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Material analysis with polarization holography and machine learning

Yanmin Zhu,[1] Yuxing Li,[1] Jianqing Huang,[1,2] Yunping Zhang,[1] and Edmund Y. Lam[1,*]

[1] Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam, Hong Kong SAR, China.

[2] Key Lab of Education Ministry for Power Machinery and Engineering, School of Mechanical Engineering, Shanghai Jiao Tong University, 800 Dongchuan Road, Shanghai, 200240, China.

[*] elam@eee.hku.hk

Abstract: We design a polarization holographic system to record the sample holographic images with rich polarization states, amplitude, and phase information. Material analysis and characterization are realized with machine learning. We demonstrate the system feasibility on specific microplastic material identification.

1. Introduction

Polarization imaging can provide information about the physical properties of light that interacts with a material. When light reflects, refracts, or scatters off a material, it undergoes changes in its polarization state, related to the composition, structural, and other physical characteristics of the material [1]. For example, a polarization imaging system has been applied to identify specific fibers with their optical axis and anisotropic properties [2]. It also has been successfully used to identify the presence of birefringent crystal materials, which have different refractive indices in different optical directions.

Digital holography (DH) can record the interference patterns of the light scattered by the sample. By analyzing the holographic images, we can retrieve information about the sample's shape, refractive index, thickness, and other physical and optical characteristics [3,4]. In addition, DH is a versatile, non-contact, and high-speed imaging method without the need for sample preparation or staining [5], and is suitable for in-situ detection. Currently, DH has demonstrated its capability for quick and high-resolution material identification on a wide range of materials, such as biological tissues and microplastics. While DH alone may not be sufficient for precise material identification, incorporating additional composition-related features can offer a more comprehensive understanding of a material's characteristics and identity.

In this work, we propose a polarization holographic system to record optical and polarization features simultaneously. It can record the holograms under different polarization angles in a single shot, eliminating the manual adjustment of the polarizer and analyzer. A machine learning method is applied for further feature classification. It can be applied to rapid material identification and intelligent material diagnosis in the field. We demonstrate the system's capability on the microplastic identification task.

2. Methods and experiments

We build an in-line holographic system with a good compactness. A polarization camera is used to replace the traditional-used complementary metal-oxide semiconductor (CMOS) camera and realize the simultaneous feature capturing. The polarization camera is mounted with a specific-made polarization mask, which separates the whole field of view of the imaging sensor into sub-regions with different polarization states. This system can eliminate the manual rotation of the polarizer and realize quick image recording. Materials used in the experiments include microplastic films, natural particles, and microorganisms. Microplastic films are labeled by their categories, which are polycarbonate (PC), polyethylene terephthalate (PET), polypropylene(PP), and polyvinyl chloride (PVC). Natural particles are collected from seawater in Hong Kong. Microorganisms include the daphnia and paramecium. The natural particles and the microorganisms are labeled as others. We show the sample raw images in Fig. 1(a).

Specific optical features are calculated and extracted from the record images, which are shown in Table 1. The polarization states are described by the Jones matrix S_0, S_1 and S_2 with $S_0 = \frac{1}{2}(I_0 + I_{45} + I_{90} + I_{135})$, $S_1 = I_0 - I_{90}$, and $S_2 = I_{45} - I_{135}$. In addition, we introduce two auxiliary variables ε_1 and ε_2 for the calculation of polarization features, defined as $\varepsilon_1 = (I_{90} - I_0)/(I_{90} + I_0)$ and $\varepsilon_2 = (I_{45} - I_{135})/(I_{45} + I_{135})$.

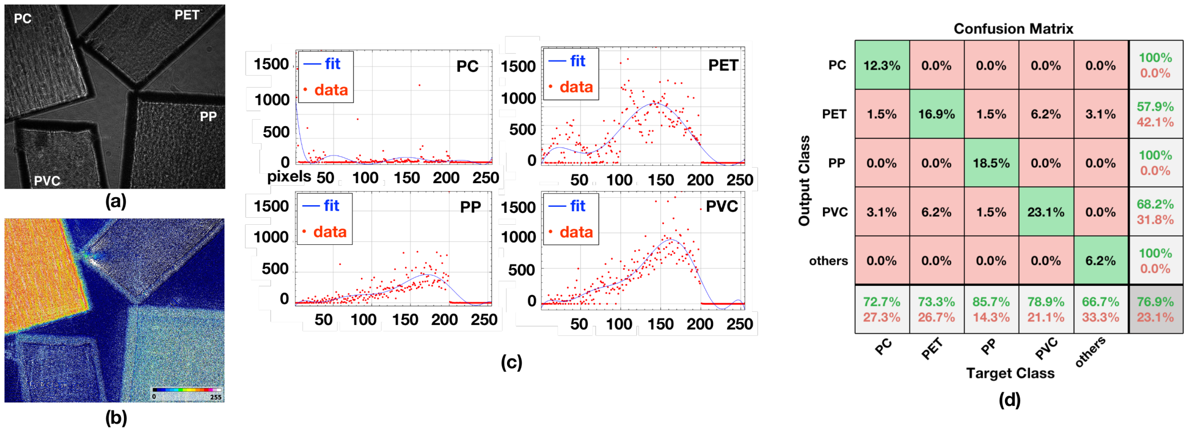

Fig. 1. (a) Raw holographic image recorded by the optical system. (b) Calculated angle of polarization (AoP) plot of the sample image in (a). (c) AoP distribution plots and corresponding fitting curves for different microplastics films. (d) Confusion matrix for the classification.

Table 1. Polarization and holographic features used for the machine learning discrimination and their calculation formulas.

Feature Category	Formula	Feature Category	Formula
phase retardation	$\sin^{-1}\sqrt{\varepsilon_1^2+\varepsilon_2^2}$	angle of polarization	$\frac{1}{2}\tan^{-1}(S_2/S_1)$
optical axis orientation	$\frac{1}{2}\tan^{-1}(\varepsilon_1/\varepsilon_2)$	fringe contrast	$(I_{max}-I_{min})/(I_{max}+I_{min})$
degree of linear polarization	$\sqrt{S_1^2+S_2^2}/S_0$	circularity	$A_{particle}/A_{sphere}$

3. Results and discussion

Different kinds of microplastic materials present distinguishable features. We choose the angle of polarization (AoP) as the representation and demonstrate the calculated AoP plots of four plastic films and their corresponding scattering plots in Fig. 1(b) and (c). PC presents distinguished distribution with other plastic materials. This is because PC has a different intrinsic structure based on its higher glass transition temperature than PVC, PP, and PET.A support vector machine is used for feature classification. We show the confusion matrix of the classification results in Fig. 1(d). It is shown that the classification accuracy is up to 80%, which is significantly higher than the morphological-based eye identification. It is also a feasible alternative for quick in-situ detection with a dramatically increased detection speed compared with other in-the-lab chemical identification methods. This method would potentially be applicable in real-time high-throughput particle counting and pollution monitoring.

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