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# Polarization Holographic Imaging for High-throughput Microplastic Analysis

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**Abstract:** We propose a polarization holography system with deep learning. It allows dynamic analysis and high-throughput detection in an aqueous phase, facilitating real-time multimodal monitoring of microplastics. 

## 1. Introduction

Microplastics (MPs), referring to plastic fragments smaller than 5 mm, are prevalent pollutants in the natural environment and are harmful to wildlife, human health, and ecosystems [1]. Identifying MPs and assessing water quality have gained public attention [2]. Recently, researchers used learning-based imaging methods to characterize MPs [3]. However, to avoid extensive sample preparation in the laboratory, the imaging system needs to be capable of distinguishing MPs in the aqueous phase, where most of them are found.

This study employs a fluidic channel to achieve high-throughput in situ detection. We use polarization holography to record and extract multimodal information, such as light intensity, complex holographic patterns, and polarization state [4]. It registers the characteristics of the light wave and can classify material composition and structures based on birefringence features. Additionally, the YOLO v5 and Strong-SORT models automate real-time counting, quantification, and classification of different plastic fragments based on large quantities of data. This system improves the dynamic monitoring of MPs and provides valuable information for their filtration and governance.

## 2. Methods and materials

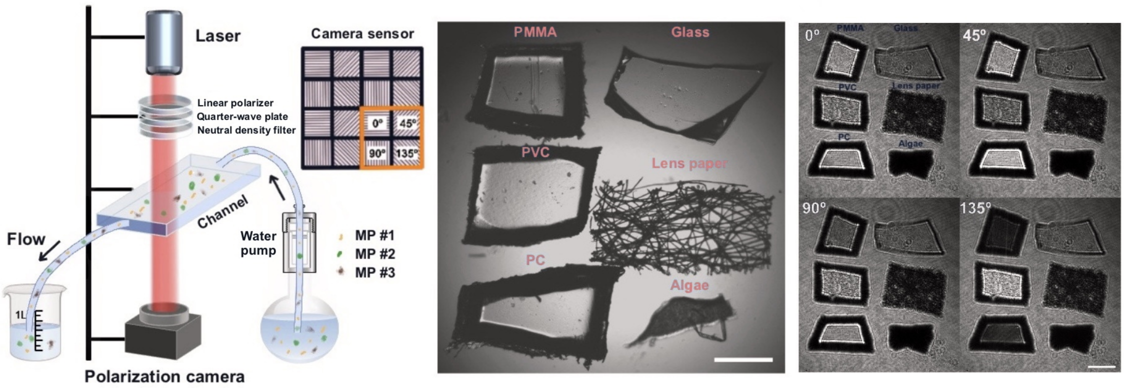
The optical configuration is illustrated in Fig. 1(a). The laser source with a wavelength of 632.8 nm is used, which passes through a linear polarizer (LP) and a quarter-wave plate (QWP) to generate a circularly polarized light. A neutral density filter (NDF) is placed to ensure a suitable light intensity. The polarization camera (MC-A500P-163) is used to record holograms with different polarization states. The pixels with size 3.45 μm are arranged in a group of $2 \times 2$ grid arrays, which simultaneously capture the polarization states at 0°, 45°, 90°, and 135°, respectively. These polarization states are used to calculate birefringence-related features [5].

Detection of sample particles in flow is carried out using a customized fluidic channel with dimensions of 5 mm (inner thickness), 10 mm(width), and 50 mm(length). The flow speed is precisely controlled by a water pump (NKCP-C-SO4B), capable of reaching a maximum volume flow rate of 15 ml/min. The samples used in this study include three types of plastic varying in birefringence values: polycarbonate (PC), polyvinyl chloride (PVC), and polymethyl methacrylate (PMMA). Additional materials such as glass, lens paper, and algae are included in the control group to enrich the sample diversity. The samples are also imaged by a stereo microscope and compared with polarized holograms.

For image processing, the standard deviation is calculated by Matlab algorithms to facilitate material classification. The YOLO v5 model, a lightweight convolutional neural network (CNN), is combined with a Strong-SORT network to segment, measure, and count the MP samples.

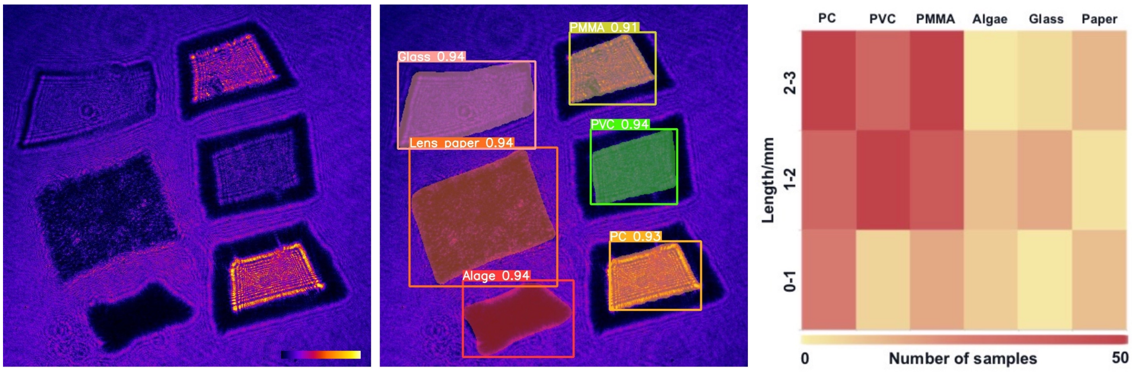
## 3. Results and discussion

Fig. 1(b) shows a stereo microscope image of six samples, which are difficult to distinguish when they are transparent. However, plastic films with anisotropy can alter the polarization state of the transmitted light at different angles. The sample intensity differences in the four-angle images indicate their optical anisotropy, which is helpful for material classification, as shown in Fig. 1(c). For instance, the PVC film has a similar intensity in the four images, whereas PMMA and PC films show significant intensity changes at different angles, which is consistent with their respective birefringence values. The four images are quantified as total input, and the stack standard deviation (SSD) is used to demonstrate the birefringence difference for further training and identification, as presented in Fig. 2(a).




(a) (b) (c)

Fig. 1. (a) Layout of the polarization holographic imaging system. (b) Microscope image of six samples. (c) Polarized digital holograms at four angles. Scale bar: 0.5 mm.




(a) (b) (c)

Fig. 2. (a) The stack standard deviation (SSD) image illustrates the birefringence-related features. (b) Sample identification results with YOLO v5 and Strong-SORT. (c) Heatmap indicates the number of samples in different sizes and material groups.

The volume flow rate of water was optimized at 8 ml/min, allowing stable and high-throughput detection. Various samples of different shapes and materials flowed through the experimental device, and the captured 600 image dataset was split into training-validation-test with a ratio of 8:1:1. By using YOLO v5 and Strong-SORT, the samples were counted and classified with an accuracy of up to 96% (Fig. 2(b)). The maximum Feret diameter (MFD), which represents the longest dimension of the samples, was used to measure the samples' size and provide information for MP filtration and filter pore size. The generated heatmap comprehensively illustrates the number of MPs in different size ranges and material types (Fig. 2(c)).

In summary, this study proposes a real-time, high-throughput MP analyzer that combines polarized and holographic features with deep learning. The multidimensional information obtained aids in the better identification of MPs and can provide a treatment strategy.

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