

Deep learning ghost polarimetry

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Introduction. Ghost polarimetry (GP) is one of the important branches of ghost imaging. GP solves the issue of the effect of radiation polarization on the generated polarization ghost images (PGI) [1, 2]. To date, most of the results have been obtained for bright (classical) light. However, in [3–5] it was shown that the ideas underlying GP in bright light can be combined with the principles of quantum optics.

As was shown in [6], for restoring the PGI, i.e. the spatial polarization profile of an object, the measuring a complete set of the correlation intensity functions (CIF) obtained at different orientations of polarizers and analyzers is required. In this regard, a rather complicated problem of solving the inverse problem arises, namely, calculating the elements of the Jones matrix from a set of CIF. However, for an object with arbitrary polarization properties, this problem still remains unsolved and, moreover, it cannot be said in advance that it can be solved in principle.

In this paper, we report for the first time, to our knowledge, about using neural networks to solve GP problem. We demonstrated this for objects with one of four types of anisotropy [7]: linear amplitude anisotropy; linear phase anisotropy; circular amplitude anisotropy and circular phase anisotropy. To address this challenge, we developed a specialized Ghost Polarimetry Deep Neural Network (GPNN) that identifies the type of anisotropy.

Description of optical scheme. For clarity, consider the GP circuit shown in Fig. 1. By analogy with computational ghost imaging [8], a source of linearly polarized light with pseudo-thermal statistics is used. The object's polarization properties are generally described by the Jones matrix $\hat{\mathbf{M}}$. In such a geometry, it is not difficult to show [6] that $g(\mathbf{r}) = \left|\hat{\mathbf{M}}_p \hat{\mathbf{M}}(\mathbf{r})\, \mathbf{e}(\mathbf{r})\right|^2$. Here $g(\mathbf{r})$ – CIF; $\hat{\mathbf{M}}_p$ – Jones matrix of polarizer; $\mathbf{e}$ – the normalized Jones vector.

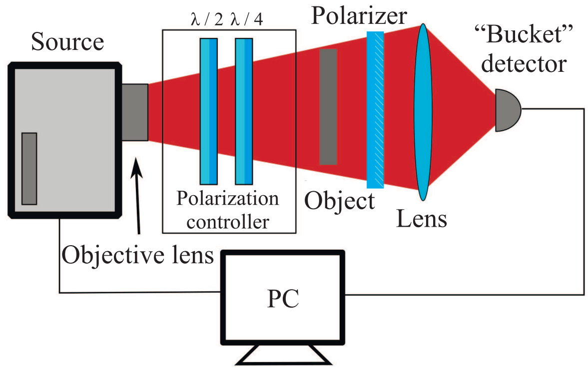

Fig. (Color online) Scheme of the GP facility. Light from a source of linearly polarized radiation with pseudo-thermal statistics (Source) passes through an objective lens, a polarization controller, a polarization-sensitive object, and a polarizer. Then, the light is collected by a lens on a photosensitive "bucket" detector area. The control of the source and signal processing from the detector are carried out by a computer (PC)

In the general case, for the objects under consideration, the GP problem with spatial resolution is reduced to an inverse problem, in which it is necessary to restore the distribution of type of anisotropy in the cross section of the object from the measured CIF. To solve this problem, a specialized neural network GPNN was developed, which determines the type of anisotropy point by point. For training and testing we generate a numerical dataset consisting of 7000 points. The vector formed from the five normalized CIF is fed to the input "Embedding stack" consisting of four Linear layer. The new vector is fed to the inputs of the Classifier stack, which solves four binary classification tasks.

As a result of training, we demonstrate a neural network that achieves a prediction accuracy of more than 98 % for the linear and circular amplitude anisotropy by the 19th epoch. A similar epoch yielding a prediction accuracy exceeding 95 % for linear and circular phase anisotropy.

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Conclusion. For the first time, it is demonstrated that deep neural networks can be utilized to reconstruct distribution of type of the anisotropy of random objects, whose properties are determined by linear and circular amplitude and phase anisotropy. This technique has the potential to be used in solving the quantitative problem of GP, aiming to determine the value of anisotropy parameters (P, θ, α, Δ, ϕ and R).

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Conflict of interest. The authors declare no conflicts of interest.

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