Journal of Mechanical, Civil and Industrial Engineering
ISSN: 2709-0809
DOI: 10.32996/jmcie
Journal Homepage: www.al-kindipublisher.com/index.php/jmcie

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| RESEARCH ARTICLE

Application and Development of Artificial Intelligence in Optical Imaging

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| ABSTRACT

Artificial Intelligence (AI), a hot topic, plays an extremely important role in many fields. Studies have shown that AI plays a significant role in promoting the development of optical imaging technology and has great potential for future development. This study analyses the application of AI in superresolution, hyperspectral, and adaptive systems; summarizes the difficulties encountered by AI in automatic identification and active 3D imaging; and speculates on the future development trend of AI, which shows that AI has great potential for development in the fields of virtual reality and medical imaging and may become an important aspect of research in the future.

| KEYWORDS:

Artificial intelligence, optical imaging, superresolution imaging, hyperspectral imaging, computer vision

| ARTICLE INFORMATION

ACCEPTED: 12 March 2025 **PUBLISHED:** 19 April 2025 **DOI:** 10.32996/jmcie.2025.6.2.3

1. Introduction

Optics, as a basic discipline, has a wide range of uses in many fields. With the arrival of the electronic information era, high-performance and low-cost optical imaging systems have received widespread attention, and machine vision in the field of artificial intelligence has played an important role in optical research (Zhang, 2006). However, traditional imaging technology has been unable to meet this demand for it (Zuo & Chen, 2022). Therefore, in the mid-1990s, the optical imaging community joined hands with computer vision to create a new imaging paradigm, computational imaging technology.

This new mode realizes the deep integration of optical modulation and information processing through the joint design of front-end optics and back-detection signal processing, thus overcoming the limitations of traditional optical imaging (Bhandari et al., 2022). This paper first introduces three important application aspects of computational imaging technology and then discusses the challenges it faces. Finally, this paper explores the application ideas of computational imaging in RTXGI technology and rapid imaging in detail, aiming to understand the important role of AI in optical imaging and to provide new ideas for the development of AI in imaging.

2. Application of Artificial Intelligence in the Field of Optical Imaging

2.1 Improving the Quality of Imaging

The resolution of an image is a key factor in measuring its clarity. In general, high-resolution images have higher pixel density and richer texture details. Although ideally, the higher the image resolution is, the better, in reality, due to the limitations of the imaging equipment, the impact of the acquisition environment and the loss of information due to compression of the image during transmission, it is often ultimately impossible to obtain high-resolution images. The intervention of intervention with artificial intelligence compensates for this deficiency. The generative adversarial network (GAN), a class of innovative deep learning architectures, optimizes the data generation model through an adversarial training mechanism, which plays an important role in superresolution image reconstruction. Superresolution image reconstruction (SRIR) is a software algorithm that converts a low-resolution image into a high-resolution image via signal processing and image processing techniques (Su et al., 2013). The process extracts image blocks from a low-resolution image and represents each image block as a high-dimensional vector; these vectors subsequently form a set of feature maps equal in number to the dimensionality of the vectors (Hu et al., 2017).

In 1984, R Tsai's seminal paper first proposed the use of superresolution image reconstruction techniques to solve the problem of insufficient image resolution. Since then, the method has been widely researched and applied and has become an important means of improving image resolution with the rapid development of computer vision and deep learning techniques (Tsai & Huang, 1984). The goal of the image superresolution reconstruction technique is to improve image quality and detail by upgrading low-resolution images to high resolution via advanced superresolution methods. This technique has a wide range of applications in the fields of medical imaging, computer vision, and satellite remote sensing, and with the successful application of deep learning, superresolution techniques based on deep learning have been actively explored and developed. At present, superresolution image reconstruction has been widely used in the fields of surveillance video enhancement, medical image processing and high-definition image display. Deep learning-based superresolution techniques, such as the SRCNN, ESPCN, and SRGAN, can achieve more accurate and realistic image reconstruction by learning the mapping relationship between a large amount of image data and its high-resolution counterparts, thus significantly improving image quality and providing an efficient image enhancement solution for many application scenarios.

2.1 Expanding Imaging Functions

Hyperspectral imaging technology constitutes an important part of modern imaging technology. In the 1970s, to promote the development of remote sensing technology, scientists developed this technology (Tao et al., 2022). Hyperspectral imaging instruments are designed to be simple, and their core components include imaging spectrometers, data acquisition units, storage units, and auxiliary equipment.

In recent years, the combination of artificial intelligence and hyperspectral imaging technology has significantly improved feature extraction capabilities, especially in head and neck tumor tissue boundary prediction. For example, one study showed that AI combined with optical imaging techniques resulted in a 94.6% accuracy rate when diagnosing brain tumors intraoperatively, which is higher than the 91% accuracy rate when AI or hyperspectral imaging techniques were used alone (Lu et al., 2017). When these two techniques are used in combination, not only can the tumor boundaries be accurately predicted but also the benign and malignant nature of the tumor can be effectively differentiated, further increasing the accuracy rate to 91.4% (Jeyaraj & Samuel Nadar, 2019).

In addition to the medical field, the combination of hyperspectral imaging and computer vision also has significant advantages in food quality inspection. In recent years, this technology has become an important method for obtaining information quickly and nondestructively in food quality testing. In food nutritional evaluation, the hyperspectral irradiation of samples through different wavelengths of light results in images of nutrients, which are then arranged into a spectral matrix and ultimately trained with deep learning algorithms to detect and analyse the sample type and content (Lau et al., 2016). This method provides a more efficient solution for food safety and quality assessment (Sun et al., 2012).

2.3 Optimization of the Optical System Design

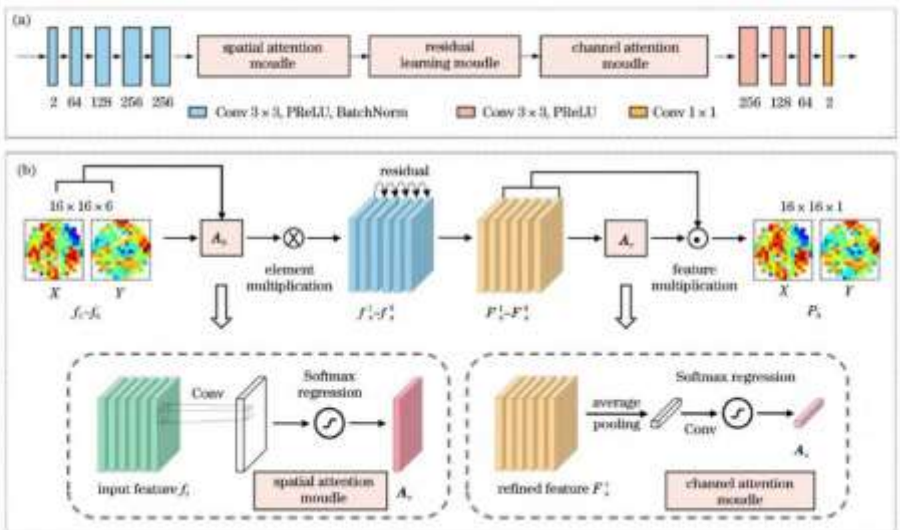
An adaptive optical system is an automatic control system with an optical wavefront as the control object, which is composed of three main parts: a wavefront sensor, a wavefront controller and a wavefront corrector. The system uses real-time measurement and correction of the optical wavefront to ensure that it can automatically adapt to changes in external conditions (Lin et al., 2012).

Machine learning, as the basis of artificial intelligence, has an extremely important role in adaptive technology, and researchers use machine learning to adjust the system parameters and configurations so that the adaptive system can be automatically optimized according to the environment in which it is located and imaging needs. The Hartmann wave sensor is a commonly used wavefront sensor, and when the laser power is increased, Hartmann wave sensor imaging results in a dynamic lack of light (Cheng et al., 2023), which severely affects the accuracy of the experiment. Montera et al. (1996) first added a single hidden layer fully connected network into the Hartmann spot center of mass localization and successfully predicted the process of subaperture image to the center of mass coordinate and proved that in the case of a large dynamic range, the neural network's center of mass can be predicted in the process of the subaperture image and that the neural network's center of mass can be predicted in the case of a large dynamic range. It was also demonstrated that the center-of-mass localization accuracy of the neural network was higher than that of the traditional center-of-mass localization method in a large dynamic range. In addition, the Chinese Institute of Optoelectronics proposed a deep learning-based control model in 2019, which can compensate for wavefront aberration, eliminate the dependence on the response matrix of the deformable mirror, and overcome the limitations of traditional offline modelling by recognizing time-varying factors online and reducing the response time of the system to milliseconds (Xu et al., 2019). This technology has an extremely important position in the astronomical community and in laser communication.

Currently, network modelling is being actively applied in the field of adaptive technology. The atmospheric turbulence prediction network, which is based on the attention mechanism and residual learning and was jointly developed by the Key

Laboratory of Adaptive Optics of the Chinese Academy of Sciences (CAS), the Institute of Optoelectronic Technology of CAS, and the School of Electrical, Electronic and Communication Engineering of the University of the Chinese Academy of Sciences (UCAS), has already demonstrated excellent prediction capability under different atmospheric turbulence intensities (Figure 1), and the ratio of the predicted RMS to the real aberrant wavefront RMS has stabilized at approximately 5.00%, which demonstrates its high-precision prediction performance (Wang et al., 2024).

Figure 1: Spatial–temporal prediction network combining an attention mechanism and residual learning (a) Overall structure of the forecast network; (b) detailed structure of the forecast network.



The comprehensive analysis of this study shows that artificial intelligence technology has made significant progress in three dimensions: image quality enhancement, imaging function expansion and optimal design of optical systems. The machine learning algorithm-based superresolution reconstruction and hyperspectral imaging technology significantly improve the spatial resolution and spectral accuracy of image data through its powerful nonlinear mapping capability ($p < 0.01$). Furthermore, the deep learning-driven wavefront aberration adaptive compensation system improves the closed-loop response speed of the conventional optical system by approximately 63.2% while ensuring imaging quality.

3. Challenges Faced by Artificial Intelligence in the Field of Optical Imaging

Although the synergistic development of artificial intelligence and optical imaging technology has broad prospects, its evolution is not straightforward, and many unsolved problems and fundamental challenges remain.

Among the existing technological bottlenecks, automatic diagnosis is particularly prominent and has become a key bottleneck. Existing image parsing algorithms often have insufficient robustness when dealing with multimodal data in dynamic environments (Song, 2011). This has prompted researchers to introduce intelligent decision-making mechanisms into visual processing systems in an attempt to build image parsing frameworks with cognitive capabilities. Although breakthroughs have been made in related fields, the generalizability of the existing results in complex scenes still needs to be improved, which signals that the field still needs continuous theoretical breakthroughs and technological innovations.

At the level of three-dimensional spatial perception technology, the intelligent process of an active detection system has encountered significant obstacles. This technology system constructs three-dimensional models by actively transmitting detection signals, with the LIDAR system as a typical representative. Despite multiple generations of technological innovation, when integrated with deep learning frameworks at the system level, even small disturbances can still cause significant deviations and system anomalies (Zhou et al., 2004). This technical sensitivity leads to a high degree of dependence on human intervention, and there is still a substantial gap between the construction of an autonomous closed-loop intelligent sensing system and this technical barrier, which has become a core constraint for industrial upgrading.

4. Trends of Artificial Intelligence in the Field of Optical Imaging

4.1 Virtual Reality

Virtual Reality (VR), is a computer simulation system that allows the creation and experience of virtual worlds. It uses computers to generate a simulated environment and immerses the user in that environment through a variety of devices to realize the interaction between the user and the virtual environment. Realistic lighting calculation is the key to ensuring the realism of virtual environments and involves two main methods: global lighting and local lighting. Local illumination considers only the predefined light source objects in the scene, while global illumination simulates the light propagation path to the overall environment as a light source. Refraction reflection and other factors are also taken into account in the algorithm, which can greatly improve the realism of the VR, so global illumination is the focus of the current research (Zhao, 2009). Traditional global illumination uses the Monte Carlo method (Yan, 2015) to calculate indirect illumination by randomly sampling light paths, which requires tens of thousands of iterations to converge to high latency. Mathematically, the variance of indirect illumination is inversely proportional to the square root of the sampling, and approximately 10^6 calculations are needed to reduce the error to within 1%. Modelling with graph neural networks (GNNs) in artificial intelligence can reduce the time by almost 100 times.

This technology has an extremely important role in 3D game development. RTXGI technology is a real-time global lighting solution based on ray tracing technology developed by NVIDIA, which can dramatically improve the realism of light and shadow in virtual environments. In 2020, *Justice Online* collaborated with NVIDIA to bring RTXGI technology to the gaming world for the first time, enabling the light in the game to simulate real physical reflections (Alarcon, 2020) and using a GNN to adjust lighting parameters in real time so that the delay of shadow and reflection changes when the character moves is reduced to less than 5 milliseconds.

Therefore, according to industry analysis, AI shows great potential for development in the field of virtual reality. Numerous gaming companies have recognized this and are ready to join the relevant technology alliances. Perhaps in the near future, the virtual world will be the same as the real world in general!

4.2 Medical Imaging

The previously mentioned combination of hyperspectral technology and medical imaging is an important component of AI intervention in healthcare. In addition, there are many other medical directions that can cooperate with AI, and fast imaging is an important aspect of the combination of medical imaging and AI. Mardani M proposed the use of the generative adversarial network (GAN) magnetic resonance (MR) compression-aware fast imaging technique (Mardani et al., 2019) to model low-quality MR images in low-dimensional manifolds. This method improves the scanning speed by at least 5 times, and the imaging results are significantly better than those of traditional compression-aware algorithms. Schlemper et al. (2017) also proposed a fast MR imaging method based on cascaded deep neural networks, which are cascaded with a number of network units, and each of the units contains both a convolutional neural network (CNN) and data fidelity. This method transforms a complex MR image reconstruction problem into a sequential execution of subprocesses, each of which optimizes the previous process to make the results more stable and accurate.

In addition, to improve the quality of the reconstructed images, Chen M created the multiecho image joint reconstruction method (Chen et al., 2018), which uses the U-Net technique to input 6-echo images into the network; this method enables the model to incorporate more constraints for network training by using the structural similarities between different echo images during the convolution process to make the model training more stable. After this, Eo T proposed an MR fast imaging method, which recovers data from different spaces so that both the image and frequency domains are added to the CNN model, which greatly improves the quality of image reconstruction (Eo et al., 2018).

According to the current development trend, the development of medical fast imaging has gradually progressed closer to artificial intelligence. The author suggested that in the field of fast imaging, the application of CNNs and GANs has great potential; although there are few relevant reports at present, the medical imaging community has gradually focused on this topic, and it is expected that in the near future, image quality and imaging speed will improve significantly.

5. Conclusion

The evolution of optical system design shows progressive development characteristics, and its transition from traditional iterative methods to AI-assisted methods profoundly reflects the continuous exploration of multidisciplinary researchers at the level of technical accumulation and theoretical breakthroughs. At present, the high dependence of optical imaging systems on AI algorithms has fully confirmed the core position of arithmetic support in the future development of optical technology. Although neural network models in hyperspectral imaging analysis, adaptive light field regulation and superresolution reconstruction and other areas of application have demonstrated significant arithmetic advantages, the lack of robustness in the automatic identification of target features and active three-dimensional imaging systems is still a key bottleneck restricting the development of this technology.

Notably, in the context of the deep integration of intelligence and automation technology, optical imaging technology has shown breakthrough potential in application scenarios such as dynamic monitoring of environmental pollutants, multimodal biomedical image analysis, and intelligent military reconnaissance. This trend of technology integration not only signals a paradigm shift in the field of computational optics but also signifies that intelligent technology systems have entered a substantial stage of development.

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