

REVIEW

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Structured light meets machine intelligence

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Abstract

Structured light, where light is tailored in all its degrees of freedom, has shown tremendous power in unlocking new modalities of light, with its impact felt across dimensions, disciplines, and applications. This richly textured light comes with deeply embedded complexity, making the design, analysis, and recognition of such complex light patterns highly non-trivial. In recent years artificial intelligence (AI) has come to the fore, not only for the design, characterization, and optimization of structured light but also for increasingly important roles in adding new functionalities and breaking old paradigms. An exciting twist is the flip side of the coin, where complex light in complex media acts as a light-speed neural network, ushering in a new era of ultrafast optical-based “machines” for intelligence and learning. In this review, we focus on how AI has enhanced structured light technologies, and vice versa, touching on imaging, microscopy, sensing, communication, and optical neural networks as topical application areas, while covering scales from the macroscopic to the microscopic, and from classical to quantum. We highlight the symbiotic relationship between intelligence and light in these processes and offer a perspective on the open challenges and future prospects of this emerging research direction.

1 Introduction

Structured light, the deliberate tailoring of light in all its degrees of freedom (DoFs) has emerged as a transformative optical technology with profound implications across multiple scientific domains. In the modern context it involves accessing exotic properties of light beyond the textbook, enabling applications ranging from high-capacity optical communications to super-resolution imaging and quantum information processing. It is beyond the scope of this review to cover advances in structured light, and instead the reader is referred to many excellent reviews on the topic [1–6].

To truly harness these new DoFs requires an ever more sophisticated toolbox, with capabilities that are at once agnostic and multi-modal: we should be able to determine on the fly which DoFs to use and how many. Traditional approaches fall short in this regard, failing to capture the rich interdependencies among multiple optical properties that characterize advanced structured light, particularly when imbued with unwanted complexity, such as after passing through complex channels, e.g., atmospheric turbulence, scattering from living tissue, and multimode fiber. This development gap has created

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an urgent demand for novel approaches capable of harnessing the multidimensional nature of modern structured light fields. Such complexity-driven challenges have catalyzed the convergence of structured light with Artificial Intelligence (AI), creating a symbiotic relationship that addresses fundamental limitations in both fields. Artificial intelligence, especially Machine Learning (ML) technology, offers powerful data-driven approaches to extract meaningful patterns from complex datasets, making them ideally suited to the high-dimensional sophisticated structured light. From Convolutional Neural Networks (CNN) that classify multifaceted spatial modes [7] to Generative Adversarial Networks (GAN) that reconstruct distorted patterns [8], ML techniques provide versatile tools for advanced optical characterization and control. In parallel, structured light has come to aid ML in the form of all-optical intelligent machines, moving ML from a heavily electronic-based resource to an optical one [9, 10], with the potential for harnessing complexity to compute at the speed of light.

This review examines the convergence of structured light and machine intelligence, both addressing and harnessing complexity for advanced applications. It discusses the integration of ML in unravelling complex structured light, and evaluates its roles in optical communications, precision metrology, quantum technologies, Optical Neural Networks (ONN), and super-resolution imaging, as shown in Fig. 1. Particular attention is given to the use of structured light propagating through complex media as a means of harnessing its complexity in light-speed neural networks, paving a potential pathway toward ultrafast optical-based “machines” for intelligence and learning. The review further outlines the interrelationship between light and intelligence, and provides an overview of current challenges and future prospects of this interdisciplinary domain.

How many DoFs does light have, and how might they be controlled? With that control in hand, how might they be exploited for enhanced functionality in applications? Answering these questions is the central task in structured light [1], as shown in Fig. 2, resulting in light tailored for purpose [11]. In the context of structured light, traditional DoFs such as wavelength, polarization, phase and amplitude are combined to form multimodal light, enhanced by new DoFs that were hitherto hidden from view. For instance, azimuthal phase engineering has resulted in light carrying orbital angular momentum (OAM) [12], opening a pathway to high-dimensional states of light with an infinite encoding alphabet [4]. Combining polarization and OAM has seen the emergence of multi-dimensional light [13], for instance, the natural modes of optical fiber and non-separable states of light [14]. Digging a little deeper reveals more abstract

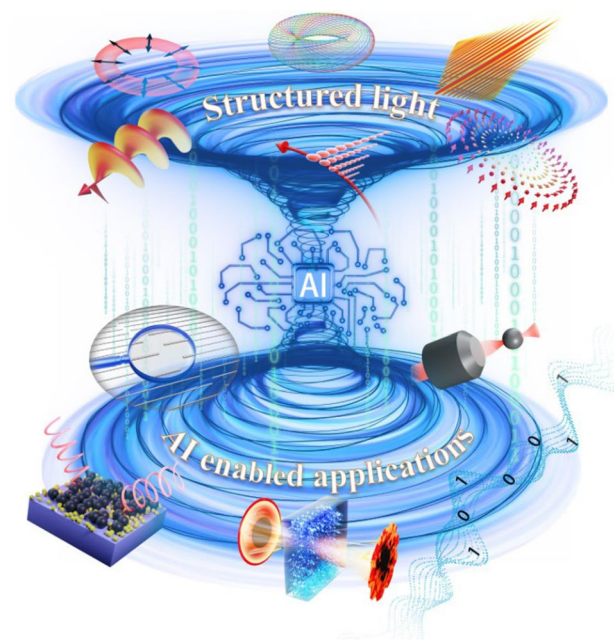


Fig. 1 Contents of this review. When AI and structured light meet, the intersection facilitates the generation of new forms of light, the unravelling of structured light, and the application of structured light in diverse areas. Structured light too can be an intelligent machine: when passed through complex media, it acts as an optical neural network, offering new forms of AI. This self-referential cyclic interaction, a rapidly developing field of research, is rich with potential

notions of topologies, where the DoFs now merely facilitate maps rather than are observables in their own right [15], such as topological charges in phase and polarization, as well as Skyrmion wrapping numbers. Such control has seen an explosion of activity as it fosters new forms of light beyond the textbook [16] and enhanced functionality in applications [17].

2 Basic principles of ML

ML simulates human intelligence in machines, allowing them to learn, reason, and solve problems autonomously. Deep learning, a branch of ML, uses multi-layered neural networks to detect and interpret complex patterns in large datasets. Its evolution can be divided into three major waves: the 1940s, featuring early neural networks [18] and the perceptron model in 1958 [19]; the 1980s, introducing backpropagation and convolutional neural networks [20]; and the 2000s, epitomized by Deep Belief Networks [21, 22], the groundbreaking AlexNet in 2012 [23, 24], and features like Rectified Linear Unit (ReLU) and Dropout. In this section we first give a concise summary of artificial intelligence, and then review the synergy at the meeting place of the two.

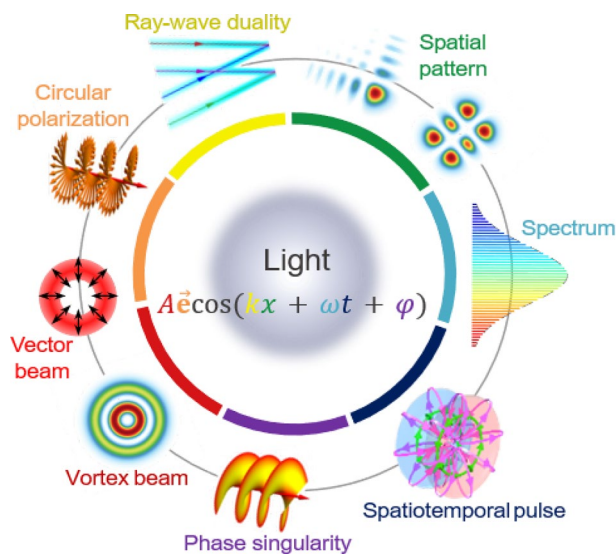


Fig. 2 Structured light. The traditional DoFs that are distinct and separable in space and time, as highlighted by the cartoon equation, can be recast to form new forms of light with exotic properties, from quantum-like behavior to underlying topologies, coupling DoFs together. We show examples such as spatial in the path (ray-wave duality) and spatial patterns, the latter in various symmetries to give Airy, Hermite-Gaussian and vortex beams. Other DoFs such as polarization and OAM can be combined to make vectors beams, while temporal and spectral properties can be mixed with space for spatio-temporal light

2.1 The ML toolbox

ML has undergone rapid development in recent years, providing researchers across fields with a wealth of tools. Here we briefly summarize the technological development trajectory with some examples of core ML technologies, as illustrated in Fig. 3.

2.1.1 Classical machine learning methods

ML comes in two broad flavors: supervised learning and unsupervised learning. Supervised learning trains models using labeled data, primarily for classification and regression. In contrast, unsupervised learning requires no external labeled data and can autonomously discover inherent structures within data.

2.1.2 Deep learning methods

Deep learning [25, 26], as an important branch of machine learning, handles the same classification and regression tasks as classical machine learning, but breaks through the limitations of relying on manual feature engineering, achieving higher efficiency and performance. Deep learning employs architectures such as Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), CNN and Transformer to extract specific patterns from input data, enabling end-to-end

feature learning. Additionally, deep learning has developed advanced generative models such as Variational Autoencoder (VAE), GAN, and Diffusion Models, which can accurately capture the underlying distribution of data to generate highly realistic and diverse new samples. Meanwhile, deep learning training techniques have also achieved breakthroughs compared to classical ML methods, continuously expanding from supervised learning and unsupervised learning to improve model application efficiency.

2.1.3 Emerging forms of ML

To move away from computationally expensive electronic implementation, new emergent forms of AI have arisen. These include Scientific Machine Learning (SciML) to address issues of high computational costs, inaccurate models, or insufficient data in scientific computing, utilizing machine learning as a supplementary solution, ONN to speed up the process with light, and Quantum Machine Learning (QML), harnessing quantum states to make the process more energy efficient.

2.2 Processing data

One application of ML is the processing of existing data, for instance, to classify data sets, and has undergone continuous innovation in architectural design. The core of this is machine learning. For classification tasks, Support Vector Machines (SVM) [27] seek optimal separating hyperplanes, while Random Forests [28] improve classification accuracy by assembling multiple decision trees. In regression tasks, linear regression serves as a fundamental model that fits linear relationships between features and outputs. In these examples, the learning is supervised. Unsupervised learning requires no external labeled data and can autonomously discover inherent structures within data, for example: K-means [29] iteratively divides data into preset clusters; Apriori [30] is used for mining frequent item sets; Principal Component Analysis [31] reveals data structures through dimensionality reduction; and Kernel Density Estimation [32] provides non-parametric statistical methods for anomaly detection.

An important branch of machine learning is deep learning. Here, multi-layer perceptron [20], as the most basic architecture of deep learning, utilizes fully connected layers with non-linear activation functions [33] to automatically learn data representations through multi-layer neural networks, though its generalization ability for image data is limited. CNN addresses this issue by introducing convolutional and pooling operations with inductive bias, effectively capturing spatial hierarchical features in images, significantly improving model performance, and demonstrating excellence in image classification tasks [34, 35] and object detection [36–38]. Recent

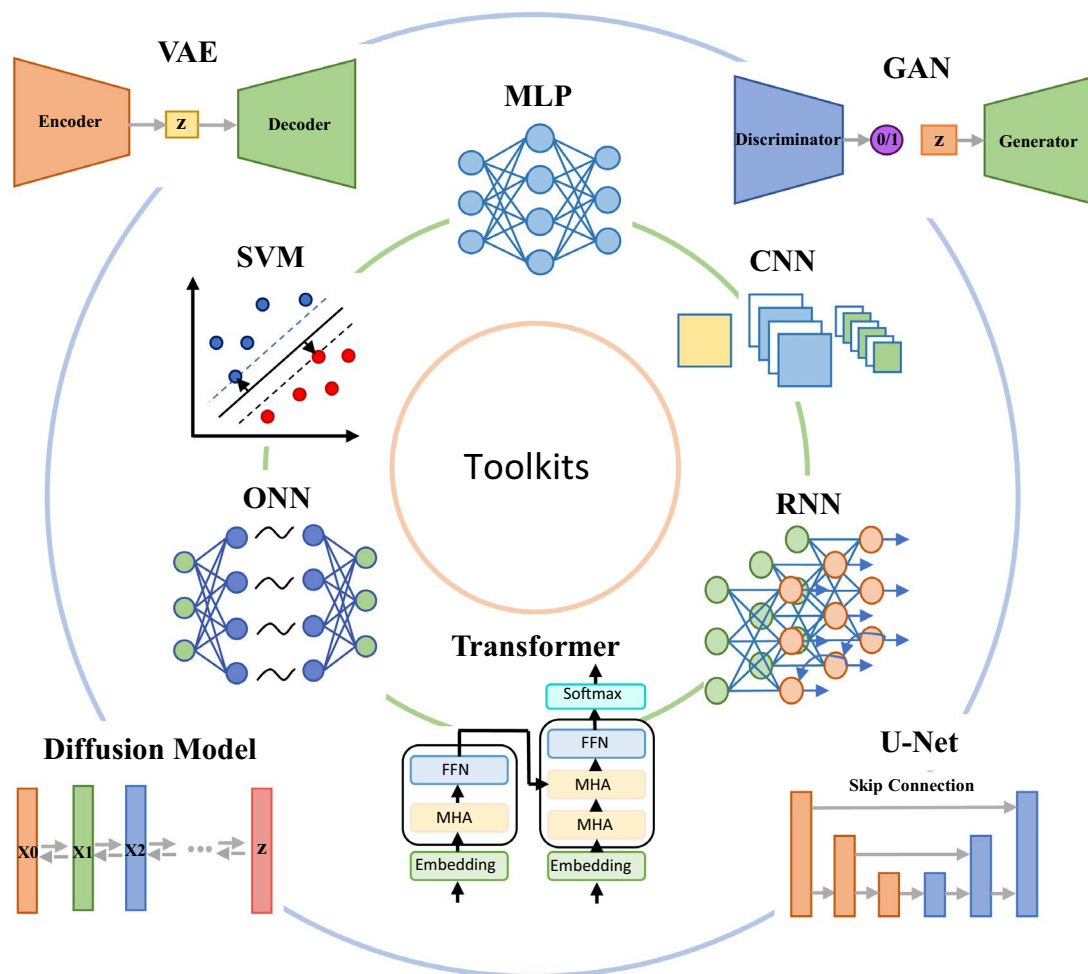


Fig. 3 ML Toolkits. Machine learning toolkits for data recognition and image generation

years, the Transformer architecture [39] overcame the limitations of sequence models like RNN [40–42] through self-attention mechanisms that enable parallel computation and global dependency modeling, surpassing many traditional CNN models in image classification performance [43], demonstrating the powerful potential of the Transformer architecture.

2.3 Manipulating data

A more recent application of ML is to create data from some input prompt. In this example, the field of generative models has undergone systematic technical evolution, from encoder-decoder [44, 45] structures that compress input into latent space for flexible generation, to U-Net [46] which enhances image processing precision by solving information loss problems through skip connections; subsequently, GAN combined CNN with adversarial training [47], laying the foundation for image super-resolution [48] and style mixing [49]; while diffusion models [50] pioneered an entirely new paradigm,

different from the direct reconstruction of encoder-decoders or the adversarial training of GAN models, generating high-quality images through a gradual denoising process; multimodal generative models integrate Transformer architecture to process multi-source conditional information, achieving precise understanding of external instructions, thereby generating high-quality image content that matches requirements [51].

Deep learning training techniques continue to evolve. In unsupervised learning, pretraining techniques such as self-supervised learning methods [52, 53] break through the limitations of traditional methods by learning rich representations from unlabeled data through cleverly designed pretraining tasks, greatly reducing dependence on supervised signals. Reinforcement learning techniques not only enable models to exceed human expert decision-making levels in specific domains [54], but also make generative model outputs more aligned with human preferences through reinforcement learning from human feedback [55], or enhance reasoning abilities [56].

Additionally, through parameter-efficient fine-tuning [57] techniques in transfer learning compared to traditional machine learning's full parameter optimization, computational resource requirements are significantly reduced while enabling models to achieve performance comparable to base models in downstream tasks.

2.4 Application to structured light

Ongoing advancements in structured light and neural networks have made their integration a popular research field. Deep learning techniques have achieved significant success in image processing. Using multiple convolutional and pooling layers, CNNs can extract hierarchical features from images, enabling precise classification and fast recognition of structured light just by the intensity image processing. The directly recognizing features from modes has significant applications, such as in Free-Space Optics (FSO). In this process, neural networks are used to classify and recognize received structured light modes. This approach enhances the accuracy and efficiency of information decoding, ensuring reliable and stable transmission. By optimizing feature extraction techniques, the system can better cope with environmental noise and signal interference, thereby improving overall communication quality. In practical scenarios, structured light can interact with various media, such as atmospheric turbulence, water flow fluctuations or tissue scattering. These interactions often cause image blurring and distortion, making it challenging for both human observers and neural networks to accurately recognize and interpret the images. However, by constructing more complex Deep Neural Networks (DNN), deep learning can still achieve high-precision pattern recognition and classification capabilities. Besides, GANs can provide an effective solution to repair and reconstruct distorted images, by adversarial training between the generator and the discriminator, the generator is ultimately able to output realistic reconstructed images of both the structured light and the structured light assisted imaging techniques.

The approaches described above are all computationally intensive, and rely primarily on electronics for implementation. Emergent forms of AI offer alternatives to the conventional. For instance, SciML [58, 59] complements traditional scientific computing to address issues of high computational costs, inaccurate models, or insufficient data in scientific computing, utilizing machine learning as a supplementary solution. ONNs [9] employ optical devices for neural network computation, aiming to leverage the properties of light to enhance the computational efficiency of deep learning. QML [60] introduces quantum computing, providing new capabilities in fields such as encryption, optimization, and simulation. These machine learning methods, combined with scientific

principles, constitute practical tools for solving complex scientific problems beyond the capabilities of traditional machine learning and deep learning approaches. When blended together, ML-empowered structured light integration has been enabling enhanced functionality and adaptability, while new structured light applications are simultaneously contributing to the development of AI technology.

3 Structured light recognition with machine intelligence

The rapid advancement in structured light research has led to the development of numerous methods for sorting and analyzing structured light field, such as interference method using simple elements [61, 62] or interferometers [63–65], diffraction methods with apertures [66–68] or two-dimensional gratings [69], spatial modulation method with optical elements [70] or computer-generated holograms [71, 72], spatial mode decomposition [73], multi-plane light conversion (MPLC) [74] or specially designed interferometers [75], mode transformation method [76, 77], time mapping method [78, 79] and near-far field intensity recording [80]. Some of these methods require complex optical setups, which limits their range of application scenarios. The intensity recording method, in contrast, is notable for its simplicity, relying only on a CCD camera to capture intensity information. However, when it comes to recognition, the accuracy of manually designed operators is limited. Employing deep learning to recognize these images offers a solution that combines both simplicity and accuracy. The following sections will discuss various neural network approaches used for different structured light recognition tasks.

3.1 Networks for recognition

Chapter 2 discusses the classical neural networks and their features. Among them, certain neural networks are particularly suitable for structured light classification and recognition. Compared to digital graphics, pattern coefficients and optical parameters more accurately reflect the characteristics of structured light. DNNs consist of multiple fully connected layers, offering a relatively simple structure that facilitates training multi-task neural networks and uniformly predicting pattern coefficients and optical parameters.

CNNs are structured by stacking convolutional and pooling layers, with convolutional layers sliding over input data to extract local features. This architecture is particularly well-suited for processing data with a two-dimensional spatial structure. Since structured light is often stored in the form of two-dimensional digital images, CNNs are highly effective for transfer learning

in structured light pattern classification and recognition. When structured light propagates in free space, scattering caused by medium inhomogeneity leads to blurred and distorted images. Solely relying on CNNs for structured light pattern recognition may reduce accuracy. Moreover, simulating disturbed structured light poses challenges and requires a large amount of simulation data. To address this issue, GANs are introduced to model interference, reconstruct distorted images, and then input the resulting clear images into CNNs for recognition, thus improving the accuracy of the recognition.

ONNs as a very promising strategy for replacing the electronic elements in data processing and calculations, possess the advantages of speed and energy efficiency. As one of the practical cases of ONNs, deep diffractive neural networks (D²NN) represent a novel optical neural network architecture, integrating deep learning with optical diffraction to execute neural network functions. D²NNs leverage the diffraction behavior of light through various optical elements, such as diffraction layers, to perform calculations. These optical elements are engineered with specific shapes and materials to perform computational functions such as convolution operations and matrix multiplications. It is a highly promising tool to achieve fast, energy-efficient classification of both structured light and symbols images, offering strong generalization capabilities and scalability. While the physical system of D²NN for optical wavelength remains immature, the network discussed below in this section is numerically simulated.

3.2 Structured light recognition

3.2.1 Structured light classification

Structured light field recognition can be categorized into two types: single-mode classification and superposed mode recognition. Traditional single-mode classification relies on manual feature labeling, whereas deep learning can automatically extract features from the beam intensity profiles without manual design, offering superior generalization capabilities.

Among various structured light modes, OAM modes are the most widely used. Recognition of OAM modes can be achieved using methods such as Feedforward Neural Networks (FNN), CNNs, and Extreme Learning Machines (ELM) [81–83]. The specific recognition indicators lie in the radial index (p) and angular index (l) of OAM beams. Earlier studies demonstrate that DNNs can recognize Laguerre-Gaussian (LG) beams ($p = 0$) with l ranging from 1 to 100 [84]. This recognition relies on the characteristic that LG beams with different topological charges exhibit distinct maximum intensity radii. However, for conjugate OAM beams with identical intensity distributions, the sign of l cannot be determined solely

from beam intensity. To resolve this limitation, the intensity profiles of OAM beams interfered with Gaussian beams are utilized for recognition [85]. Based on this approach, an 8-layer CNN has successfully recognized OAM beams with l ranging from $(-50, 50)$ [86]. For high-order OAM beams, OAM modes with mode indices of up to $p \sim 3$ and $l \sim 30$ can be accurately identified, even under turbulence conditions [87]. OAM beams with fractional topological charges can also be recognized, with a minimum mode spacing of only 0.01 [88]. Beyond OAM beams, other single-mode beams are also classifiable [89, 90]. For instance, a CNN achieved the simultaneous classification of six structured light modes, including Hermite-Gaussian (HG), LG mode, Mathieu-Gaussian (MG), Bessel-Gaussian (BG), Airy vortex mode and SU(2) vortex mode [7].

3.2.2 Mode decomposition

Numerous networks facilitate the recognition of dual-OAM-mode superimposed beams [85, 91–93], identifying the topological charges of the two constituent OAM modes. When superimposed, modes may exhibit varying weights and phase differences. Mode decomposition refers to predicting each mode's index and its corresponding intensity and phase characteristics. Conjugate mode sorting, a widely used optical method for mode decomposition, is hindered by its time-consuming nature, sensitivity to disturbances, and high cost. Deep learning, implemented using both computer and optoelectronic processors, offers significant advantages in mode decomposition, enabling recognition of various types of superimposed modes [7, 94, 95]. This is particularly effective for mode decomposition of OAM mixed states [96–98], where up to 50 modes (l ranges from -150 to 150) can be demultiplexed in 20 ms [96]. With advantages in accuracy, noise resistance, and processing speed, ML is also applicable for mode decomposition in few-mode fibers [100–101]. Mode decomposition can extend to polarization dimension analysis. For instance, vector vortex beams, obtained by superimposing orthogonal polarizations onto LG modes, can be recognized by CNNs to determine the LG mode numbers and polarization states [93]. Additionally, the D²NN has also achieved recognition of Vector Vortex Beams (VVB) generated by the superposition of multiple LG modes (with l ranges from -7 to 7 , p from 0 to 3), together with polarizations of $|H\rangle$ and $|V\rangle$) [102].

3.3 Structured light recognition in complex media

In practical applications, structured light often propagates through various complex media, where turbulence and dispersion cause distortion, blurring, attenuation,

direction drift, and other adverse effects on the beam. ML exactly plays a crucial role in recognizing of distorted structured light.

3.3.1 Turbulence

Turbulence is the primary disturbance on laser beams [103]. It refers to a complex and chaotic state of fluid motion commonly found in atmospheric and oceanic environments. Atmospheric turbulence results from temperature inhomogeneities and variations in atmospheric pressure [104], while oceanic turbulence arises from differences in salinity, temperature, and seawater density [105]. Turbulence causes random variations in the refractive index along the beam's propagation path, distorting the received beam pattern and hindering mode recognition.

Two traditional approaches have been developed to mitigate turbulence-induced effects on structured light. The first focused on identifying beams less affected by turbulence, such as searching for turbulence eigenmodes [106] and leveraging the insensitivity of polarization to turbulence [107]. The second employs adaptive optics technology to compensate for the distortion experienced by the beam [108, 109]. Compared to these two approaches, machine learning approaches, such as CNNs and FNNs, offer faster and more straightforward solutions for recognizing distorted beams [110–113]. Additionally, CNNs can learn turbulence parameters to predict phase distortions, facilitating real-time compensation through inverse phase loading [114]. Combining CNNs with Long Short-Term Memory networks (LSTM) further allows for prediction of turbulence evolution in advance, supporting the pre-compensation of beams [115].

3.3.2 Scattering

Scattering is a common phenomenon in beam propagation through complex media. In atmospheric transmission, factors such as fog, rain, sandstorms, and airborne particles scatter the beam. In underwater environments, bubbles and suspended particles similarly contribute to scattering. Scattering also occurs when beams pass through biological tissues, glass and other materials. A similar process takes place in optical fibers, where light beams with dispersion effects may generate speckle patterns [116].

Although the speckle patterns of structured light appear chaotic, they retain characteristic information. Traditional methods typically recover this information using a transmission matrix, which defines a linear relationship between the incident field and the output field [117]. However, this method is ineffective for rapidly changing dynamic scattering media [118], such as

biological tissues, or for non-orthogonal incident field information. Neural networks excel at learning the non-linear relationships between incident light and speckle patterns [119]. They can map the incident light and the speckle pattern, enabling the extraction of incident field information from a single speckle image [120–122]. A speckle-based CNNs can achieve off-axis recognition, eliminating beam alignment constraints, as even a small portion of the speckle field contains sufficient information for beam identification [123].

Beyond recognizing scattered structured light, the integration of deep learning with structured light also offers notable advantages in imaging through scattering media. Unlike traditional Gaussian beam illumination, using structured light as the illumination source can improve image reconstruction performance and enhance the generalization ability of neural networks. Currently, the primary types of structured light used in scattering imaging are vector beams with polarization characteristics [124] and vortex beams carrying OAM [125]. Traditional Gaussian beams often fail to achieve high-precision image reconstruction in complex scattering systems or relatively thick scattering media. In contrast, vector beams and vortex beams demonstrate greater resistance to scattering-induced distortion and possess higher transmissivity [126], making them more suitable for dynamic scattering environments such as underwater settings [127] and biological tissues [128]. Moreover, polarization information can emphasize subtle variations in the target, leading to clearer and more detailed reconstructed images. The superior transmissivity and the richer feature information provided by structured light contribute to the development of neural networks with enhanced generalization capabilities. These characteristics offer a promising solution for improving imaging performance in scattering environments.

Although highly effective, these ML tools applied to structured light demand significant computational resources. For instance, CNNs demonstrate robust classification capabilities for structured light, under varying environmental conditions; however, the network training requires extensive data preparation, leading to increased training time and resource consumption. Combining CNNs with other networks, such as GANs [8] or transfer learning [116], has been explored to mitigate the training workload to some extent. Currently, machine learning architectures are implemented on electronic platforms, which are characterized by considerable computational latency and energy consumption. In the future implementations, D²NNs have been proposed to offer faster and more energy-efficient beam recognition [102, 129, 130]. The above content covers the applications of deep learning in structured light recognition. Figure 4 presents

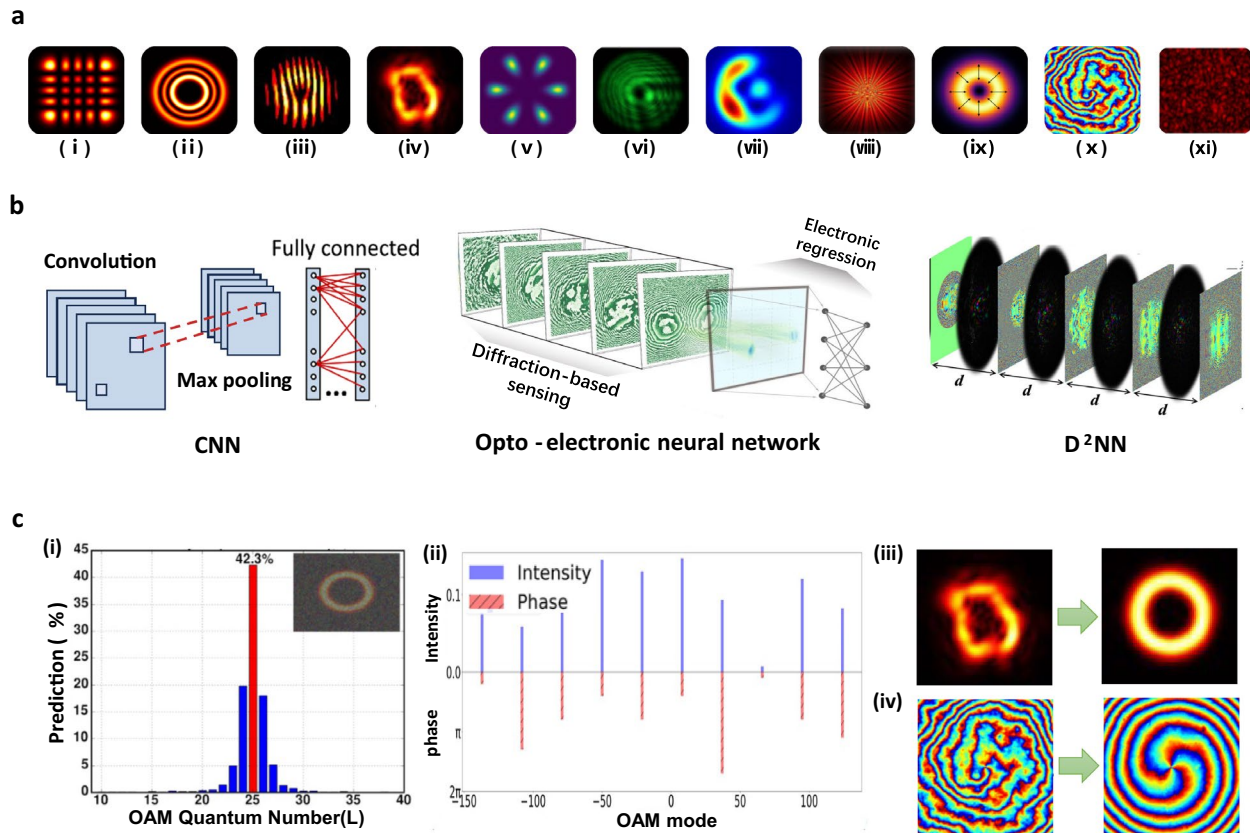


Fig. 4 Structured light recognition processes and capabilities. **a** Input modes are various structured light: (i) $HG_{4,4}$ mode, (ii) $LG_{10,2r}$, (iii) interferogram of VB and Gaussian beam [86], (iv) distorted OAM mode [87], (v) $SU(2)$ [7], (vi) OAM modes with fractional topological charge $l = 1.28$ [88], (vii) HG modes superposition [99], (viii) multiplexed OAM beam [97], (ix) vector vortex beam [93], (x) phase distribution of OAM mode with turbulence [114], (xi) speckle patterns. **b** The ML networks contain CNN [93], opto-electronic neural network [98], D^2NN [102]. **c** Recognition results are different recognition results: (i) the prediction of OAM angular index [84], (ii) OAM complex spectrum [97], (iii) recognition of distorted OAM mode [87], (iv) recovered phase of OAM mode after phase compensation [114]

the types of structured light that can be recognized, examples of electronic, opto-electronic, and all-optical neural networks, as well as examples of their recognition results.

4 Learning-based structured light communications

One significant application of structured light lies in optical communication technology. By integrating multiple degrees of freedom (such as time, phase, polarization, spectrum, etc.) with spatial degrees of freedom, the structured light field greatly enhances the information-carrying capacity of light waves, paving the way for groundbreaking advancements in optical communication. The spatial intensity distribution of light field can be captured by CCD/CMOS or other devices, enabling the acquisition of light field information through image processing techniques. The rapid advancement of machine learning offers an ideal

solution for image-based structured light field recognition. Currently, the integration of machine learning and structured light field shows promising advancements in optical information transmission.

Structured light has two main applications in communication: mode-division multiplexing (MDM) and shift-keying (encoding). MDM transmits different orthogonal modes through the same channel (coaxially or in parallel) and separates and decodes them at the demodulation end. Shift-keying, also known as encoding, transmits information by recognizing different modes directly. In both approaches, machine learning plays a crucial role.

4.1 Mode-recognition-based communication using machine intelligence

Structured light communication relies on the encoding and decoding of spatial modes, including OAM modes, HG modes, superposed eigenmodes, and

nonlinearly converted modes [131]. As discussed in Sect. 3, machine learning, particularly deep learning, has proven to be a powerful tool for recognizing these modes, even under complex environmental conditions, with some of the advantages highlighted in Fig. 5.

OAM modes are currently the most commonly used laser mode in optical communication. They can be coupled into optical fibers for transmission or directly transmitted through free-space environments such as vacuum, atmosphere and underwater. In a non-vacuum medium, the phase and intensity distribution of OAM modes are inevitably affected by the non-uniformity of the medium, leading to distortions in beams' original perfect doughnut-shaped intensity profile. As mentioned in Sec. 2.3, machine learning provides an effective tool for recognizing these distorted modes.

Similar to wave-division multiplexing (WDM) or polarization-division multiplexing (PDM) used in conventional communication systems, OAM (or other modes) can be applied via MDM, where independent channels are carried by distinct and orthogonal structured modes [137]. The orthogonality of individual modes allows

simultaneous transmission of multiple beams through the same spatial medium, with minimal crosstalk, enabling N of them to carry N times the data. Mature mode-division (de)multiplexing schemes including hologram [138, 139], wavelet conformal mapping [140] and chips specifically designed and fabricated for handling MDM problems [141].

However, this type of multiplexing is primarily a means to increase channels, akin to coupling mutually non-interfered fibers together, rather than the following one, fully leveraging multi-dimensional features of OAM. The other approach, simply called encoding, involves OAM modes encoded as a sequence of different data symbols, respectively transmitted in the time domain, then separated and decoded at the receiver with bare crosstalk. For N different states, the number of encoded bits per symbol period is $\log_2 N$ [142], suggesting potentially higher photon efficiency achieved in quantum communication systems [143]. To tackle disturbance issues in practical circumstances, learning methods have tended to be employed.

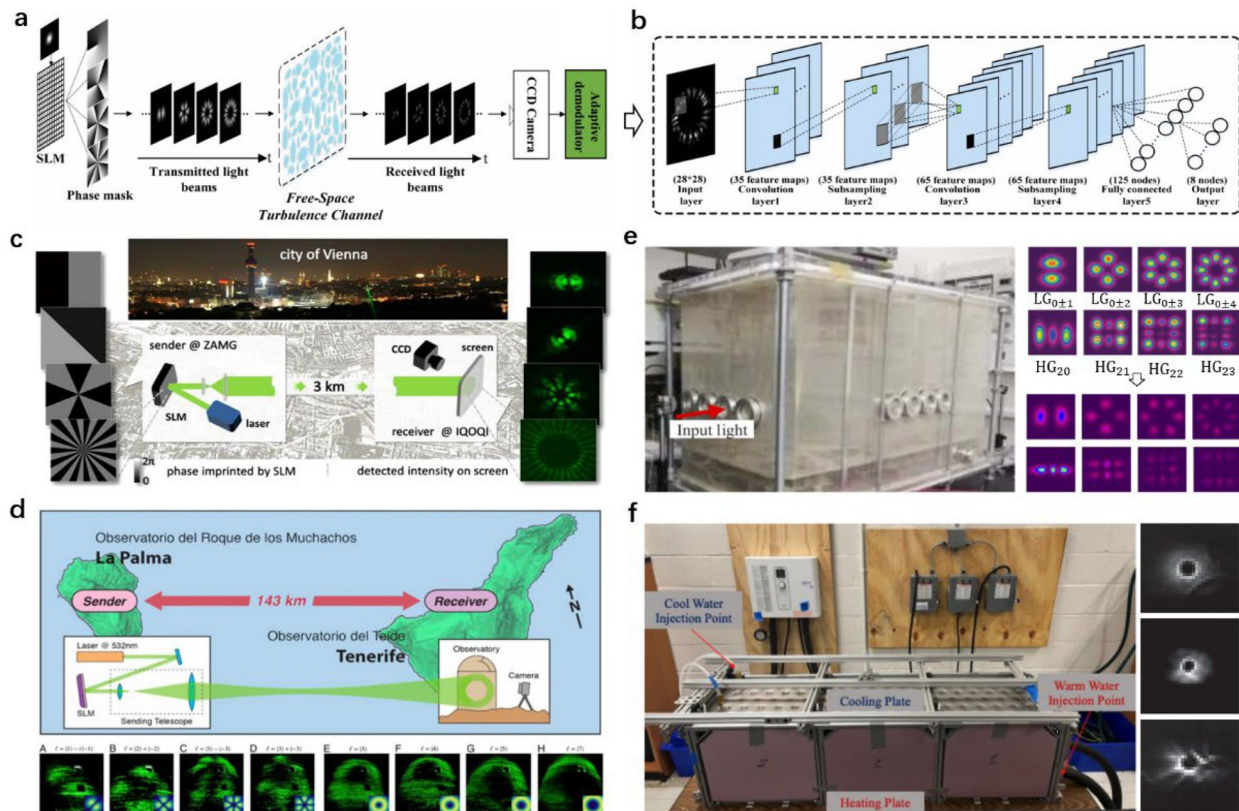


Fig. 5 Machine-learning-based structured light communications. **a** The experimental principle of the machine learning decoding method [132]. **b** The detailed example of a CNN geometry [132]. **c–f** All based on the similar method with (a and b). **c**. The first realization of the ML based structured light communication [133]. **d** An experimental achievement of 143 km communication [134]. **e** The experiment with desert environment simulation [135]. **f** The experiment with underwater environment simulation [136]

The earliest attempt to apply artificial neural networks (ANNs) in optical communication based on OAM structured light fields dates back to 2014. By introducing the back-propagation artificial neural network (BP-ANN), the intensity information of OAM modes was directly recognized, transforming the traditional coherent measurement of OAM states into an incoherent measurement of light intensity patterns. Later in 2016, a self-organizing-map (SOM)-based machine learning method was used to distinguish several twisted light superpositions over a propagation distance of 143 km [134]. In 2016–2017, CNN was first brought to recognize OAM modes, proven to surpass the optical conjugate mode sorting method [144, 145] and other algorithms such as K-nearest neighbor (KNN), naive Bayes classifier (NBC) and BP-ANN [132], since CNN naturally excel at addressing original images without requiring feature extractors, and they are less prone to issues like poor local minima and overfitting, but limitations constrain generalization performance of BP-ANN. Afterwards, CNN was also proved to be resilient to signal distortions due to physical environmental effects, namely, atmosphere turbulence [132], underwater optical turbulence [146–148], turbid water attenuation [149], desert environment [135] and beam misalignment [148]. In the aforementioned research, CNN achieved a recognition accuracy of up to 100 % for undistorted OAM modes forming an alphabet, within up to 256 characters. Under moderate atmospheric turbulence conditions ($C_n^2 = 10^{-16} \text{ m}^{-2/3}$ to $C_n^2 = 10^{-14} \text{ m}^{-2/3}$), and after mode transmission over a distance on the kilometer scale, the recognition accuracy of CNNs remained above 90%. In underwater environments, with turbulence levels ranging from $C_n^2 = 10^{-11} \text{ m}^{-2/3}$ to $C_n^2 = 10^{-9} \text{ m}^{-2/3}$, CNNs achieved recognition accuracies exceeding 90% for 16 symbols after meter-scale transmission. However, as the number of characters increases, the recognition accuracy correspondingly decreases.

To date, CNNs have become the mainstream tool for recognizing beam patterns in structured light field optical communications. Depending on the specific challenges encountered in communication, CNN architectures have been continuously improved to address various problems effectively. In case of lateral displacement misalignment, a deep learning method using an alignment-free fractal multipoint interferometer can exquisitely recognize the OAM beams, achieving stable diffraction intensity patterns [150]. For super high-resolution recognition, OAM-recognition neural network with deep learning was brought up to accurately distinguish modes at 0.01 intervals within sub-divisible space between adjacent eigenmodes [88]. In challenging or

high-demand circumstances, considerable instrumental or conceptual solutions have been proposed to optimize networks' performance. Apart from CNN, other neural networks have also been employed to implement OAM mode recognition and communication [151, 152], aiming to achieve a balance between recognition accuracy and processing speed.

Despite the OAM mode, deep learning algorithms have been also applied to HG modes, superposed eigenmodes, and spatial nonlinear conversion modes analysis in structured light communications. For instance, CNN is first used to detect the lowest 21 unique superposed HG modes with an accuracy exceeding 99% [90]. It is also trained to perform decomposition of superposed HG modes [94], handling up to 1924 modes [95]. This method offers a fast, economical and robust way to acquire both the amplitude and phase information of HG beams from a single-shot intensity image. Whereas under free space jamming, ML-based methods like SVM and HOG have achieved 100% classification accuracy for HG modes even at low SJR values [153]. Utilizing a simple CNN to transmit high-precision and -capacity information, the accuracy of the coding-decoding process with over 500 spatial nonlinear conversion (SNC) states achieves 99.5%. As structured light, compared to the basics, SNC with smaller initial phase difference displays superior caliber for communication; moreover, the intensity distribution of SNC is appropriate to recognize and further learned by ML given its identifiable distinction, let alone that using CNN can sufficiently lower BER during information transmission under disturbance conditions such as atmospheric turbulence [154].

4.2 Network performance evaluation and comparison

The effectiveness of machine learning models in structured light communications is typically gauged by accuracy, speed, and robustness [88, 152]. Accuracy is paramount as it directly influences the reliability of the communication system, measured by models' ability to correctly classify or predict desired outputs, which often pertains to the recognition of specific beam patterns or modes in the context of structured light. Speed is another critical metric, especially for real-time applications requiring timely processing and feedback. Robustness evaluates the models' performance under varying conditions, including different levels of noise, turbulence, and changes in the communication environment [155].

Comparative analyses of neural network architectures emphasize the advantages of customized CNNs over pre-trained ones, particularly in accuracy and speed [136]. Study of neural network architectures also

reveals that while traditional CNNs have been successful, more complex models like ResNet18 offer enhanced recognition capabilities, leading to improved accuracy compared to AlexNet [154], which suggests that deeper network architectures with advanced features can better capture the intricate details of structured light, thus providing a more reliable classification under challenging conditions.

Emerging trends in machine learning, such as deep learning and reinforcement learning, promise significant advancements in structured light communications. Deep learning, with its hierarchical feature extraction capabilities, could achieve unprecedented mode recognition accuracy by discerning complex patterns in structured light previously deemed indistinguishable [156]. Reinforcement learning could enable systems to autonomously adapt to dynamic environments, optimizing performance in real-time [157]. Furthermore, learning techniques are increasingly integrated with new equipment. For example, meta-surfaces can enable the construction of advanced high-throughput OAM-based integrated optical neural network acceleration systems [152].

Beyond these conventional performance metrics, latency and energy consumption are emerging as decisive factors for practical deployment. ONNs and photonic neural networks (PNNs) exhibit exceptionally low latency—on the scale of nanoseconds or even sub-nanoseconds—due to light-speed propagation and intrinsic parallelism [158–161]. For example, FPGA-based recurrent neural network (RNN) accelerators for optical wireless communication have demonstrated a 96.75% latency reduction compared to unoptimized designs and a 61% reduction compared to GPU implementations [162]. Additionally, optical network-on-chip (ONoC) architectures have achieved up to 79.7% latency reduction over electrical interconnects [163].

ONNs also provide exceptional energy efficiency, with energy consumption per operation in the femtojoule (fJ) range—orders of magnitude lower than that of digital electronic processors [160–160, 164, 165]. VCSEL-based ONNs, for instance, have achieved 7 fJ/operation [164], and photonic RNNs can process signals with significantly reduced power consumption compared to digital signal processing (DSP) chips [160]. In optical wireless communication scenarios, FPGA-RNN accelerators have shown 90.7% lower energy consumption per symbol than unoptimized implementations and 58.1% lower than GPU-based counterparts [162]. Furthermore, ONoC-based ANN accelerators can reduce energy use by up to 46.8% [163], while neural network-based power prediction models in silicon photonic interconnects can save up to

83.64% of optical input power while maintaining system reliability [166].

4.3 Open challenges and mitigation methods

Real-world challenges include the susceptibility of structured light to environmental disturbances, such as turbulence of the medium, misalignment of the optical system, information capacity within a specific beam divergency and algorithm efficiency. Machine learning solutions have been instrumental in addressing the turbulence issue by using adaptive algorithms to learn and predict the distortions, enhancing system resilience in both air and underwater environments. Misalignment issues often require a precise tracking system to maintain dynamic alignment between the transmitter and receiver. Alternatively, the image recognition-based machine learning method enables the point-to-multipoint communication by imaging the structured light's projection on a screen receiver with cameras. This approach enhances system robustness against misalignment and the beam jitter caused by the turbulence. Beam divergence determines the beam propagation distance required for efficient information transmission. For structured-light-based communications, realizing long-distance transmission and high information capacity is essential, then achieving large-scale dense data generation at relatively low mode orders with high accuracy recognition. Corresponding efforts from various disciplines are also being made currently to address these challenges [167–169]. Future improvements in system efficiency and accuracy will likely arise from advancements in both hardware and software. Faster processors and more efficient algorithms will enable real-time structured light processing, facilitating broader adoption in practical applications.

In parallel, the feasibility of deploying neural network-based optical communication systems in real-world environments is becoming increasingly promising. Integrated photonic platforms are maturing, enabling compact, scalable, and low-power neural architectures. Recent demonstrations have shown that ONNs can match or even surpass digital approaches in recognition accuracy while dramatically reducing latency and energy consumption [159, 164, 165]. Nonetheless, several technical challenges remain, such as the integration of nonlinear elements, limitations in device footprint, inter-channel crosstalk, and the development of efficient training and weight-update mechanisms [160–160]. Hybrid optical-electronic systems may offer a practical balance for environments where ultra-low latency and power efficiency are prioritized over peak inference accuracy [170].

Future researches are expected to prioritize real-world challenges by improving the robustness of machine

learning approaches and refining the neural network architectures. Despite inherent flaws and environmental effects, machine-learning approaches encounter limitations in structured light communications, such as model complexity, high computational costs, and the requirement for large labeled datasets for training. These issues necessitate research into more efficient learning algorithms and the development of synthetic data generation techniques to reduce reliance on manual labeling. Potential research directions involve designing lightweight neural network architectures for structured light recognition, as well as applying unsupervised and self-supervised learning methods to better utilize unlabeled data.

In the long term, the integration of advanced ML with structured light technologies aims to enable autonomous communication systems with intelligent environmental adaptability, enhanced reliability, and improved security in data transmission. In particular, optical networks—with their ultra-low latency and minimal energy demands—represent a transformative path forward for real-time, scalable deployment. Ongoing architectural optimization focused on system-level integration, training flexibility, and resilience under dynamic conditions will be key to bridging the gap between laboratory demonstration and field-ready implementation.

5 Learning-based structured light metrology

Optical metrology, which uses light as its primary measurement tool, provides highly precise and flexible techniques without requiring physical contact. Compared to traditional mechanical approaches, optical methods offer superior accuracy and are widely used in quality control for manufacturing, scientific research, and detailed analysis in fields such as materials science and engineering [171]. Recently, the integration of ML with structured light has demonstrated considerable potential to enhance metrology, including achieving picometer-scale precision [172], surpassing diffraction limits, and improving both surface and volumetric measurements. The following sections trace the historical progression of structured light metrology and illustrate how ML-driven strategies are pushing its capabilities beyond previous limits.

5.1 Structured light in metrology

Structured light for metrology is a rapidly growing topic, moving away from simple fringes of scalar light approximations to new complex forms essential for precision metrology [17]. For instance, a major breakthrough came in 2006 with stochastic optical reconstruction microscopy (STORM), which employed a kind of structured light—namely, optical vortices [173]—to control photo-switchable fluorophores for high-precision molecular localization. By 2009, the method achieved a resolution

of approximately 20 nm, supported multicolor and 3D imaging using standard equipment, and greatly expanded super-resolution microscopy for detailed cellular studies [174]. Still, how does one measure finer structures on the scale of a few or even sub-nanometers? One emerging approach is to exploit more complex structured light fields.

Building on earlier work, superoscillatory structured-light-based methods arose as a powerful extension. In 2018, researchers significantly improved confocal Laser Scanning Microscopy (LSM) by implementing superoscillation focusing with radially polarized LG beams [175], reaching lateral spot sizes of about 100 nm without specialized fluorophores or overly complex setups. The theory of superoscillation dates back to its introduction by Aharonov [176] and subsequent advances by Berry [177, 178]. Experimentally, it was verified in 2007 by Huang and colleagues, who observed optical superoscillation in diffraction patterns of light passing through quasi-periodic nanohole arrays [179]. Optical superoscillations, as described by Zheludev [180], are rapid, subwavelength spatial variations in the intensity and phase of light occurring in complex electromagnetic fields formed by the interference of multiple coherent waves. These superoscillations create sub-diffraction hotspots, permitting interactions with objects at scales finer than the wavelength of light. This capability underpins high-precision measurements and imaging [181].

Insights from superoscillation physics paved the way for advanced lenses engineered from dielectric, metallic, and metamaterial nanostructures. Such innovations enable far-field, label-free, nonintrusive subwavelength superresolution imaging and dimensional metrology, achieving accuracies comparable to those of cryogenic electron microscopy (cryo-EM) [172], surpassing the constraints of standard optical methods. Effectively, superoscillation-based imaging has propelled researchers into “no man’s land,” where conventional optical approaches fall short. By harnessing superoscillations’ unique features, scientists have unlocked new possibilities for observing and measuring phenomena once considered unresolvable.

The core advantage of structured light over traditional illumination in metrology lies in its ability to generate steep intensity and phase gradients, especially near optical singularities. These gradients dramatically enhance sensitivity to minute structural features, allowing precise detection of displacements or deformations far below the diffraction limit. When combined with ML, particularly deep learning techniques, the complex scattering patterns induced by such light fields can be decoded efficiently. ML models trained on large datasets can infer spatial or morphological information with sub-nanometer—even

picometer—precision, enabling single-shot, real-time analysis that surpasses traditional reconstruction techniques. This synergy of structured light and ML forms the backbone of recent breakthroughs in ultra-precise optical metrology.

5.2 ML in structured light metrology

In 2019, researchers proposed an “optical ruler” as an electromagnetic analog to a physical ruler—achieving sub-nanometer displacement measurements [182]. By creating a superoscillatory light field embedded with singularities, they paved the way for next-generation applications in nanometrology and nanofabrication. Soon thereafter, the same group extended this concept, using far-field scattering patterns of deeply subwavelength singularities to reveal fine structural details. By training a neural network on numerous scattering events, they attained imaging resolutions beyond the conventional diffraction limit, enabling noninvasive techniques for biomedicine and nanotechnology [183–185].

Such milestones paved the way for further recent achievements, as a comprehensive review of superoscillation technologies revealed how rapidly varying, subwavelength light fields have driven innovations in lensing, imaging, and metrology, as illustrated in Fig. 6a–c [180]. Another study highlighted the effectiveness of deeply sub-wavelength, non-contact optical metrology by analyzing coherent light diffraction patterns scattered by sub-wavelength objects, achieving remarkable accuracy that challenges conventional techniques like scanning electron microscopy [186].

Moreover, the combination of deep-learning approaches with topologically structured light yielded another major advancement. Experiments achieved sub-atomic precision in single-shot measurements, enabling nanowire localization with thermal oscillation amplitudes around 150 pm and measurement precision down to 92 pm, as shown in Fig. 6d. By leveraging structured light and sophisticated data analysis, researchers revealed new pathways for non-invasive picometer-scale metrology [187].

While the above achievements were only for the metrology of simple 1D displacements or objects, extending AI-assisted optical metrology into higher dimensions is an emerging direction. Recently, a groundbreaking 2D super-resolution metrology technique was presented using superoscillatory light [189]. Building on earlier progress, the group advanced from 1 to 2D nanometrology of coronavirus-like nanoparticles with topologically structured light and ML, and they are now driving toward 3D. The schematic diagrams and corresponding results are presented in panels

e1, e2, f1, and f2 of Fig. 6 [188]. Initial work achieved nanometer-level accuracy in 1D localization with superoscillatory illumination. Transitioning to 2D further refined 3D position measurements, reaching retrieval standard deviations below 10 nm in the x–y plane and about 20 nm along the z-axis. Recently, the phase singularity of light was also applied in optical ruler metrology to enable 3D metrology with a precision down to ~4.5 pm [190, 191]. By minimizing mechanical vibrations and optimizing the field of view, the researchers aim for even higher precision, underscoring the profound potential for sub-diffraction-limit accuracy.

Future investigations plan to employ higher-dimensional light fields, such as photonic spin skyrmions, which offer deep-subwavelength features and potential applications. Recent work [192] achieved pico-metric sensitivity in displacement sensing by designing a photonic skyrmion-pair with a carefully engineered spin texture. ML-driven methods can optimize these textures, further increasing measurement reliability and advancing optical metrology to unprecedented levels of detail and precision.

The evolution of optical metrology—from early holography to modern ML-assisted structured light—has significantly advanced resolution, precision, and functionality. The combination of superoscillation, topological beam shaping, and deep learning have not only enabled capabilities to surpass classical diffraction limits, but also approach the nanoscale, and in some instances, even atomic-level imaging. This synergy between photonics and ML facilitate progress in materials science, nanotechnology, biotechnology, and manufacturing, about to promise faster, more accurate, and noninvasive measurement solutions.

Ongoing research into complex topologically structured light fields, such as photonic spin skyrmions, is anticipated to extend both the precision and the range of optical metrology. Characterized by spatially varying spin textures and subwavelength features, these light fields offer new possibilities for enhanced sensitivity, selectivity, and robustness. Combining advanced beam-shaping with AI-driven optimization and data analysis promises transformative breakthroughs, allowing researchers to probe the finest details of biological samples, engineered nanostructures, and quantum materials. Through continued interdisciplinary collaboration and targeted technological development, next-generation metrology systems may achieve unprecedented spatiotemporal resolution, with broad implications for both fundamental science and applied technologies on multiple fronts.

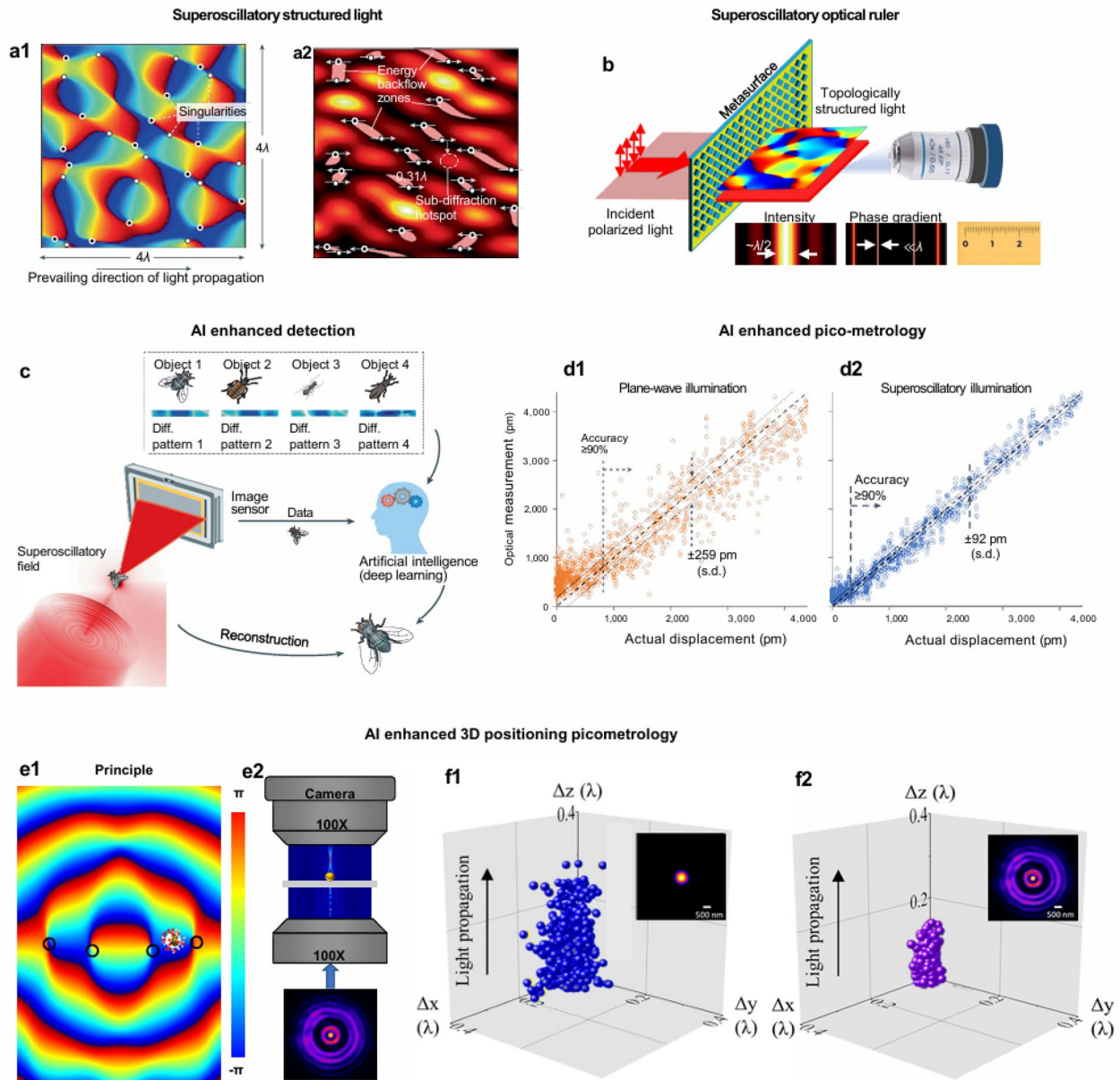


Fig. 6 Structured light metrology. **a1** Map of the phase $\varphi(r)$ of the superscillatory electromagnetic field, from $\varphi = -\pi$ (blue) to $\varphi = +\pi$ (red). Circles indicate singularities, points where intensity goes to zero and the phase of the wave is not defined. The field of view is $4\lambda \times 4\lambda$, where λ is the wavelength of light. **a2** Intensity of the superscillatory electromagnetic field, with white corresponding to the highest intensity and black corresponding to zero intensity [180]. **b** The figure depicts a superscillatory field generated when a polarized light goes through a Pancharatnam–Berry phase metasurface which is then detected using a 1D optical ruler displacement picometry approach which uses phase singularity of a superscillatory light field [180]. **c** The image intensity sensor detects the intensity profile of the diffraction pattern resulting from scattering of the superscillatory light field on the object. A number of different diffraction patterns are recorded. The artificial intelligence program, is trained on a large number of scattering events from known objects, reconstructs the imaged object from the collected data with high resolution [180]. **d1, d2** Optically measured versus actual values of nanowire displacement for plane-wave **d1** and topologically structured superscillatory **d2** illumination. Dashed lines show the smallest nanowire movements measured with over 90% accuracy [187]. **e1** Phase ($\varphi(E_y)$) profiles of the topologically structured superscillatory light in the x – z plane. **e2** Schematic showing how superscillatory illumination is used to probe a virus-like nanoparticle, generating diffraction images and positional data for neural network training [188]. **f1** The trained network accurately predicts the nanoparticle's position from new diffraction images. **f2** Comparison of Gaussian versus superscillatory illuminations confirms that the structured superscillatory beam yields more precise 3D localization with smaller measurement errors. In the 3D scatter plots, each dot indicates the absolute difference between measured and true nanoparticle positions [188]

6 Learning in quantum structured light

In this section we consider the interplay of quantum structured light with intelligence and learning, illustrating how it can enhance quantum state engineering, how information can be discerned from few measurements, how complex media can be unscrambled and how quantum images can be sped up in speed and quality.

6.1 Quantum structured light

Quantum structured light [193], following its classical counterpart [1, 13], refers to the ability to describe a quantum state beyond the usual two-dimensional qubits ($d = 2$), exploiting all of light's many DoFs for both multi-dimensional and high-dimensional quantum states [194, 195]. These could be single photon or entangled states, fueling exciting applications that includes imaging, sensing, computing and communication, with the promise of imaging with few photons, sensing beyond the classical light and communicating in a fundamentally secure manner. A popular example of a basis for high-dimensional state encoding is OAM [196], a property of light that is conserved down to single photons [197], allowing easy access to very large Hilbert spaces, moving from qubits to qudits ($d > 2$). This allows a higher information capacity per photon, while making such states harder to clone and more resilient to noise. Such a d -dimensional state of a single photon can be written as the superposition,

$$|\Psi\rangle = \sum_{j=1}^d c_j |j\rangle = \underbrace{c_1 |1\rangle}_{\text{dimension1}} + \underbrace{c_2 |2\rangle}_{\text{dimension2}} + \dots \quad (1)$$

where c_j are complex coefficients that determine the state Ψ , and the basis vectors $|j\rangle$ could be expressed in any appropriate DoF such as time–frequency [198, 199], pixels [200] and path [201, 202]. Extending to two photons and using the OAM basis, the entangled state reads,

$$|\Psi\rangle = \underbrace{c_1 |l_1\rangle |l_p - l_1\rangle}_{\text{dimension1}} + \underbrace{c_2 |l_2\rangle |l_p - l_2\rangle}_{\text{dimension2}} + \underbrace{c_3 |l_3\rangle |l_p - l_3\rangle}_{\text{dimension3}} + \dots \quad (2)$$

Here the basis states are $|\ell\rangle \equiv \exp(i\ell\phi)$, where ϕ is the azimuthal angle, referring to photons with a wavefunction characterized by a twirling azimuthal phase, and ℓ_p is the OAM of the light that creates the entangled photon pairs (typically the pump light to a spontaneous parametric downconversion process). If this pump light has no OAM then we find the vanilla version of the state as $|\Psi\rangle = \sum_{\ell=0}^{\infty} |\ell\rangle |-\ell\rangle$. We see that the large alphabet of OAM allows access to high-dimensional Hilbert spaces, and can be extended past just two photons to multi-photon entanglement too [203].

Multi-dimensional states usually involve the mixing of two or more DoFs, for instance, polarization and OAM

for hybrid entangled states. Mixing the polarization and OAM DoFs will produce a state of the form

$$|\Psi\rangle = c_1 \underbrace{|l_1\rangle}_{\text{DoF1}} \underbrace{|R\rangle}_{\text{DoF2}} + c_2 |l_2\rangle |L\rangle, \quad (3)$$

spanned by the new basis, $\{|\ell_1\rangle |L\rangle, |\ell_2\rangle |L\rangle, |\ell_1\rangle |R\rangle, |\ell_2\rangle |R\rangle\}$. Such states have been shown to be a powerful tool in quantum information processing [204, 205], communication [206, 207] and imaging [208], and recently demonstrated to be imbued with a topology [209].

6.2 Quantum structured light by intelligence

Machine intelligence has a recent but rich history in the context of quantum science [210]. We often think of learning as a mean to correct problems, or recognize features in noisy data. But it can also be used as a design principle. MELVIN [211] was the first such example, a machine learning algorithm that can be used to design quantum experiments with desired features, a concept now extensively deployed to engineer particular quantum states or protocols [212, 213]. This notion has since been applied more broadly to the physical sciences [214], raising profound questions as to the nature of scientific understanding [215]. Beyond state design, machine learning has successfully been deployed to distinguish quantum light sources [216], and in place of conventional quantum state tomography for characterizing quantum states, using an ANN to classify the separability of states without full information of the density matrix [217]. This is an important step forward given how unfavorably the number of measurements for a full quantum state tomography (QST) scale with state dimension. Following these approaches, we now have the ability to fully classify states by conditional GAN applied to QST with orders of magnitude speed up [218, 219], with similar success in quantum process tomography [220], the act of characterizing quantum channels. Machine learning has been used for fast and accurate fidelity estimation of multi-qubit states [221], for similarity tests of quantum states [222], applied to efficient tomography on mixed states [223] and shown to be accurate even when information is missing or noise levels are high [224]. The inherent randomness of quantum systems can itself be exploited, as is done in quantum extreme learning machines (QELMs) [225, 226], an approach based on known but uncharacterized time-dependent dynamics of a state and requiring far less training while offering versatility in deployment. Such approaches have been successfully used to deduce the polarization properties of quantum light using OAM as an ancillary DoF [227]. These examples highlight

the exciting progress in this exploding field of learning enhanced quantum structured light experiments.

6.3 Quantum light in complex media

When structured light passes through a complex channel the structure is in general distorted and must be carefully tailored if it is to be distortion-free [106, 228, 229]. Similarly, when quantum states pass through a complex medium the state can evolve in a non-trivial manner. The probabilistic nature of quantum light introduces an extra layer of complexity, for example, sorting the random noise from the randomized signal, detecting and correcting errors without measuring them, and predicting the evolution of a quantum state without disturbing it. The quantum (complex) channel may be one-sided (acts on only one photon or one DoF) or two-sided (acts on both photons or both DoFs), unitary (the entanglement remains intact but not necessarily the state) or non-unitary (both the state and degree of entanglement may evolve). This fascinating topic, of quantum light in complex media, has gained in interest in recent years [230], where the evolution of the state can be used to infer information about the channel, and deep learning can be used to unravel channel operator, unscrambling the information.

One approach to doing so is to exploit the isomorphism between quantum states and quantum channels, where a measurement on one entity reveals information on the other. To this end, one may harness the analogy between quantum entangled states of light and classically entangled states of light [231, 14]. For instance, a complex channel that acts on one DoF of a classical vectorial beam results in the same non-separability decay as a one-sided quantum channel acting on an entangled state. This allows probing the classical beam to infer information on the quantum state, learning the errors that have been introduced to allow real-time correction, demonstrated for qubits in OAM [232]. This approach harnesses classical light for learning quantum errors, the former allowing many measurements without affecting the state. Another approach is to use the full high-dimensional space as a complete probe of the channel. By passing one photon through the channel and applying correction procedures to the other, the quantum information could be unscrambled even in a highly distorting medium [233]. In these examples the channel operator is deduced by a series of measurements and then inverted for pristine transmission. This approach leverages off Klyshko's advanced wave notion, where back propagating classical light can be used as a direct inference of forward propagating quantum light [234]. In a similar vein, this allows application to adaptive optics and has been used to transport spatial entanglement through scattering media [235, 236]. This

type of correction has been successfully applied to quantum imaging for enhanced performance [236]. It is also possible to apply neural networks to learn the aberration and self-correct, as has been shown for single photon polarization scrambling in optical fiber [237] and phase distortions with single photon states in the Laguerre-Gaussian basis [238]. A CNN was used to correct the turbulence-distorted spatial profile of the single photons at time scales comparable to the medium's change, for near unity corrected fidelity. So far, this approach has not been extended to high-dimensional quantum states, with most machine learning applied to OAM of classical light. The task of quantum information processing, computing and communication with machine intelligence and quantum structured light remains a largely unexplored topic.

6.4 Intelligent quantum imaging

Arguably the most developed of all learning tools in quantum is in the realm of quantum imaging [239–241], where AI and ML have been essential to improve image quality and reconstruction times, for so-called intelligent quantum imaging [242], as illustrated in Fig. 7. It is generally appreciated that quantum imaging offers enhanced resolution [243–245], where quantum-correlated N -photon states can achieve a measurement sensitivity that scales as $1/N$, a significant improvement over the $1/\sqrt{N}$ that can be achieved with classical light, as well as a higher signal-to-noise ratio and flexible imaging configurations [246–248]. Entanglement-based solutions allow probing the object with one wavelength while imaging with another more optimal wavelength, where detectors are more sensitive or inexpensive [246, 249]. A pressing problem in all quantum imaging experiments is the time of data acquisition: the balance between time and image quality. Using a pixel basis, the collection time can be many hours, yet still returning poor quality images in comparison to classical approaches with bright light. This is where the merging of computer vision, modern deep learning tools, and quantum imaging have made the largest impact: extracting features, reconstructing objects and pattern recognition, all originate from the 1960s but have been given a new perspective with deep learning. Indeed, ML and AI have been core to recent advances in pushing the boundaries of what is possible with sparse and non-ideal data [242]. In the context of structured light, this is intelligence applied to entangled states in the pixel basis, for what we might conventionally call objects and images.

The first application of learning to this field was in classical versions of quantum ghost imaging, where thermal light or a computational approach is used to reconstruct an image from an object. A good example was the application of a deep CNN to improve the quality of the image

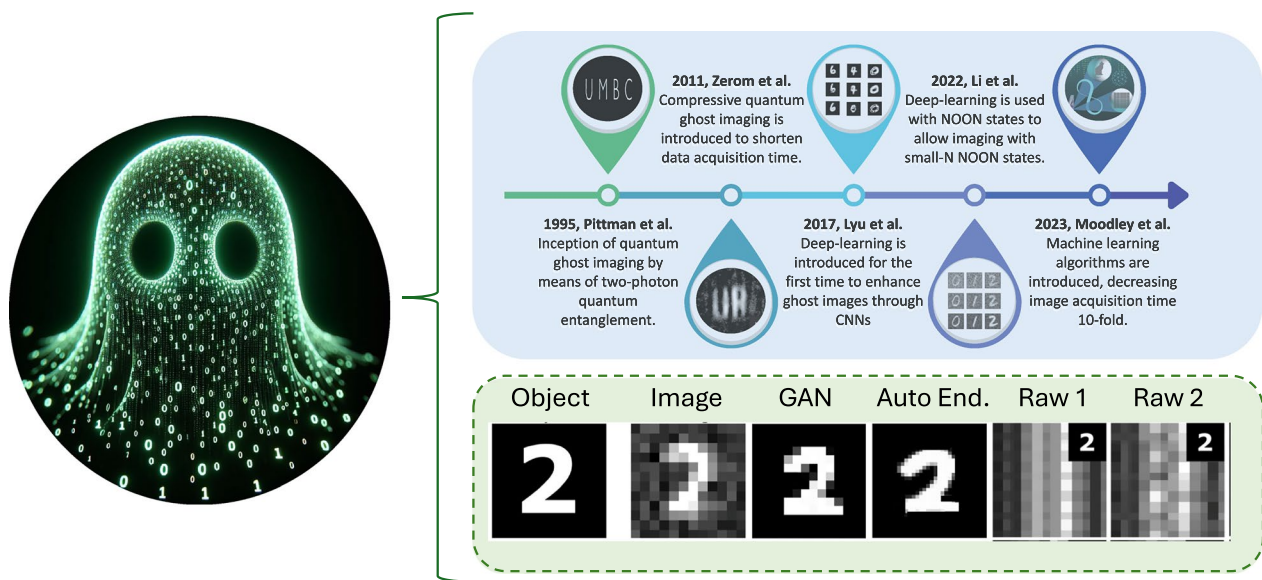


Fig. 7 A brief history of intelligent quantum ghost imaging. The concept of AI and quantum ghost imaging (left) has matured, shown as a timeline in the top panel, from the first ghost imaging demonstration in 1995 [250], to the use of computational tools in 2011 [251], and then deep learning tools from 2017 [252]. Recent applications have shown imaging with reduced photon numbers in NOON states to reduction in time for imaging objects [253]. The bottom panel captures an example of the power of AI and quantum states in imaging, using the object “2” [254]. The quantum image after a long time is poor quality, but can be enhanced by first GANs and then Auto-encoders. Rather than reconstruct the object, the AI system can instead recognize the symbol long before a human could, as shown for two examples of raw data taken with the symbol “2”

reconstruction formed from an under-sampled object [255], followed a few years later by the use of GANs for enhancing the detection of the object even with low resolution images [256]. Because GANs are notoriously difficult to implement (they consist of two internal networks, a generator and a discriminator, which are trained competitively), Autoencoders have come to the fore, where an encoding and decoding function form an unsupervised neural network that learns unlabeled data. They are highly valuable for what they are trained to do, but lack versatility. Blending layers of CNNs can form these more exotic architectures, but the depth of the convolutional layers must be balanced with the speed of computation and the complexity of the task [257]. The first study to introduce deep learning to quantum ghost imaging used a fifty node neural network as an identification algorithm to recognize the image reconstructed after each mask, revealing that for recognition purposes it was convenient to use masks with low resolution and short integration times [258]. Rather than a single step process, learning can be blended with other traditional machine vision approaches. For instance, by first performing image denoising with an autoencoder and then a neural classifier to recognize the image, a 5 speed-up in acquisition time could be attained [259]. In a more complex arrangement, low-resolution data was converted into a super-resolution image by a multi-step process:

a GAN was employed to denoise the low-resolution image, followed by a super-resolving autoencoder to enhance the resolution of the denoised image, resulting in a high-resolution image [260] with missing structure restored [261], highlighted the power of blended techniques. The aforementioned approaches were all deep learning in origin. Machine Learning on the other hand requires fewer resources, and has been used in real time to try and classify the object based on partial information as it is gathered, one projective mask at a time, for a 10 speed-up in recognition by the machine (not a human), and thus a concomitant decrease in required data [262]. Together these approaches resulted in a 30x speed-up, a crucial leap towards an intelligent quantum camera that is practical.

Beyond quantum ghost imaging, there are quantum imaging approaches based on photon statistics and the bunching/anti-bunching of photons, but once again the random nature means large data collection to reveal the statistics. For instance, although measuring high-order autocorrelation functions can result in quantum light exceeding the resolution of its classical counterpart (by a factor $\sqrt{n}$ by analyzing the n -th order autocorrelation function, $g^{(m)}(\tau=0)$, at zero-time delay, the time-consuming acquisition of multi-photon event histograms is highly prohibitive. Already it is possible to analyze sources of quantum light by CNNs that interrogate $g^{(m)}(0)$

with only sparse data [263]. Leveraging on this for anti-bunching-based super-resolution imaging, it has been shown that by incorporating learning, the 12 times speed up in data acquisition time can be won [264]. When more DoFs are utilized, for instance, polarization and space by metasurface assisted quantum experiments, the imaging task becomes more complex. A variational autoencoder trained in an unsupervised manner could form high quality polarization and space imaging with as few as 88 photons per pixel [265], opening a new path to coincidence-based quantum imaging with low light levels. These exciting advances are driving new applications of ML enhanced quantum imaging, for instance, in photon-sparse microscopy [246] and imaging with NOON states [253].

The intrinsic randomness of quantum states makes them a valuable resource, but this same trait in some applications makes for time consuming processes, for example, in collecting the random arrival of photons to form an image of an object, or to reconstruct a quantum state from a small set of measurements due to statistical limitations. Here AI has the potential to the fore, offering an intelligent “look” at the arriving data to reach some inference. So far, the benefits have been shown promise in quantum laboratories, but the deployment of such approaches in practical applications remains limited. In parallel, this randomness may be leveraged as a computational asset for quantum-based AI, for instance, quantum extreme learning machines, analogous to harnessing complexity for optical-based neural networks. The research at the intersection of quantum structured light and AI remains in its early stages, with substantial opportunities for future exploration.

7 Optical neural networks with structured light

The increasing demand for high-speed information processing and advanced methods for generating and detecting structured light fields has driven research into more efficient computational techniques. However, tools for controlling complex mode mappings are still in their early stages, and access to robust implementations could unlock high-dimensional optical operations [266–268], improve the classification of structured light families [269–272], enhance noise filtering techniques [273, 274], and refine methods for shaping multimodal light [275]. Developing these capabilities often requires significant computational resources, particularly when employing machine learning models trained on GPUs to classify optical modes. The accuracy of such models depends on large datasets and extensive training times, which can become computationally prohibitive. Moreover, traditional digital electronics impose fundamental constraints, including limited processing speed due to

electron transport, high energy consumption from heat dissipation, and increased cost as system complexity scales. For example, measuring a d -dimensional entangled state generated using structured light requires an exponentially increasing number of measurements, making classical approaches progressively inefficient as dimensionality increases [276, 277].

To overcome these challenges, the deployment of machine learning and artificial intelligence within all-optical systems has emerged as a promising alternative, offering lower power consumption, reduced latency, and improved scalability. ONNs leverage the interference of light to encode and process information, bypassing the limitations of electron-based computation [278]. This approach provides significant advantages over conventional digital processors, particularly for structured light applications.

The benefits of ONNs for structured light processing are multifaceted. First, they enable parallel information processing at the speed of light by exploiting optical interference, allowing for ultrafast computational throughput [279–281]. Second, ONNs serve as universal processors, capable of performing arbitrary transformations by performing complex field mappings, making them versatile tools for structured light manipulation [282–284]. Finally, ONNs are applicable to both classical and quantum domains, utilizing similar architectures for information processing across different regimes. This adaptability makes them valuable for rapidly handling structured light-encoded data in both classical and quantum optical systems [285, 286, 287].

7.1 Working principle

Optical neural networks borrow their functionality from artificial neural networks, which are multi-layer perceptrons; a perceptron processes input vectors $\bar{y}^k$ and maps them onto output vectors $\bar{y}^{k+1}$ from the k to the $k+1$ layer following

$$\bar{y}^{k+1} = f(W^k \bar{y}^k + \bar{b}^k) \quad (4)$$

where W^k represents the weight matrix, $\bar{b}^k$ is the bias vector, and $f(\cdot)$ is a nonlinear function. Collections of the perceptrons form nodes that can, for instance, encode a feedforward neural network, shown in Fig. 8 (a). The nodes transfer information from node to node with tuneable weight matrices (W^k) and biases ($\bar{b}^k$) that can be optimised to learn the complex relationship between input and output data sets.

It can be shown that feedforward networks can be realized optically, where the layers can be broken down into simple matrix operations, for example, by interlacing diagonal matrices and discrete Fourier transforms [291,

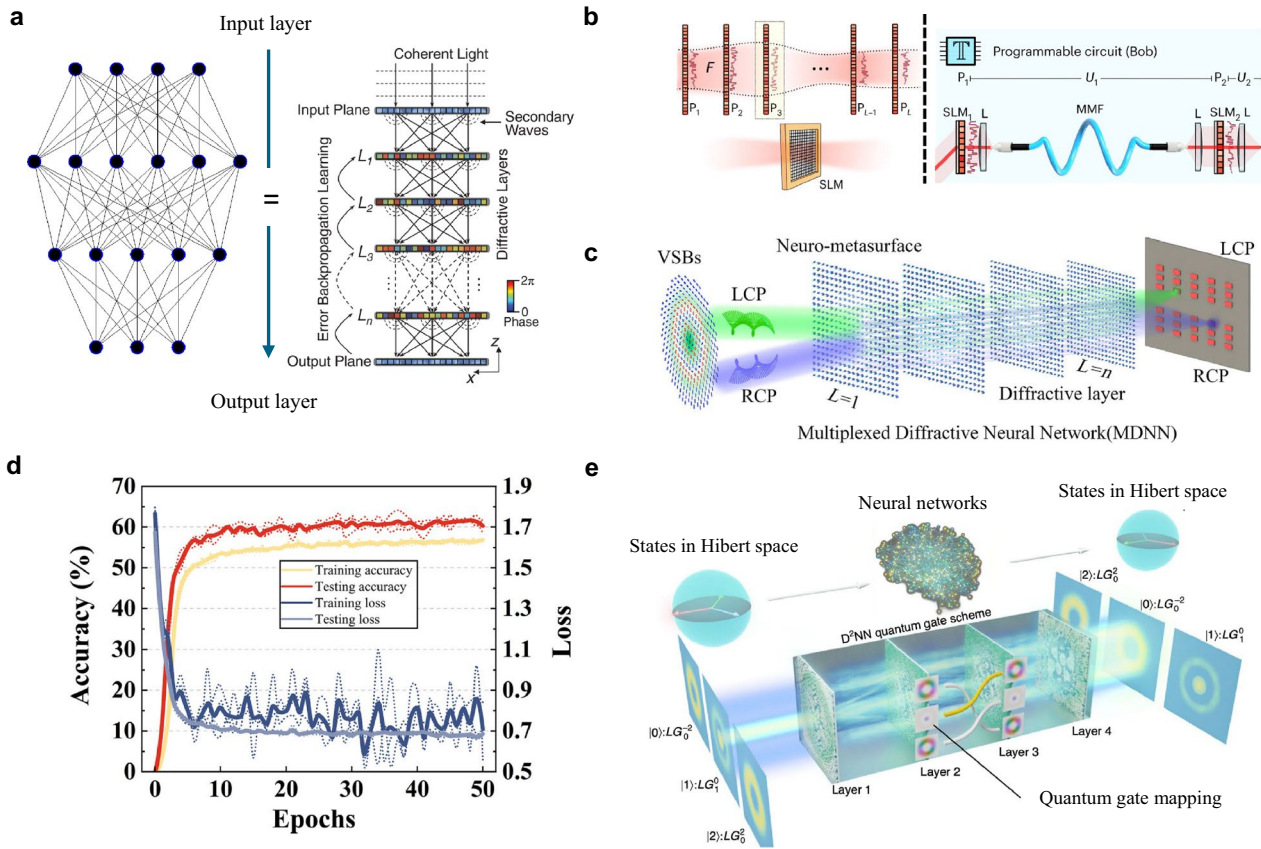


Fig. 8 Optical diffractive neural networks for structured light. **a** A feed forward neural network mapping information between layers by propagating the information through perceptrons (circled nodes). This can be realised optically by propagating light through phase masks that alter the amplitude and phase after each subsequent layer. Each phase mask diffracts the incoming field, mapping it onto a new one resulting in a complex network that is capable of solving classification problems [9]. **b** Realising the optical circuits that are capable of encoding diffractive neural networks using SLMs or complex media such as multimode fiber [288]. **c** Implementation with cascaded metasurfaces, capable of exploiting spatial and polarisation encoding to classify complex vectorial fields [289]. **d** Example training data for a diffractive neural network with phase layers that are being optimized on a digital computer [290]. The diffractive network was optimized for processing information encoded with OAM modes. **e** Example of a deep diffractive neural network that is trained to apply complex unitary matrix operations in the OAM and radial quantum numbers of quantum structured light [287]

[292]. This approach can be easily realised using free-space optics such as lenses since light propagation performs the analogue of a Fourier transforms but of optical waves, while phase modulations can enact the diagonal matrix operations in the position basis of light fields. Therefore, the transfer of optical information between the layers is facilitated by the Huygens-Fresnel principle, diffractive and interference mimic feedforward neural network that uses perceptrons to transfer data across the interconnected layers.

These types of optical neural networks are called D²NN (See detailed reviews at Ref [10, 293]). In the k^{th} layer, where the incident field has a profile, $\psi^k(r)$, the field is converted to an output field $\psi^{k+1}(r')$ by the phase elements and freespace diffraction following:

$$\psi^k(\bar{r}) = \int \psi^k(\bar{r}) D^k(\bar{r}) h(\bar{r}, \bar{r}') d^2r \quad (5)$$

where $D_k(\bar{r}) = e^{i\theta_k(\bar{r})}$ represents the transmission function of each k^{th} layer which can be a phase (or amplitude) modulation, and $h(\bar{r}, \bar{r}')$ is the transfer function for freespace. The phases $\theta_k(\bar{r})$ of each mask at a given layer, representing the trainable parameters, are analogues of the weights in an ANN. Further, notice that each layer has a spatially dependent phase and so in practice, the phases are represented as a mesh where each element/pixel is adaptable.

The response of the entire system of layered phase masks performs a linear mapping on the optical field, or equivalent encodes a matrix–vector multiplication operation on the state space of optical fields. This can be seen in the discrete position basis, where these mappings act

like matrix–vector operations which can be rewritten compactly using vector (Dirac notation) notation [288]

$$|\phi_{out}(\bar{\theta})\rangle = \hat{T}(\bar{\theta})|\psi_{in}\rangle, \quad (6)$$

$$= \left(\prod_{k=0}^{L-1} P_k D_k(\bar{\theta}_k) \right) |\psi_{in}\rangle, \quad (7)$$

where $\hat{T}(\bar{\theta})$ is the matrix representation of the operator encoding the action of the system on the optical fields, $\bar{\theta} = (\bar{\theta}_0, \bar{\theta}_1, \dots, \bar{\theta}_{L-1})$ is the collection of the phases that are encoded in the layers. The operator is made up of subsequent products of layers encoding the operator, $P_k D_k(\bar{\theta}_k)$, with $D_k(\bar{\theta}_k)$, corresponding to the diagonal matrix representation of the transmission function (discrete version of the phase modulation, $D^k(\bar{r})$), while P_k is the operator that encodes the propagation from layer to layer and becomes the discrete fourier transform for far field propagation and $|\psi_{in}\rangle$ ($|\phi_{out}\rangle$) are the vector representation of the normalized input and output fields. The authors in [288] also showed that these complex networks used to encode these gates can be executed using optical fibers as shown in Fig. 8b and can be extended to include polarisation encoding following Fig. 8c, therefore allowing one to classify vectorial states of light.

To train the network to learn the operator, that maps the input fields to the desired output fields, for example, achieving the mapping $|\psi_n\rangle \rightarrow |\phi_n(\bar{\theta})\rangle$ where n labels optical modes in the input set and output set, requires an optimization procedure that minimizes a suitable cost/goal function. An example of such a function can be

$$Cost = \left| \phi_n^{target} - \phi_n(\bar{\theta}) \right|^2 \quad (8)$$

where ϕ_n^{target} and $\phi_n(\bar{\theta})$ are the expected (or target) field profiles and the fields that are produced by the network, respectively. There are several methods to minimize the cost function, e.g. which involve stochastic gradient descent methods [294, 295], that use steepest descent approaches to find the minimum of the cost function or wavefront matching methods which are commonly used to design multiplane light convertors which are closely related to diffractive neural networks [74, 267, 296]. The training is usually performed digitally using conventional computing hardware and then learned phase parameters are then imprinted on the optics (SLMs, metasurfaces, 3rd printed optics). For example, in Fig. 8d the training optimization is shown while an iterative routine runs to find the desired phase layers showing that the accuracy and loss functions are being maximized and minimized, respectively. There have been methods to perform the training in real time as training on conventional hardware

can be time-consuming and sometimes cannot capture all the features of the physical systems (aberrations, noise), for example, Ref. [297] and [298] have developed schemes that utilise in-situ implementation of backpropagation, which is the main training approach of conventional neural networks on solid state devices. Further, increasing the depth (number of phase layers) of the diffractive networks also increases the dimensionality of the subspaces of complex-valued linear transformations that can learnt by the networks—this can be beneficial for structured light since it is inherently higher dimensional [282]. Next, we discuss how ONNs have been exploited for applications with structured light.

7.2 Deployment platforms

Optical neural networks are implemented using a series of optical elements that perform multiplexing and demultiplexing operations [299]. Various architectures have been explored, including nested Mach–Zehnder interferometer (MZI) interconnects [300], optical fibers [301, 302], scattering media [303] and diffractive layers [9, 304]. Each of these approaches provides unique advantages for implementing optical neural networks and can be of benefit for processing structured light fields.

Interferometer-based approaches [305] have significantly matured, enabling compact and scalable ONN implementations through optical matrix decomposition techniques. These methods allow for the efficient construction of ONNs by factorizing large transformation matrices into smaller submatrices, which can then be implemented using MZI arrays composed of beam splitters and phase shifters. One widely used method employs discrete Fourier transforms (DFT) as the primary computational building block [287, 306], which can be efficiently realized through MZI-based networks. A key advantage of MZI-based ONNs is their integration into photonic chips, making them cost-effective and scalable.

An alternative approach involves metasurfaces and metamaterial-based diffractive networks, which are currently being developed [307, 308] and are better suited for structured light as they can modulate the transverse spatial profile, wavelength and polarisation characteristics of optical fields. Further, these diffractive approaches have already demonstrated the ability to perform all-optical processing, e.g., cascaded metasurfaces for performing logical operations [285, 309] on light fields. While metasurface-based modulation layers are generally static, the emergence of active metasurfaces allows for electronic and real-time control of optical properties, making them reprogrammable and highly adaptable [304, 310].

Another widely used platform for implementing diffractive networks is spatial light modulators (SLMs), particularly phase-only SLMs. These devices are favoured

for their adaptability, allowing for dynamic optical modulation. They have been shown to perform high-speed matrix–vector multiplications, enabling parallel information processing and classification tasks with transverse optical fields [279, 287, 297, 311, 312]. However, a major drawback of SLM-based implementations is their lower resolution and efficiency compared to metasurfaces, due to reduced fill factors. Additionally, losses tend to increase unfavourably with the number of modulation layers, making scalability a challenge. Despite these limitations, SLMs are at the forefront of research into real-time training of optical neural networks, as demonstrated in recent works [297, 313] where the training is applied *in situ* rather than on digital computing hardware.

7.3 DNN for structured light

The architectures discussed above, including diffractive networks, form linear programmable circuits capable of processing input and output fields through metamaterials or SLMs, layer by layer, similar to a feedforward neural network. In this section, we explore how diffractive network approaches have been applied to structured light.

The first seminal demonstration of diffractive neural networks was in the classification of handwritten digits and fashion items, where the information was imprinted onto transverse spatial optical beams with the goal of developing all-optical diffractive processing units [9]. Beyond object classification, this approach inherently involved the classification of light fields, as each laser pattern encoding different digits could be mapped onto independent spatial points and detected by an array. Two key processes take place: (i) the input field, imprinted with a digit, undergoes transformation after passing through the network, and (ii) it is spatially displaced for easy distinction. This means the network simultaneously performs mode conversion and mode sorting, both essential for structured light manipulation. Mode sorting and conversion are highly sought-after capabilities in structured light applications, facilitating on-demand detection of optical (scalar and vectorial) fields [74, 269, 314, 315]. These capabilities are crucial for applications such as cryptography [316], controlling and detecting quantum structured light [317], and implementing optical logical operations [318].

Diffractive neural networks have successfully demonstrated these operations for scalar [319–321], vectorial [322–324], and spatio-temporal fields [324], showcasing capabilities for sorting, multiplexing, and real-time processing across multiple degrees of freedom in light. For instance, the authors in [325] achieved successful combining and separation of vortex modes. Similarly, [321] demonstrated a diffractive network trained

to multiplex and demultiplex OAM modes, including OAM switching operations. Other works have shown that information can be encoded into the spectrum of OAM modes (i.e. mapping handwritten digits onto OAM superpositions), and have been able to show that diffractive networks can efficiently classify the OAM spectra [290]. While these demonstrations primarily focused on scalar beams, more recent work has explored mixing degrees of freedom. For example, [102] demonstrated the classification of 120 vector modes (encoded in polarization and spatial modes) using a D²NN implemented with SLMs, although additional linear optical elements were required to control polarization. A more compact approach was demonstrated in [322], where phase layers were engineered with anisotropic metamaterials, allowing for simultaneous modulation of both spatial and polarization degrees of freedom.

An emerging research direction in diffractive neural networks for structured light lies in error correction, particularly in mitigating aberrations and distortions from complex media. Reference [326] demonstrated that the negative effects of turbulence on OAM beams could be corrected by training a diffractive network to counteract distortions induced by refractive index fluctuations. This development is particularly important as structured light modes are highly sensitive to spatially dependent distortions [327]. However, a key limitation of this approach is the loss incurred due to the dissipative nature of diffractive networks, which could pose challenges for low-intensity optical fields or single photons. For quantum applications, lossless and unitary transformations are required. This is especially crucial for quantum computing, where unitary transformations preserve quantum states within a given Hilbert space, enabling qudit-based quantum computing [328], which can outperform traditional qubit-based computing.

Several demonstrations have established diffractive neural networks as viable platforms for lossless unitary operations in structured light quantum regimes [287, 321, 329]. It has been shown that these networks can encode universal quantum gate sets, essential for higher-dimensional quantum logic. For instance, diffractive networks have been trained to implement the X, Hadamard, Z, and CNOT-gate with fidelities reaching 99% [287]. A conceptual illustration of the approach is shown in Fig. 8e where a qutrit state is constructed from spatial modes while the network performs a desired quantum gate. The Hadamard gate ($\hat{H}$), in particular, was demonstrated to map input states encoded with azimuthal (ℓ) and radial (p) quantum numbers, where an input state:

$$\hat{H}|l_n, p_n\rangle = \sum_{j=0}^{d-1} h_{nj}|l_j, p_j\rangle \quad (9)$$

It is mapped onto a superposition state, with h_{nj} representing the transformation coefficients defined by the operator. Using these unitary transformations, the authors further demonstrated a quantum computing algorithm, implementing the Deutsch-Josza algorithm with $d=4$ structured light modes encoded in single photons. This approach is equivalent to using two qubits ($d=2$), demonstrating the advantage of high-dimensional structured light in quantum information processing. The same authors also reported a technique for implementing a Toffoli gate by incorporating polarization control [329].

Additional applications of diffractive neural networks include the generation of novel quantum states through spatial, path, and photon-number encoding [330], as well as advancements in imaging systems through direct imaging of complex structured light fields [295, 331–333]. These developments hold significant potential for quantitative phase and spectral imaging, opening up new possibilities for controlling structured light at both classical and quantum levels.

ONNs have demonstrated considerable potential for processing structured light fields, enabling classification and conversion across both classical and quantum domains while exploiting various degrees of freedom. While significant progress has been made in polarization control, exploiting temporal-wavelength components remains an open challenge.

In addition to structured light processing, ONNs also have the potential to classify nonorthogonal quantum states of photons, a task known to be quite challenging at the single-photon level [334]. For instance, Ref. [335] demonstrated that a multi-plane light converter (MPLC) can achieve this for nonorthogonal states of photons and coherent fields encoded in arbitrary spatial mode superpositions. Nonetheless, the extent to which diffractive neural networks could further enhance robustness and performance, particularly in input conditions remains an unresolved question. From a deployment architecture prospective, alternative implementation strategies, such as those that exploit complex media, have not yet been thoroughly investigated. A recent example is presented in Ref. [288], where a complex medium (multimode fiber) was employed to synthesize quantum gates. This architecture consisted of two layers: an optical fiber for mode mixing and SLMs forming the input and output layers. By harnessing the inherent mode mixing properties of the fiber as a computational resource, the study demonstrated the ability to synthesize various quantum operations and the certification of two-photon entanglement.

Whether mode-mixing complexity could provide advantages comparable to or even surpassing optical nonlinearity remains an open and relevant question.

This consideration is crucial as nonlinearity is essential for diffractive neural networks to achieve the computational capability on par with traditional artificial neural networks. The ONN architectures discussed in this work are inherently linear, limiting their capacity for advanced processing. Several studies have explored the integration of nonlinear mechanisms into these networks, including electro-optic induced transparency, achieved by controlling atomic transitions [336], saturable absorption using graphene, which enables nonlinear light-matter interactions [298], commercial optical intensifiers, used to introduce intensity-dependent transformations [337], ferroelectric thin films and photorefractive crystals, offering optical memory and dynamic refractive index tuning [338] to name a few. These approaches aim to scale the output field nonlinearly with respect to the input field, emulating the nonlinear activation functions found in traditional ANNs, such as atanh, sigmoid (logistic function), and rectified linear unit (ReLU). Developing efficient and scalable nonlinear optical activation functions remains one of the key challenges in bridging the gap between ONNs and conventional deep learning models.

Besides nonlinearity, there are practical issues around the physical implementation of ONNs. One major issue is their sensitivity to fabrication imperfections and alignment errors, which can significantly degrade performance. High-purity metasurfaces have emerged as a promising solution, offering superior phase control and reduced fabrication tolerances [323], while alignment robustness can be improved by training the network with modeled layer misalignments [339]. As ONNs scale with deeper architectures, the physical footprint and alignment requirements become increasingly demanding. To address this, integrated photonic chips and 3D-printed optics are being employed to enable compact, scalable implementations [307]. Another limitation is the inflexibility of many ONNs, which are often task-specific. Recent work has introduced modular architectures and the exploitation of multiple degrees of freedom, such as spatial, polarization, and wavelength domains, to enable multifunctional ONNs [340, 341]. For example, polarization-sensitive matrix diffractive neural networks (M-D²NNs) leverage polarization multiplexing to perform simultaneous multi-task operations [341]. Reconfigurability remains a trade-off, as spatial light modulators (SLMs) and digital micromirror devices (DMDs) offer programmability but lack the subwavelength control of metasurfaces; however, recent advances in electronically tunable metasurfaces may offer a promising route

to solving this [342]. Lastly, the training of ONNs, usually performed on digital hardware, can become computationally intensive as the number of diffractive layers grows while achieving high accuracy becomes harder. Strategies to improve training accuracy include refining cost functions, applying input field filtering (analogous to data pruning), and in some cases, adopting ensemble learning approaches [343]. In the latter, enhanced accuracies can be seen when using multiple DNNs instead of a single one. Further, hybrid architectures also offer improved training performances, relying on the fusion between well-established electronic neural networks implemented with digital electronics and ONNs [344].

Therefore, ongoing development of these techniques will be essential for realizing the full potential of optical neural networks in structured light processing.

8 Learning structured light for super-resolution imaging

Super-resolution imaging is a technique used to observe dynamic changes in nanostructures within living cells. It provides high spatial resolution beyond the Abbe diffraction limit, and enables the investigation of subcellular structures such as organelles, which is critical for advancing life sciences research and uncovering the mechanisms of cellular function [345]. Structured light technology has been applied to super-resolution imaging since the late twentieth century for the enhancement of spatial resolution, depth of field, and other imaging parameters [346]. The rapid advancement in artificial intelligence further enhances these capabilities by enabling data-driven reconstruction and adaptive system control, thereby significantly improving imaging quality, imaging speed and computational efficiency. The following sections will discuss how the integration of structured light and machine learning techniques has facilitated the advancement of various super-resolution imaging modalities, enabling higher resolution, deeper tissue penetration, and faster imaging speed.

8.1 STED microscopy

One notable example is stimulated emission depletion (STED), which combines a doughnut-shaped depletion beam and another Gaussian excitation beam to create an effective emission point spread function (PSF) beyond the diffraction limit, allowing for super-resolution imaging [347]. The resolution in STED can be further enhanced by tailoring the system's PSF with structured light techniques. For instance, by employing an annular vortex depletion beam, the effective PSF of STED microscopy can be further narrowed, enabling a more than 20% enhancement in lateral resolution [348]. Similarly, applying an annular radially polarized excitation

beam to continuous wave STED can improve the lateral resolution by about 12% [349]. The utilization of Bessel beams would significantly extend the depth of field of STED for deeper tissue penetration, such as a hollow Bessel beam for depletion allowing STED to maintain consistent lateral resolution up to the depth of 155 μm , outperforming traditional STED at similar depths [350]. In addition to STED, super-resolution imaging can also be achieved by using a single excitation beam shaped into a doughnut-shaped Laguerre-Gaussian beam [351, 352], or Bessel Laguerre-Gaussian beam [353]. Leveraging the nonlinear optical response and near-infrared (NIR) emission of lanthanide ions doped nanoprobe, this technique achieves resolutions below 50 nm and tissue penetration depths exceeding 90 μm . Super-resolved multiplexing imaging can also be achieved by utilizing the nonlinear optical response under a vortex beam excitation. The nonlinear optical response adds an orthogonal dimension to existing multiplexing dimensions such as emission color, polarization, and lifetimes [354].

Recently, with more powerful data analysis capacity, machine learning has provided significant opportunities to further enhance super-resolution imaging with improved resolution, imaging speed, imaging depth [355], and imaging throughput [356]. Using deep learning-based super-sampling of under-sampled images acquired on a point-scanning system, high spatiotemporal resolution imaging has been achieved with a U-Net architecture [357]. Deep learning-based single-molecule localization microscopy using a subpixel edge map and multicomponent optimization could reconstruct super-resolution images from single diffraction-limited frames, substantially decreasing the imaging time [358]. Machine learning algorithms have also been introduced to structured light-based super-resolution imaging for enhanced performance. For instance, a GAN has been proposed to enhance STED microscopy resolution, achieving 30-nm resolution from 60-nm image resolution by generating high-resolution counterparts through physical modeling and synthetic data (Fig. 9a) [359]. This approach significantly outperforms traditional methods like Lucy-Richardson deconvolution and U-Net-based super-resolution networks in resolution enhancement and noise reduction. Subsequently, a deep learning-based fluorescence lifetime analysis utilizing a generative adversarial network has been shown to significantly enhance spatial resolution by up to a 1.45-fold resolution improvement in low-powered STED imaging under photon-starved conditions (Fig. 9b) [360]. The deep learning model effectively denoises low-photon-count data, resulting in robust, high-quality phasor representations that improve resolution even under challenging imaging conditions, facilitating low-power STED imaging for live-cell or

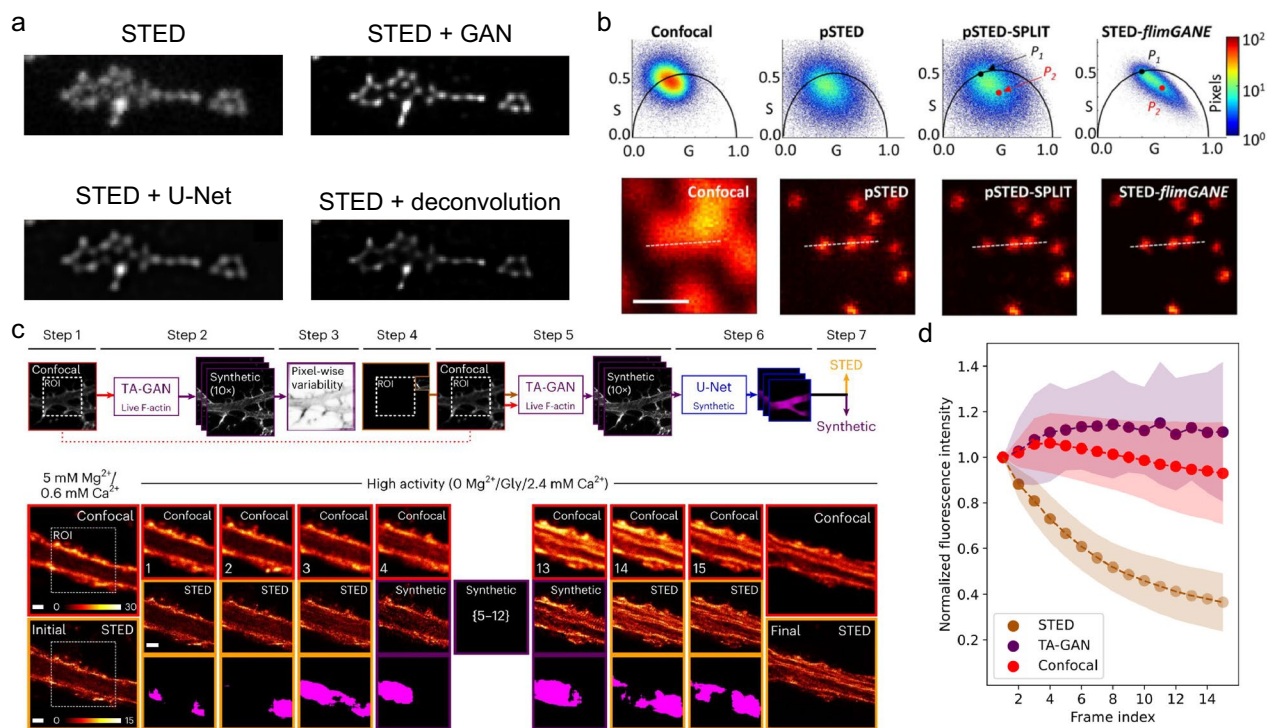


Fig. 9 Machine learning assisted STED super-resolution microscopy. **a** Deep generative adversarial network enhanced STED result (STED + GAN), with the comparison of results with the other three methods: input low-resolution noisy STED (STED), STED with U-Net based network (STED + U-Net), Lucy–Richardson deconvolution (STED + deconvolution). Adapted from Li et al. [359]. **b** Comparison results between confocal microscopy, pulsed STED (pSTED), pulsed STED with SPLIT method (sSTED-SPLIT) and STED with a deep learning-based phasor analysis algorithm (STED-flimGANE). Adapted from Chen et al. [360]. **c** The task-assisted generative adversarial network (TA-GAN) that integrated into the acquisition loop of an STED microscope, for automatically taking decisions. **d** The reduced photobleaching effects by TA-GAN. Adapted from Bouchard et al. [361]

live-tissue imaging applications. It has also been reported that a task-assisted generative adversarial network (TA-GAN) was introduced to optical nanoscopy, including STED and other imaging modalities, to enhance the resolution and incorporate auxiliary tasks such as binary segmentation, semantic segmentation, and localization to characterize nanoscopic biological structures (Fig. 9c) [361]. The TA-GAN can be integrated into the acquisition loop of STED microscopes for automatically taking decisions, toward optimizing the photon budget and reducing photobleaching. A machine learning-based adaptive optics system has been reported to correct wavefront aberrations for doughnut-shaped beams in scattering media, achieving a 97.5% correction accuracy and paving the way for deep-tissue STED applications [362].

8.2 Structured illumination microscopy

Another related super-resolution imaging technique is Structured Illumination Microscopy (SIM) [363], which uses structured light fields such as striped or speckle patterns for illumination. Integrating superoscillation into SIM, which generates multi-lobe superoscillation

patterns with higher frequencies, enables a resolution improvement that exceeds the traditional two-fold enhancement of conventional SIM [364]. Meanwhile, machine learning has significantly advanced SIM by improving imaging speed and resolution, and reducing phototoxicity. Deep learning techniques, e.g. U-Net and the deep Fourier channel attention network, have enabled high-resolution imaging with fewer raw images and under low-light conditions [365, 366]. By integrating physical models of SIM to generate simulated training data, a deep residual neural network helps SIM to achieve high-quality super-resolution imaging in multiple color channels [367]. As reported, a fast and lightweight network, based on a multiscale CNN and incorporating a noise estimator and bandpass attention, enables SIM reconstruction from only a single raw frame [368]. Additionally, using a custom CNN with an encoder-decoder architecture for blind SIM with random illuminations offers enhanced performance compared to traditional deconvolution algorithms [369]. It achieves a 2.17-fold resolution improvement and

reduces artifacts, ensuring robust performance even in noisy or variable illumination conditions.

Furthermore, structured light, such as propagation-invariant Bessel and Airy beams, has been applied to various microscopy techniques beyond super-resolution imaging, including light-sheet microscopy [370, 371], photoacoustic microscopy (PAM) [372], confocal laser scanning microscopy (CLSM) [373], two-photon microscopy [374] and so on. These beams improve imaging depth, field of view, and contrast, especially in challenging environments like thick or scattering tissues. For example, Airy beams can provide a tenfold larger field of view for light-sheet microscopy [370] and can also enhance photoacoustic microscopy with >17-fold improvement in depth of focus [372]. The Bessel beam has been reported to achieve a 45-fold improvement in depth of field compared to a traditional Gaussian focus [375]. The integration of machine learning further boosts these techniques by improving image reconstruction, artifact reduction, and contrast enhancement. The combination of an Airy beam and a pre-trained GAN model could enhance widefield light sheet microscopy with a two-fold improvement in spatial resolution and improved imaging contrast, while maintaining a wide field of view and extended imaging depths [376]. The Airy beam enables deeper tissue penetration, while a deep learning algorithm provides a two-fold improvement in spatial resolution and enhances image contrast. With the assistance of a conditional GAN, Bessel beams enable photoacoustic microscopy (PAM) to achieve accurate functional imaging with an extended depth of field, effectively eliminating out-of-focus issues and reducing errors by 13 to 58 times compared to conventional methods [377]. An experimentally unsupervised deep learning deconvolution method for light-sheet microscopy with Airy beams offers robust, rapid deconvolution, improving image contrast two-fold without requiring paired high-resolution training data [378]. Additionally, the implementation of a GAN model accelerates the deconvolution process in Airy beam light sheet microscopy, achieving speeds approximately 20 times faster [379].

Structured light techniques, enabled by precise PSF engineering, facilitate enhanced light focusing control, leading to higher spatial resolutions and deeper tissue penetration. These benefits include improved signal-to-noise ratios, reduced photodamage, and the ability to probe structures at greater depths with minimal scattering and aberrations, particularly for super-resolution imaging in complex biological specimens. The integration of machine learning into structured light and super-resolution imaging represents a substantial advancement in imaging performance. By improving resolution, imaging speed, and depth, as well as reducing phototoxicity,

machine learning offers new possibilities for dynamic biological imaging. Nanoscopy techniques, including STED, superoscillatory imaging, and SIM, have greatly benefited from these advancements, enabling more efficient image reconstruction, improved signal fidelity, and extended field of view, and depth of field. As machine learning algorithms and structured light technologies continue to evolve, their integration will expand further capabilities for clearer, deeper, and faster imaging across a range of challenging biological applications, ultimately, holding promise for deeper insights into biological processes and life sciences.

9 Outlook

In this review we have attempted to capture the exciting advances that the integration of ML with structured light has seen across diverse fields. In optical communications, where the practical use of structured light is impeded by its distortion in real-world channels, machine learning algorithms have given new hope to fast recognition and unravelling with remarkable accuracy, significantly enhancing data transmission capacities and revitalising mode and space division multiplexing. The time to compute and recognise is still a limiting factor, but the switch to optical neural networks may hold the key. It is intriguing to wonder if the complexity of the medium itself could not be used to unravel the distortion: distortion used to compute the distortion. In optical metrology, ML-assisted structured light techniques have achieved unprecedented picometer-scale precision, surpassing conventional diffraction limits, opening a new path to seeing smaller with intelligence enhanced structured light, while in super-resolution microscopy, neural networks enhance the resolution and imaging speed into territory once considered impossible to reach. In quantum systems with structured light, the high dimensions possible hold enormous potential, but have been held back by the time for measurement and the complexity of developing the toolkit to control operations in high-dimensional spaces. Deep learning has given this field a boost, facilitating efficient engineering and characterization of high-dimensional quantum states, even designing the experiments of the future! More intriguingly, structured light itself can function as the physical substrate for optical neural networks. By leveraging the interference and diffraction properties of light, these networks perform computational tasks at the speed of light, offering great advantages in energy efficiency and processing speed compared to electronic implementations.

In such reviews there are necessarily many topics that must be omitted, yet may significantly benefit from this intersection too. One such field is that of mixing space and time DoFs for spatio-temporal structured light [380,

381]. By sculpting both the transverse mode profile (e.g., orbital angular momentum or vector beams) and the femtosecond-scale envelope of pulses with durations below 100 fs, researchers gain access to time-resolved imaging and metrology at sub-100-fs resolution. Such ultrashort structured pulses can track carrier relaxation dynamics in semiconductor and perovskite materials, resolve coherent phonon oscillations in solids, or follow real-time bond dynamics in photochemical reactions—capabilities fundamentally inaccessible to continuous-wave or nanosecond-scale techniques whose temporal widths are orders of magnitude too long to probe femtosecond processes. A future trend to watch is the use of ML-driven inverse algorithms to reconstruct the full spatio-temporal field, potentially enabling high-fidelity recovery of ultrafast dynamics, even under photon-limited conditions.

The review touches on ML-aided beam shaping but stops short of device-level innovation. A powerful complement is the inverse design of the optical elements—metasurfaces, diffractive optics, and 3D-printed free-form components—that produce structured modes. By harnessing generative models (diffusion networks) coupled with topology-optimization algorithms, the dream is for researchers to easily explore vast parameter spaces and propose realizable nanostructures that generate high-order OAM superpositions, topological light structures, or complex nonseparable states with unprecedented purity and fabrication tolerances.

To move beyond static hologram libraries and fixed metasurface patterns, next-generation photonic computing systems should integrate adaptive intelligence directly into the optical processing pathway. By incorporating reinforcement-learning or meta-learning algorithms into the control loop of programmable diffractive layers or multimode photonic circuits, these systems can continuously adapt their structured-light-based computation kernels in response to real-time feedback. Such self-learning photonic processors could dynamically reconfigure mode multiplexing for optimized neural-network inference, implement adaptive kernel selection for image processing through scattering media, or compensate for fabrication and environmental perturbations without external retraining. Realizing this vision requires co-design of low-latency ML inference accelerators, high-speed optical modulation systems, and simulation-to-experiment training methodologies with domain randomization and few-shot hardware adaptation. This integration would yield fully closed-loop, environment-aware structured light computing platforms.

Finally, we have not covered the topic of structured illumination (not to be confused with what is meant by structured light) and its use in 3D imaging

and holography, where computational approaches are standard to the field [382, 383]. A modern direction that is fueling rapid advances in this direction is augmented reality (AR) and virtual reality (VR), where “intelligence” is essential in many ways [384], from design of the optics to processing of the scene and its user experience, for enhanced visualization and interpretation. This large research topic is deserving of a review of its own.

To conclude, there is plenty of room at the intersection of photonics and artificial intelligence: we believe the continued convergence of structured light and artificial intelligence will revolutionize photonic technologies across scales from the macroscopic to the quantum, shaping the future of structured light and ML advanced capabilities beyond what either could achieve independently. The exciting future is when quantum, optical and AI are meshed together, offering speed, efficiency and perfect randomness for optimal circuits. There is an exciting opportunity to deploy these technologies in real-world applications, beyond the beautiful laboratory-based demonstrations we have covered in this review. Only then will the true promise of the meeting of structured light and machine intelligence be fully realized.

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Author contributions

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