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Review of Deep Learning Approaches for Orbital Angular Momentum Mode Distinction in Spatial Mode Diversity

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ABSTRACT

Orbital angular momentum (OAM) modes have recently emerged as a promising avenue for increasing the channel capacity and spectral efficiency of data communications and quantum information processing systems. The distinction of OAM modes is important for eliminating crosstalk between channels. Recently, leveraging deep learning for the separation and distinction of OAM modes has garnered substantial attention for enhancing the performance of spatial mode diversity. This paper presents a review of state-of-the-art in OAM mode distinction using deep learning. The paper commences with a preview of applications of OAM modes. This is followed by a review of deep learning techniques for the distinction of OAM modes through pattern recognition, focusing on convolutional neural networks (CNNs), recurrent neural networks (RNNs), derivatives of these and transfer learning. The review covers key features, advantages, and limitations of deep learning under different OAM modalities and atmospheric turbulence conditions.

1. Introduction

The thrust for higher bandwidth in communications systems in scattering media has prompted the exploration of new paradigms for channel diversity and multiple access [1]. Spatial modes offer a new dimension for this in addition to intensity, frequency and polarization [2]. The orbital angular momentum (OAM) is imparted on an optical wavefront for spatial mode diversity using spatial phase patterns through the design of devices such as cylindrical lenses [3,4], spiral phase plates [5,6], metamaterials [7,8], spatial light modulators [9–11], multi-plane light converters [12–14], laser cavities [6,15,16], photonic crystal fibers [17–19], fiber gratings [20,21], multicore fibers [22–24], vortex lenses [25–27], axicon lenses [28,29] and others. Modes with distinct topological charges are orthogonal to one another, thus enabling the transmission of several independent data flows through the same physical medium [30,31] This enhances the capacity and spectral efficiency of multi-channel

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systems, for a wide range of applications in data communications, imaging, sensing and quantum information processing.

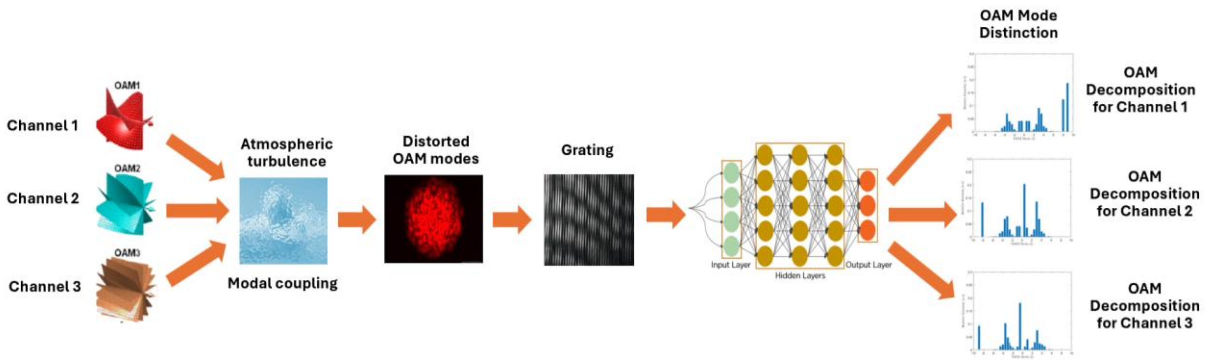

Fig. 1. Multiplexing, propagation and distinction of distorted OAM modes

Figure 1 illustrates the modulation of data from various data sources on to OAM modes, propagation of OAM beams and distinction of OAM modes through turbulent media in a spatial mode diversity system. The propagation of spatial modes through turbulent media such as the atmosphere or water current, is influenced by the refractive index structure parameter and Fried parameter, which vary due to temperature, pressure, humidity and water salinity gradients [32]. This results in phase fluctuations, scintillation, beam wander and modal coupling, which lead to the redistribution of power among modes [33–35]. The effects of turbulent media have been investigated using meteorological observations in various media and weather conditions [36–38]. Turbulence has also been measured through scintillation, pointing error, angle of arrival of the beam and thermal levels [39–42]. To emulate the effects of turbulence, phase screens based on the Kolmogorov model, modified Von Karman model, sparse spectral method, and others are deployed [43–46]. In addition, scintillation due to turbulence has been modelled using log normal [47–49], Gamma-Gamma [50,51] and Malaga [52,53] probability distributions, for terrestrial and unmanned aerial vehicle-based communications. The degradation of the transmitted signal is more pronounced as the modes propagate over long distances. At the receiver, the output wavefront is decomposed into distinct OAM modes defined by their topological charges [54], or by mapping the output wavefront into Zernike polynomials [55].

Advanced adaptive optics and phase correction mechanisms are required to mitigate the effects of turbulence [56,57]. Towards this end, accurate distinction of OAM mode is instrumental for precise modal profiling, to enable the compensation of crosstalk between spatial channels for attaining high signal fidelity. Previous algorithms used for mode distinction and equalization are based on minimum mean squares [58–60], recursive least squares [61–64], swarm-based algorithms [65,66], singular value decomposition [67,68] and principal component analysis [69,70].

Advancements in various artificial intelligence techniques (AI) have recently opened new doors for insightful classification, prediction and optimization [71–77]. Various AI approaches have been harnessed for distinction of OAM modes and other spatial modes, driving higher system bandwidth in optical communications systems under various environmental factors [78–81]. Large-scale distorted and undistorted modal signal datasets may be imbued into artificial intelligence models to predict the reversal of the degradation effects due to modal coupling, through training, for better overall robustness and reliability of multimoded communication systems [82–85].

The [83,84,86] motivation and contributions of the paper are presented in Section 2, followed by various applications of OAM modes in Section 3. This is followed a review of deep learning techniques for the distinction of OAM modes through pattern recognition, focusing on convolutional neural networks (CNNs) in Section 4 and recurrent neural networks (RNNs) in Section 5, hybrid forms of these in Sections 6 and transfer learning in Section 7. The review covers key features, advantages, and limitations.

2. Contributions

Conventional means of OAM mode distinction resort to mostly manual feature engineering and therefore, fall short of coping with the finer nonlinear details that characterize OAM signals in the presence of modal coupling. Recently, leveraging deep learning for the separation and distinction of OAM modes has garnered substantial attention for enhancing the performance of spatial mode diversity systems. Deep learning techniques have gained much interest in the last few years, due to their automatic learning of complex representations from data, especially in the context of OAM classification. Deep learning methods utilizing convolutional neural networks (CNNs) and recurrent neural networks (RNNs) architectures, and their variants, provide effective instruments for feature extraction from the spatial phase patterns, which result in the precise classification of OAM modes.

Yet, there is an insufficient compilation of OAM mode distinction approaches through deep learning to date. Thus, this paper presents a review of the state-of-the-art in OAM mode distinction using deep learning to bridge this knowledge gap.

3. Applications Of OAM Modes

OAM has far-reaching applications, discussed in the following subsections:

3.1 Optical Communications

OAM modes present an additional freedom for spatial mode diversity using the phase front of light beams, attaining high data transmission rates on a single wavelength. This highlights the potential of OAM for next-generation optical networks that are able to cope with growing data transmission demands [87]. Owing to the special properties of OAM, free space optical (FSO) systems are able to attain robustness against atmospheric turbulence, fog, smoke and adverse weather conditions, hence enabling communications over long distances with low signal degradation [88–91].

3.2 Quantum Information Processing

Quantum systems featuring OAM states provide high confidentiality and information capacity [92] . These features are demonstrated by recent experiments with OAM-encoded qubits for secure quantum communication, enabled by quantum key distribution protocols that are robust against eavesdropping attacks [93]. Furthermore, the unique set of OAM-based quantum states of the OAM provides ways in which certain quantum algorithms, particularly the quantum Fourier transform, may be accomplished in an OAM-based quantum computing architecture with superior efficiency [94, 95].

3.3 Remote Sensing and Imaging

OAM modes have shown potential for remote sensing and imaging with the promise to increase sensitivity and resolution. Encoding spatial information into the OAM of light has spurred some very innovative imaging systems with the ability to capture fine details. There are a few notable contributions such as those that showed that OAM-based imaging can be used for object detection and recognition in remote sensing applications, and thus has the potential to improve surveillance and security capabilities [96–98].

3.4 Autonomous Vehicles

OAM modes have potential applications in autonomous vehicles with Light Detection and Ranging (LiDAR). The velocity of moving objects in close vicinity of an autonomous vehicle can be gauged from the backscattered optical signals [99]. OAM modes allow the distinction between backscattered optical signals and background noise from sunlight and the ambience [100]. Incorporating OAM modes offer more sensor modalities, due to an additional degree of freedom for sensing and channel diversity, thereby enhancing the resolution and accuracy [101].

Thus, OAM modes have risen as a versatile commodity for spatial mode diversity with a plethora of applications spanning over different research fields, as shown in the above subsections. Further improvement in OAM distinction will bring about more opportunities in these areas.

4. CNNs For OAM Mode Distinction

Convolutional Neural Networks (CNNs) have been successful in feature detection, classification and data segmentation, under which hierarchical representations of the information can be acquired [102-104]. Thus, this provides a basis for the application of CNNs for OAM spatial mode diversity.

In [105], a CNN model was developed using OAM channel impulse responses as a convolutional kernel for retrieving indistinguishable spatial features from individual OAM mode profiles. The CNN model attained dimension reduction based on the spatial features and achieved a mode distinction accuracy of 97.2% through the identification of power coupling.

In [106], to enhance the detection accuracy of OAM modes, the phase profiles of OAM modes were modulated to make the distinctive features of each mode more pronounced. This improved the transmission performance for long distance channels, under strong turbulence.

Similarly, in [107], a CNN model was developed for demultiplexing the superposition of distorted OAM modes by using a spherical convex lens to generate a tilt to extract dominant features from individual OAM mode profiles.

In [88] a CNN was developed for the distinction of higher-order OAM modes from the superposition of distorted higher-order OAM modes, based on a parameter less attention scheme for extracting key features of OAM modes. This contrasts with previous attention-based implementations of CNN which create attention weights based on several parameters and sub-networks. Thus, the proposed scheme reduces the complexity of the CNN and attains a distinction accuracy of greater than 95% under atmospheric turbulence.

[108] introduces a CNN for detecting OAM modes, with a 7% improvement in the detection accuracy compared to the previous CNN implementation based on ResNet18. The CNN design increases OAM mode accuracy by 5.5% over a 2km transmission link, compared to ResNet18.

[109] applies CNN to distinguish OAM modes in underwater FSO under turbulence, with varying temperature and salt gradients. The CNN retrieves distinctive characteristics of Laguerre-Gaussian phase profiles under the influence of turbulence from underwater currents and fine-tuned through the cross-entropy loss function. Higher accuracy detection rates were demonstrated for double-mode OAM compared to single-mode OAM transmission.

Authors in [110] demonstrated OAM multiplexing and distinction using CNN, outperforming previous benchmarks on OAM distinction by an average of nearly 95%. This study has shown that

CNNs can retrieve the OAM mode accurately for reliable communications under atmospheric turbulence.

[111] proposed a CNN model for atmospheric turbulence detection and the adaptable demodulation technique of the optical vortices in the OAM-based FSO communication. It extracted atmospheric turbulence at an accuracy rate of up to 95.2% for an 8-OAM system. The trained CNN is effective in demodulating the optical vortices.

[112] leverages on CNN to compensate for atmospheric disturbances in an FSO communications system. This CNN achieves high accuracy in reproducing OAM patterns, at 0.9935 and 0.9808 for the 3-OAM and 5-OAM modes, respectively. From these results, it is possible to infer that the environmental turbulence compensation obtained by CNN. CNN achieved high levels of gain in the received power. The power improvement by 2.5, 7, and 11 dB was performed under the turbulence condition D/r_0 = 1, 2, and 3.

[113] introduces phase compression-enhanced CNN to reduce the effects of interference from atmospheric turbulence and to improve the OAM mode demultiplexing accuracy. A hybrid vortex beam with varying power distribution characteristics is propagated through atmospheric turbulence before being demultiplexed by the CNN.

In [114] a 7-layer CNN-based OAM pattern detection was constructed for deep learning in underwater turbulence. More than 100% precision for the OAM of the CNN OAM pattern can be achieved under low to moderate oceanic turbulence up to a 100 m depth. Some parameters and settings were optimized in this regard: training samples, iteration, and turbulence intensity. The highest accuracy can be obtained when the training set contains 2,500 patterns and is trained 20 times.

4.1 Advantages of CNNs

i) *Feature Learning:*
CNNs have a very good ability to learn hierarchies of data representation automatically. Having convolutional layers enables the network to abstract characteristics at various levels from raw images, starting from the most basic—edges and textures—to complex forms and patterns. This makes manual feature engineering irrelevant and also enables CNNs to capture fine features in the images [102].

ii) *Spatial Hierarchies*:
CNNs take advantage of the spatial feature hierarchy of an image. Those high-level semantic features, like object sections or full objects, are aggregated in deeper layers, while low-level features are located in earlier levels, such as corners and edges. Hierarchical representation, therefore, allows a CNN to capture the spatial organization of images [102].

iii) *Parameter Sharing:*
CNNs use parameter sharing. CNN parameters are filters that are applied across different spatial locations in the input. This reduces the number of parameters in the network, hence better efficiency and effectiveness—especially for a large-scale dataset [115–117]

iv) *Translation Invariance:*
The architecture has convolutions that bring out translation-invariant representations. Therefore, CNNs can recognize features irrespective of the location of such features in the input. This means that CNN is insusceptible to minute position variations, rotations, or scales. This is valuable in OAM distinction due to varying OAM profiles and offsets due to the choice of optics and distance used for detection [118].

v) *Pre-Trained Models and Transfer Learning:*

Pre-trained models of CNN, previously trained on a large number of datasets for images such as ImageNet, may be fine-tuned for a relatively small dataset for solving a particular problem [102]

4.2 Limitation of CNNs:

i) *Computationally Expensive:*
Training deep CNNs is expensive computationally, particularly for large datasets and complex architectures. The convolutional operations have a huge parameter cost and hence require a lot of computational resources, which is their drawback when used in resource-constrained environments [119].

ii) *Data Efficiency:*
Most CNNs require a large amount of labelled data for training in order to generalize well over unseen examples. For most domains, for which labelled data is either scarce or costly to prepare, training deep CNNs is inconvenient and often overfitting-prone [120,121].

iii) *Lacks Interpretability*:
CNNs are usually treated as black-box models, hence, it is difficult to interpret decisions. Therefore, it is difficult to understand why a CNN classifies an image in a certain manner and hence its critical use in applications when interpretability is involved [122]

iv) *Lack of Contextual Understanding:*
CNNs treat images locally and may not understand context globally or long-range dependencies. In complex scenes, these weaknesses might result in misclassification, where the context is usually very important for recognition [123].

v) *Susceptibility to Adversarial Attacks:*
CNNs are vulnerable to adversarial attacks, where small, imperceptible perturbations to input images can cause misclassifications. Adversarial attacks exploit the sensitivity of CNNs to small changes in input data, highlighting their lack of robustness in certain scenarios [124,125].

Overall, CNNs have been shown to be a potent tool in the processing and recognition of images. Yet, CNNs have several shortcomings, such as high computational cost, data efficiency, interpretability, understanding of context, and adversarial attacks. However, CNNs have maintained their cutting-edge status in many fields.

5. RNN for OAM Mode Distinction

OAM mode distinction based on RNNs is discussed in this sub-section. [126] introduced deep learning to address misalignment issues during identification in OAM communication systems. The authors designed a misalignment assessment system using an RNN with the gated recurrent mechanism. The model considers misalignment from lateral displacement, angular error, and transceiver pointing error. With only 25 sampling points, as opposed to 201 sampling points from previous methods, high OAM distinction accuracy is attained. The model is also tolerant to Gaussian noise. The RNN model realizes better accuracy in estimating alignment values compared to the CNN and MLP models.

Authors in [127] exploited object learning and deep learning based on RNN for OAM communications with sequential data. RNN-mediated channel modeling can improve the performance of end-to-end learning in such systems, in conjunction with data augmentation. The authors also investigated self-configuration and adaptive allocation for optical networks.

[128] employed a lightweight RNN (LNN), catered for mobile devices, to measure the orientation of an image for OAM mode distinction utilizing the MobileNetV2 architecture with residual class-specific attention (CSRA) classification layer to detect unique characteristics of individual OAM modes. The LNN attains a precision of 76% on the predicted orientation angle, evaluated at varying altitudes.

5.1. Advantages of RNNs

i) *Temporal Learning Capability:*
RNNs are appropriate for sequential data processing and capturing temporal dependencies. The structure of RNN is the most straightforward, followed by the GRU, and the LSTM. However, training in GRUs is relatively simple compared to RNNs and LSTMs. RNNs are able to handle simple sequences, followed by GRUs for moderate length sequences, and LSTMs for longer and complex OAM mode sequences. The characteristics of the RNN, its different variants, and their respective possible applications, including temporal data processing and temporal dependencies captured within OAM communication, are also highlighted [129].

ii) *Adaptability to Variable-Length Sequence:*
OAM patterns can have different lengths and levels of complexity. Unlike feedforward neural networks, RNNs can handle sequences of variable lengths, making them adaptable to different OAM modes without requiring fixed-size input vectors. [127,130].

iii) *Feature Learning:*
RNNs can learn a hierarchy of features from data with automatic learning capability. In the OAM classification scenario, the RNN could extract features from dynamic changes concerning phase patterns to capture the important information from both spatial and temporal changes [131,132].

iv) *Noise Robustness:*
OAM signals are sensitive and distorted. All RNNs, especially those with memory cells like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU), are quite robust to noise and can learn how to ignore irrelevant variations in the input data. [133].

v) *Using Complicated Data Structures:*
The OAM patterns encode such complex spatial structures. In this sense, RNNs are best able to capture the complex spatial phase patterns carried in the OAM signals [134,135].

5.2 Limitations of RNNs:

i) *Training Complexity:*
RNNs are computationally demanding, especially when they are deep or have long sequences. The algorithm applied to train RNNs, backpropagation through time (BPTT), might have vanishing or exploding gradient problems, making the convergence very slow [129, 136]

ii) *Difficulty in Capturing Long-term Dependencies:*
Standard RNNs have a problem in capturing long-range dependencies within sequences. While architectures like LSTMs and GRUs go some way to reduce the problem, they are still not able to capture very long-term dependencies [135, 137] .

iii) *Interpretability:*

RNNs are considered black boxes in most deep-learning models. Thus, it is hard to understand how decisions are reached. The interpretation of why a given OAM mode was classified in a certain manner is not so straightforward [134, 135].

iv) *Overfitting:*
RNNs tend to be overfitted, especially in small or noisy data. In such a case, RNN-based OAM classifiers need appropriate model selection and regularization techniques to avoid overfitting [134].

v) *Computational Resources:*
Large RNNs, with large memory cell count, require huge computational resources for their training and inference. Computational resources consumed in the training and inference of such models lead to questioning their deployment in resource-constrained environments or real-time systems [119, 138].

As an effective method of time-based learning, adaptability to variable-length sequences, and feature learning, RNNs offer a rich framework for OAM pattern classification. Some challenges that have to be faced for the effective deployment of the OAM classifiers based on RNNs include training complexity, long-term dependency capturing, interpretability, overfitting, and computational resource requirements [109, 139, 140].

6. Hybrid Neural Networks for OAM Mode Distinction

Hybrid neural network architectures have become one powerful approach to effectively handling the features unique to OAM signals in the classification of OAM spatial patterns. They aggregate capabilities of the different deep learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), provide a thorough investigation into both spatial and temporal features which are intrinsic to the OAM pattern [141].

[142] harnesses CNN for OAM beam distinction in an optical communication mechanism to realize high system capacity. The authors introduce a hybrid optical-electronic CNN that demultiplexes superpositioned OAM beams based on Fourier optics convolution. The system has a 4F optics transporter using the Fourier optics convolution layer. This has resulted in a demultiplexing accuracy of 72.84% in the case of strong turbulence, with a training time 3.2 times faster than all-electronic CNNs.

[143] achieved precise identification of OAM modes as an optical communication using a deep feed-forward neural network model. The 15 input neurons are equivalent to seven hidden layers in the proposed FNN model, which renders the feature of hybridized OAM modes arbitrarily combined and with high tolerance to atmospheric turbulence. The accuracy was as high as 97% in the case of five superimposed modes, achieved within 0.09 ms.

[144] utilizes a hybrid RNN-CNN network to distinguish OAM modes in video frames. Low-density parity check (LDPC) codes were retrieved most accurately in a 16 OAM-moded system. Both CNN and RNN perform equally, increasing the classification precision by up to 20% with respect to conventional approaches. Nevertheless, the precision is reduced with increasing number of classes. Furthermore, a graphical processing unit (GPU) expedites the classification by over 67% and over 36% for the CNN and RNN respectively. These two DL techniques are more effective in evaluating the classification accuracy than the other traditional techniques by almost 10 - 20%.

6.1 Advantages of Hybrid NNs:

i) *Space-Time Understanding*:
In the hybrid setup, spatial and temporal characteristic extraction of OAM signals can be facilitated. It is possible to a large extent that the CNNs are best for capturing the spatial dependencies on the spatial phase patterns of the OAM, whereas the RNNs are best for modelling the temporal changes of those patterns through time. Hybrid architectures are a last resort to fully realizing a holistic understanding of the dynamic nature of received OAM signals [141].

ii) *Hierarchies of Features:*
CNNs within hybrid architectures capture hierarchies of features in the OAM patterns. The hierarchies relate to low-level features like edges and textures as well as high-level semantic features that deal with OAM mode number transitions. Hence, this allows the hierarchical representation allows the details of structural complexities in OAM signals to be captured [145–147] .

iii) *Adaptability to Different Modes:*
Hybrid architectures allow for adaption to various type of modes, for different topological charges and under various turbulence parameters. Since it is possible to combine the CNN-RNN structure, it may enable the model to classify most of the OAM patterns, and it would, therefore, be versatile and effective for different communication scenarios[148–150] .

iv) *Robustness to Noise and Distortions:*
Both CNNs and RNNs in hybrid architectures promote robustness to refractive index distortion encountered by OAM beams. This stems from the fact that CNN predictions are robust with respect to spatial noise and variations, while RNNs can handle temporal distortions. In this manner, OAM pattern classification is reliable under varying atmospheric turbulence and beam orientation [151].

6.2 Limitations of Hybrid NNs:

i) *Complexity and Computational Cost:*
Hybrid neural network architectures become computationally expensive during implementation and training when used with large-scale datasets and complex network configurations. Hybrid designs with CNNs and RNNs, therefore, imply large computational costs for training and inference [152, 153]

ii) *Interpretability:*
As with all other deep learning models, hybrid architectures are not provided with interpretability. It lacks interpretability, which makes it quite hard to understand the reasoning behind the classification results given by such a structure. In that sense, the interpretability of hybrid architectures might make it critical for practical applications to understand why a given OAM pattern is classified in some way[154, 155]

iii) *Training Data Requirements:*
Hybrid architectures typically require large amounts of labelled data for training, especially when the range of OAM mode orders is wide and the variety of environmental conditions is extremely high. Thus, obtaining labeled from distorted OAM datasets is a formidable challenge and proves to be very resource-intensive [156, 157].

iv) *Overfitting:*

The risk of overfitting rises together with the structure complexity of a hybrid architecture, especially when the size of the training data is small or the quality of the training data is not so good. Proper regularization and careful model selection will prevent possible overfitting and guarantee generalization performance. [158]

Hence, hybrid neural network architectures look to be a very promising way for OAM pattern classification by uniting spatial insights from CNNs with temporal insights from RNNs. While they provide greater insight into OAM signal analysis and an enhancement in classification accuracy, in order to make them deployable solutions for realistic OAM communication systems, issues related to complexity, interpretability, data requirements, and overfitting have to be mitigated [159].

7. Transfer Learning for OAM Mode Distinction

Transfer learning refers to applying knowledge acquired through one task to improve the performance of another related task. In the context of OAM, transfer learning can be seen as the general task of taking a pre-trained model or the pre-existing knowledge from one asset or operation to improve the performance of another asset or operation. This particularly proves beneficial in industrial applications, where data are sparse and hard to come by, and efficiency and effectiveness gains can likely be achieved by the utilization of already existing knowledge [160, 161].

[162] introduces a scheme to classify OAM modes in FSO by applying transfer learning with depth wise separable convolution. This model is tailored explicitly to the suppression of issues related to massive training data volumes and suboptimal rates of convergence, which are exhibited by some state-of-the-art models. The work revolves around the accuracy of recognizing the 4-OAM and 8-OAM modes from noisy measured OAM profiles and establishes the resilience of the model as far as the OAM transmission in a turbulent atmosphere is concerned. Their proposed approach can reach up to 99.5% distinction accuracy using engineered augmented sample datasets. The model provides suitable identification of OAM modes for various transmission ranges and turbulence levels.

[163] presents the application of transfer learning in optical sensing with OAM modes. The authors developed Resnet-based training for the applied magnetic field from a magneto-optic effect crystal to increase sensing accuracy. Optical vortices OAM of topological charge ±1 deposit a petal-like pattern when projected through a linear polarizer. The image recorded by the CCD sensor will rotate under the influence of the magnetic field applied by the crystal. The latter increases the precision of the task for identifying image rotation angles with varied signal-to-noise ratio (SNR).

[164] is able to distinguish eight distorted OAM modes after propagating through 0.1km oceanic turbulence link. Transfer learning was used to train the distorted OAM images using both atmospheric turbulence and oceanic turbulence for better training precision. Distorted OAM images from atmospheric turbulence have slightly different finer characteristics from oceanic turbulence but offer insights on prospective broader features of distorted OAM images from oceanic turbulence.

7.1. Advantages of Transfer Learning Classification:

i) *Reduced Data Dependence:*
Transfer learning reduced dependency on large quantities of labelled data. Therefore, instead of starting from scratch, models would have prior pre-training on huge datasets and only fine-tune on a small dataset that is specific to the task of interest in OAM. This particularly benefits industries which collect data expensively in terms of cost and time [165] .

ii) *Improved Model Performance:*
Transfer learning consistently attains higher performance with respect to the models that were trained from scratch. The acquired knowledge during the pre-training period tends to make the model more adaptable to the new task, directly resulting in higher accuracy and efficiency in OAM processes [166].

iii) *Faster Deployment*:
Transfer learning speeds up the deployment of machine learning solutions in OAM distinction. This is because, with pre-trained models being already available, the time and resources required to build and train models from scratch are drastically cut down [167].

7.2 Limitations of Transfer Learning Classification:

i) *Domain Mismatch*:
There may be a mismatch between the source domain in which the model is pre-trained and the target OAM domain into which the model is transferred. If the mismatch is significant and the transferred knowledge is useful, it does poorly [168, 169]. This can be mitigated by pre-training for specific OAM mode numbers within the same environment or atmospheric turbulence parameters. In addition, OAM beam orientation and beam wandering should be considered to enhance the accuracy of transfer learning.

ii) *Generalization Limited:*
Transfer learning can indeed boost the model's performance, but at the same time, it is restrained by the similarity of source and target tasks. If the tasks are very different, then the transferred knowledge might not be useful, and generalization by the model to the new OAM task would be quite difficult [160, 161].

iii) *Dependency on Quality of Pre-trained Models:*
The success of transfer learning in OAM largely depends on the quality of the pre-trained models. This is because if the pre-trained models do not fit well, this might decrease the performance of the transferred model in OAM distinction [124,128,135].

iv) *Domain Expertise Required:*

v) For the effective implementation of transfer learning, which yields success in OAM distinction, requires domain expertise to be able to construct pre-trained models, fine-tune them well, and then interpret the results accurately. Even with the best transfer learning architecture, accurate OAM distinction still poses a challenge in the absence of a good understanding of the domain [161,170].

Overall, due to the high number of benefits that transfer learning brings for better OAM in the industry, the limitations, and challenges to the practical implementation of OAM applications using transfer learning must be carefully weighed [160,161].

8. Conclusion

In conclusion, we have reviewed CNN, RNN and other deep learning approaches for OAM distinction under turbulent media. CNNs are good at capturing spatial dependencies in OAM profiles. On the other hand, RNNs are effective at capturing temporal dependencies. Hybrid CNNs and RNNs effectively represent both spatial and temporal features. Transfer learning helps to enhance OAM distinction accuracy under this kind of limitation. Data augmentation makes the classifier more robust to noise and variations. In conclusion, deep learning approaches bring new advances in OAM mode distinction—providing robust and accurate feature extraction, enhance transmission quality of OAM-based communication systems, enhance sensitivity in sensing and reduced crosstalk. The application of the deep learning models here may be extended to other domains.

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