise may affect the imaging quality. How to further reduce the noise effect in the reconstruction process is still an urgent problem.

- The RA-ACS_net network increases the computational complexity while the accuracy is improved, especially when processing ultra-high resolution images, the reconstruction time is relatively long. Therefore, how to optimize the network structure, reduce the computational cost and improve the reconstruction speed is a direction to focus on in the future.

- The experiments in this study are mainly based on specific bioimaging datasets, which may behave differently on other types of bioimaging data, despite validating the effectiveness of the method. Future research needs to explore more diverse bioimaging scenarios and extend the generality of the network.

Based on the present and looking into the future, the following entry points can be studied: firstly, integrating noise reduction techniques, which can be combined with advanced noise reduction algorithms in the future, especially adaptive noise reduction methods based on deep learning, in order to further improve the signal-to-noise ratio of the reconstructed image, and to enhance the robustness of the system under low-signal conditions. The second is designing lightweight networks; future research can be devoted to designing more lightweight network models to reduce the consumption of computational resources and enhance the reconstruction speed. For example, methods such as pruning techniques or knowledge distillation can be introduced to optimise existing reconstruction networks. The third is the fusion of multimodal imaging. Considering the complexity of bio-imaging technology, the fusion of quantum optics with other imaging technologies (magnetic resonance, X-ray imaging) can be explored in the future to build a multimodal imaging system, which can provide richer biological information and achieve more accurate diagnosis and research. Finally, in order to further promote the practical application of the method, future research should validate the performance of the system in clinical or practical biological studies and assess its applicability and effectiveness in different scenarios.

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