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Microplastic identification in marine environments: A low-cost and effective approach based on transmitted light measurements

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ABSTRACT
Microplastics have become a significant concern for the well-being of marine ecosystems. Small fragments of plastic debris are released into the environment from both the direct disposal of plastic products and the deterioration of larger items. Ingestion of microplastics by marine life can result in detrimental effects, including physical harm and the accumulation of toxic chemicals in their tissues. The aim of this research is to design a compact and cost-effective measurement system for effectively detecting and quantifying microplastics in marine environments. The proposed system uses a 2.4-inch liquid-crystal display (LCD) panel and a digital USB microscope, both of which are connected to a single-board computer, with a dedicated python-based graphical user interface (GUI). Specifically, the light transmitted through plastic and organic samples was measured in order to identify and classify them. Various types of materials, such as polypropylene, polyvinyl chloride, polycarbonate, polyethylene, and organic algae samples, were tested and the metrological performance of the system has been estimated. The transmittance of the samples analyzed was primarily influenced by their opacity and thickness. In general, thicker materials exhibited significantly lower transmittance values. This trend was particularly evident in organic components and opaque plastic samples, where transmittance was significantly low. In addition, the experimental results suggest that the colour of the material also affects transmittance, although as a secondary factor. The employed technique could be used to identify and distinguish samples based on material properties, thereby allowing the proposed system to be a valuable tool for further research on microplastics in marine environments.

Section: RESEARCH PAPER

Keywords: microplastics; measurement instrumentation; environmental monitoring; LCD panel; optical transmittance.

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1. INTRODUCTION

Plastic pollution is a global environmental crisis that has reached alarming levels in recent years. The widespread use of plastic in various sectors, such as food packaging, electronics, and construction, has led to an unprecedented amount of plastic waste being generated and dispersed in the environment [1], [2]. Plastic is now present even in the most remote regions of the world, including the ocean, where it poses a significant threat to marine life and ecosystems [1]. The health risks associated with plastics have been well documented by the scientific community. Indeed, the environmental impact of plastic waste cannot be ignored, especially in developing and least developed countries where these risks are particularly prevalent [3]-[7].

Plastic debris has the potential to permanently alter the natural balance of ecosystems, thus causing harm to humans and wildlife. The issue of plastic waste is a cause for growing concern, especially considering that by 2015, 6.3 billion tons of plastic waste had already been produced. If current trends continue, this number is expected to reach 26 billion tons by 2050, with almost half of it being disposed of in landfills or dispersed in the environment [8]. The production of plastic products, particularly single-use plastic, and their disposal are two of the major sources of marine debris. Marine debris poses a serious threat to the environment as it can affect a wide range of organisms, changing their physical, chemical, and biological characteristics and reducing their reproductive potential [9], [10]. The issue of microplastics in the marine environment has become a major concern, as it may bring significant risks to marine life and ecosystems [11]. In this context, the identification, quantification, and classification of microplastics are crucial steps in understanding and addressing this critical and challenging problem. However, the detection of microplastics is not a trivial task, due to their small size, low concentration, and the complexity of their physical and chemical properties.

The classification of plastic particles according to size has been, and still is, a topic of ongoing debate in the scientific community and it may vary from study to study [12]. Some studies categorize them as macroplastics (i.e., > 20 mm) [12], mesoplastics (i.e., 5 mm - 10 mm) [13], microplastics (i.e., < 5 mm) [12], and nanoplastics (i.e., 0.2 mm - 2 mm) [14]. Recently, the ISO/FDIS 24187:2023 standard [15] provides the following definitions: any solid plastic particle that is insoluble in water and has a dimension ranging from 1 mm to 5 mm is classified as large microplastic, from 1 μm to 1 mm as microplastic; meanwhile, ISO/TR 21960:2020 [16] defines nanoplastic as any plastic particle smaller than 1 μm. Despite their prevalence, the impact of microplastics on the environment and public health is not fully understood yet. It is crucial to accurately assess the extent of microplastic contamination and the characteristics of these particles, including polymer type, shape, and size. The effects of microplastics on ecosystem processes and organisms strongly depend on the amount of exposure and the properties of the plastic fragments. Marine biota, including corals, marine invertebrates, planktons, fish, and whales, can ingest microplastics, which can then be passed along the human food chain. This highlights the great importance of clearly understanding the impact of microplastics on marine ecosystems and the potential risks to human health. In this context, the development of tools and methods for accurately identifying and classifying microplastics is of fundamental importance. Nevertheless, the detection and classification of microplastics is a very challenging task, due to their small size and the wide range of polymers and shapes they can take. Over the years, a large number of techniques have been proposed for this purpose, including hyperspectral imaging and image processing, microscopy, spectroscopy, and chromatography [17]-[22].

Recent advances in analytical techniques such as Raman spectroscopy and Fourier transform infrared (FTIR) spectroscopy have shown promise for the detection and characterization of microplastics [20]-[23]. Both procedures fall within the macro-area of vibrational spectroscopies and are of non-destructive type. Specifically, Raman spectroscopy provides insights into molecular backbone structure, crystal lattice, and symmetrical non-polar groups. In contrast, FTIR offers information regarding hydrogen bonds and asymmetric polar groups. Although Raman and FTIR spectroscopy are widely used as analytical tools for the characterization of polymers, also present some limitations. One of the major disadvantages is their size resolution, as both techniques are not able to detect particles smaller than about 100 μm. Additionally, the measurement time for these techniques can be relatively long, making them less suitable for high-throughput applications. Furthermore, the cost of equipment and maintenance, as well as the need for specialized training, can be significant barriers to the wide use of these methods. Other techniques such as laser-induced fluorescence (LIF) and laser-induced breakdown spectroscopy (LIBS) have also been proposed for the detection of microplastics [24], [25]. LIF involves the excitation of fluorescent dyes present in microplastics, while LIBS involves the generation of plasma through the interaction of a laser beam with a sample. Both techniques have the advantage of being rapid and non-destructive, but further research is needed to optimize their use for the detection and characterization of microplastics. Finally, microwave devices have only recently been used for the preliminary detection and quantification in soil and water [26]-[28].

An alternative approach for microplastics identification is the use of hyperspectral imaging, a powerful analytical technique that allows for the simultaneous acquisition of a wide range of wavelengths across the electromagnetic spectrum. This technique is able to provide detailed spectral information about the samples, which can then be used to identify and quantify the presence of microplastics with high accuracy and precision. Compared to other techniques, such as Raman spectroscopy and FTIR, hyperspectral imaging offers faster measurement times and, in addition, the ability to analyse large areas at once. In [17], a method for detecting microplastics using hyperspectral imaging in the visible spectrum was proposed. The authors used various classifiers, including neural networks, support vector machines, partial least squares-discriminant analysis, and least squares-support vector machines, to identify microplastics both underwater and in the air. Similarly, in [29], hyperspectral imaging combined with image processing was used to identify and classify microplastics in soil. Supervised classification algorithms, including Mahalanobis distance, support vector machines, and maximum likelihood, were utilized for this purpose. The resulting system was able to distinguish microplastics from other materials. In [30], an image-based technique was employed to identify spherical engineered microplastics (polyethylene, 10-45 μm) and microalgae (Isochrysis galbana, 4-7 μm). The measurement system, which works in the visible spectrum in transmittance mode, was employed with different classifiers, including support vector machines, least squares support vector machines, and k-nearest neighbours, for the proper discrimination of microplastic fragments from organic materials like microalgae.

In this paper, a compact and low-cost measurement system for a straightforward identification of microplastics in marine environments is proposed. The system exploits transmitted light to identify microplastic debris, providing a simple and effective method for material characterization [31], [32]. One of the main advantages of the proposed system is its low cost. Compared to other competing technologies, such as hyperspectral imaging and more conventional spectroscopy, it utilizes cheaper hardware and is more compact and portable. Additionally, the proposed system is equipped with a quadcore single-board computer, which allows for the implementation of machine learning-based classification algorithms. This further expansion of the system may improve the accuracy and reliability of the results. The present work is an extended version of the one presented at the 2022 IEEE International Workshop on Metrology for the Sea [33]. In such a study, the system is tested using a wider range of plastic materials and organic samples and, in addition, provides

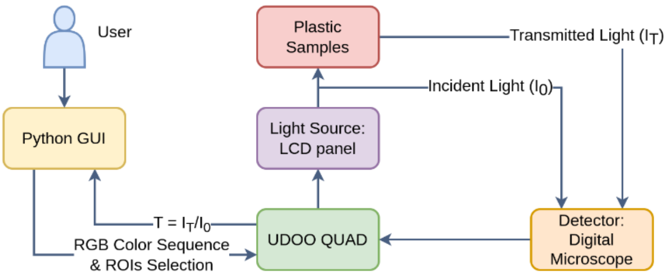

Figure 1. Schematic representation of the proposed measurement system for microplastics identification. The system employs a Python GUI to guide the user in selecting a colour sequence and ROIs. A UDOO single-board computer manages the LCD panel to generate the selected colour sequence, while simultaneously acquiring both the incident light (I_0) on the sample and the transmitted light (I_T). The transmittance T of the sample is calculated as the ratio of the two intensities and plotted as a function of the colour sequence.

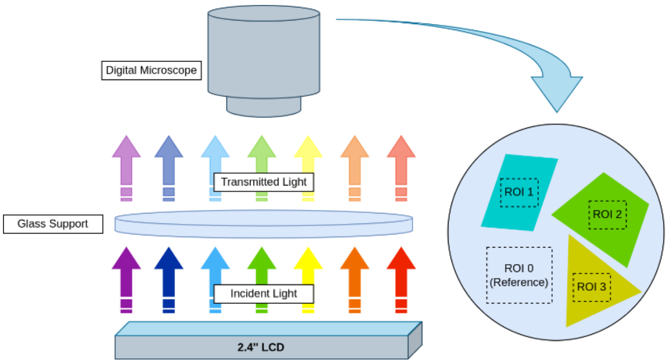

Figure 2. Measurement system schematic representation. The single-board computer UDOO is connected to the LCD Panel, surrounded by a transparent glass support, where the SUTs are placed. The light emitted by the LCD passes through the transparent glass support and consequently the samples and is captured by the USB digital microscope. From the acquired image, ROIs are selected to evaluate the transmittance value.

the first results on the identification and classification of microplastics based on type of material, colour, and thickness. The metrological performance of the system is also evaluated in terms of measurement repeatability and reproducibility. Furthermore, the software has been significantly updated, with the addition of automatic fragment contour recognition and automatic size estimation. The results of this experimental investigation suggest that the proposed system has the potential to be a valuable tool for further research on microplastics detection in marine environments.

The rest of the paper is structured as follows. The proposed prototype and its working principle are described in Section II. Next, Section III introduces the image processing algorithm for the automatic selection of the regions of interest. The experimental activity and the achieved experimental findings are presented in Section IV. Finally, concluding remarks are provided in Section V.

2. MEASUREMENT SYSTEM

In this study, a low-cost measurement system for the identification of microplastics is proposed. The prototype is built on the UDOO single-board computer (SBC), which includes an Atmel ATSAM3X8E microcontroller that has features similar to an Arduino DUE board [34]. The UDOO platform has already been successfully used in the development of measurement solutions for a variety of applications [35]-[37].

The device described in this study is based on a previously developed measurement system designed for the characterization of colorimetric sensor arrays [38]. It has been improved in both hardware and software to meet the requirements of the current investigation. In particular, the measurement system has been updated to investigate plastic samples with dimensions smaller than 3 mm and down to 200 µm. Additionally, the software for the measurement system management has been updated to allow for the automatic identification of the fragments being tested during the measurement process. A schematic illustration of the proposed system is shown in Figure 1. The system is equipped with a low-cost 2.4-inch LCD panel, a Celestron 44302 USB digital microscope, and the UDOO single-board computer. The LCD panel serves as a programmable light source to illuminate the samples under test (SUTs) with a predefined colour sequence. The microscope acts as a detector and it is used to record and analyse changes in the spectrum of the transmitted light from the SUTs. A transparent glass support is employed to hold the microplastic samples during the measurement process. The use of an LCD panel as a light source has been carefully considered. Its wide availability and relatively low cost make it an attractive choice for a cost-effective and accessible measurement system. However, it is important to note that the LCD panel offers a limited electro-magnetic spectrum, which can limit the interaction between generated light and analysed sample. Additionally, the quadcore single-board computer allows for the implementation of machine learning-based classification algorithms, which can provide even more accurate and reliable results.

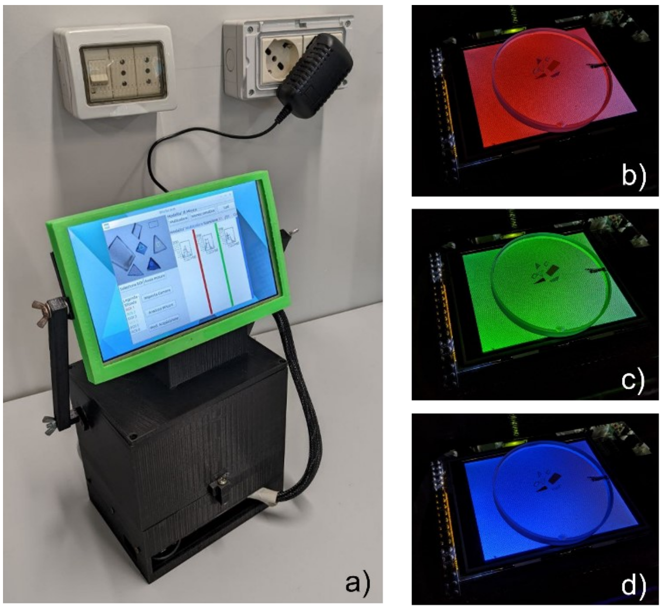

Figure 3. Photo of the developed measurement system. Inside the 3D-printed plastic box, the SUTs are arranged on the glass support above the LCD panel that illuminates the same SUTs with a pre-defined colour sequence, i.e., red (b), green (c), and blue (d).

A python-based graphical user interface (GUI) has been developed to provide easy control and management of the measurement system. The GUI allows for easy selection of the colour sequence to be generated by the light source, detector selection and configuration, and measurement acquisition and visualization. The GUI is accessible to the user via a 7-inch touchscreen that is connected to the UDOO board via an HDMI cable. The SUTs are placed on the transparent glass support in

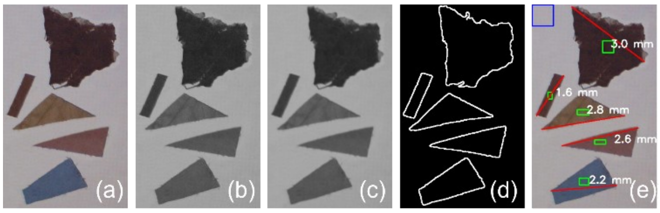

Figure 4. Illustration of the working steps of the image-processing algorithm for the automatic selection of ROIs in the measurement system. The algorithm starts by converting the acquired image (a) to grayscale to simplify the image and reduce the amount of data that needs to be processed (b). It then applies a Gaussian blur to the grayscale image to reduce noise and other small-scale variations (c). After blurring, the algorithm applies adaptive thresholding and uses the *findContours()* function to find contours in the binary image (d), and it estimates one rectangle for each contour (green rectangles), an additional rectangle for the background (blue rectangle), and the maximum size of each fragment (red lines) (e).

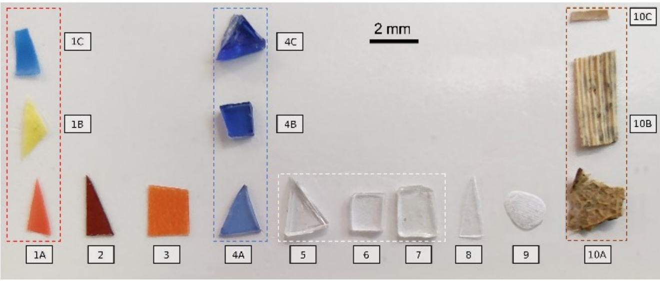

Figure 5. Photo of the samples used in the experiments. A description of each sample is reported in Table 1.

the optical path between the light source and the detector, as shown in Figure 2 and Figure 3. The detector captures the light generated by the LCD panel and that which is transmitted through the samples. This is achieved by selecting specific ROIs on the image acquired by the detector. The ROIs can be selected manually using the GUI or automatically by means of an image processing algorithm, which is described in detail in the next section. In the current implementation, a maximum of 7 ROIs can be selected, including those containing the samples under investigation and the reference (i.e., the background) that is representative of the light generated by the LCD panel. Specifically, ROIs with a width of about 400 µm were considered. This allows for the analysis of the transmitted light spectrum and the identification of microplastics based on their physical and chemical characteristics.

Once the ROIs containing the investigating samples and the background are selected, the transmittance T, as a function of the colour sequence k, can be estimated as in equation (1):

$$T(k) = \frac{I_T(k)}{I_0(k)}, \tag{1}$$

where $I_T(k)$ and $I_0(k)$ represent the transmitted and the reference light intensities, respectively, as a function of the colour sequence k. For each region of interest, the average red-green-blue (*R-G-B*) triplet is calculated for each colour in the sequence k. From the RGB triplet, the light intensity I can be calculated as a function of k using the following equation (2) [39], [40]:

$$I(k) = l \times R(k) + m \times G(k) + n \times B(k), \tag{2}$$

with l, m, and n weighting factors equal to 0.299, 0.587, and 0.114, respectively [39].

3. IMAGE PROCESSING ALGORITHM

The software used for system management includes a script that uses an image-processing algorithm to automatically select the ROIs of the SUTs. The script employs the Python OpenCV library and its working steps are illustrated in Figure 4. Once the image is acquired by the detector, it is converted to grayscale in order to simplify the image and reduce the amount of data that needs to be processed by the UDOO. Next, a Gaussian blur is applied to the grayscale image. This is a smoothing technique that reduces noise and other small-scale variations in the image. After blurring the image, adaptive thresholding is applied to the image. Thresholding is a simple image segmentation technique that converts an image into a binary image, where pixels are either black or white depending on whether they are above or below a certain threshold. In particular, the adaptive thresholding employed in this study adjusts the threshold value for each pixel based on the surrounding pixels, which can be useful in cases where lighting conditions or contrast in the image varies across the image.

The program then employs the *findContours()* function from the OpenCV library to find contours in the binary image and iterates over the found contours and calculates the ROIs, i.e., one rectangle for each contour, which is entirely included in it. Additionally, for each contour, the program estimates the maximum size of each fragment. Once the contours have been calculated, the program attempts to place an additional rectangle in the background of the image outside of any contours, i.e., the reference. This task is accomplished by iterating over a range of possible positions for the top-left corner of the acquired image.

4. METHODOLOGY

In this study, different kinds of plastic samples were used as a case study. All the fragments have dimensions lower than 3 mm and are made of various plastic materials such as PVC, PE, and PET, among others. In addition to the plastic fragments, three additional organic samples of dry algae (Posidonia oceanica) collected from the seashore were included in the study. A photo of the samples categories investigated is shown in Figure 5, and a detailed list of the samples is provided in Table 1. Among the plastic samples considered, three categories have been identified:

Table 1. Details of the samples considered in this study.

Sample	Material	Acronym	Colour
1A	Low density polyethylene	LDPE	Orange
1B	Low density polyethylene	LDPE	Yellow
1C	Low density polyethylene	LDPE	Blue
2	Polyimide (Kapton)	PI	Orange
3	High-density polyethylene	HDPE	Orange
4A	Polyethylene terephthalate (120 µm ± 15 µm)	PET	Blue
4B	Polyethylene terephthalate (460 µm ± 15 µm)	PET	Blue
4C	Polyethylene terephthalate (910 µm ± 15 µm)	PET	Blue
5	Polyethylene terephthalate	PET	Transparent
6	Polypropylene	PP	Transparent
7	Polycarbonate	PC	Transparent
8	Polyvinyl chloride	PVC	Transparent
9	Polystyrene	PS	White
10A	Organic sample	OS	Brown
10B	Organic sample	OS	Brown
10C	Organic sample	OS	Brown

- Samples with the same material, same thickness, and different colours (1A, 1B, 1C);
- Samples with the same colour, same thickness, and different materials (5, 6, 7);
- Samples with the same material, same colour, and different thicknesses (4A, 4B, 4C).

This approach allowed a comparative study of the response of the measurement system with different samples in which only one feature among material, thickness, and colour was varied at a time. Firstly, the collected samples were placed on the glass support for the transmittance evaluation in the visible range. The colour sequence generated by the LCD panel consists of 40 different colours, from violet to red. Each colour was maintained on the display for 5 s and the measurements were carried out in a dark environment to further reduce the interference of external light.

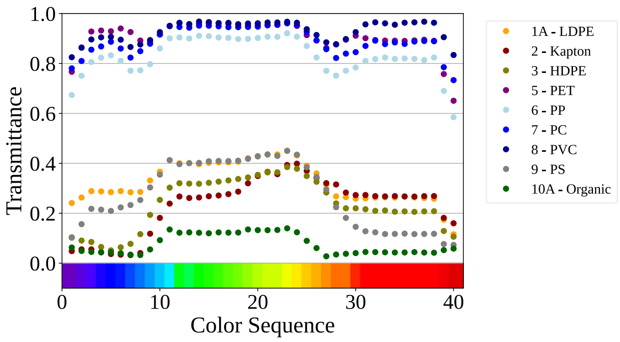

Figure 6. Transmittance of each type of material for the samples as a function of the colour sequence. Each point on the graph represents a single measurement, with labels in the legend indicating the corresponding sample number and material type.

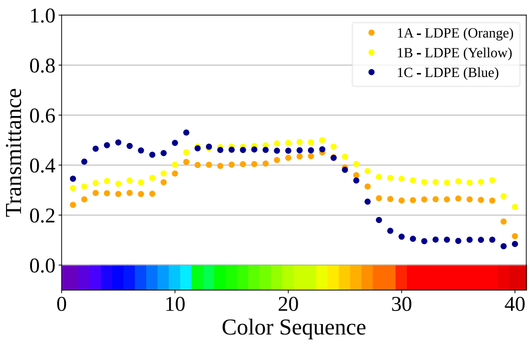

Figure 7. Transmittance of samples made with the same material and thickness, but different colours. Each point on the graph represents a single measurement, with labels in the legend indicating the corresponding sample number and material type.

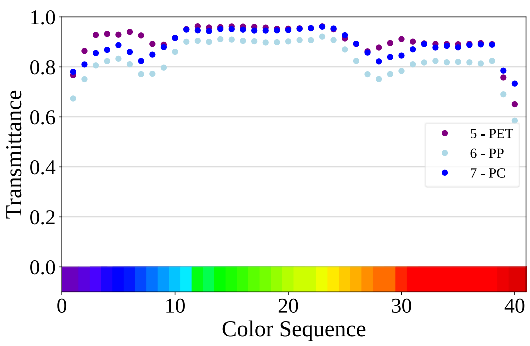

Figure 8. Transmittance of samples with the same colour and thickness, but different materials. Each point on the graph represents a single measurement, with labels in the legend indicating the corresponding sample number and material type.

5. EXPERIMENTAL RESULTS

The estimated transmittance of each material constituting the SUTs is reported in Figure 6. Initial results suggest that each material may have a characteristic response to light in terms of transmittance, although these observations are based on a limited set of samples that are, however, very common in the marine environment. Significant variations in transmittance were observed among the different materials, with a tendency for transparent or semi-transparent samples to exhibit, as expected, higher transmittance values.

The obtained data suggests that there is a notable difference in the transmittance response between the different materials, and specifically between the organic and plastic samples. Therefore, transmittance response may be easily exploited to discriminate the SUTs and furthermore to train an artificial neural network (ANN) to automatically derive additional information for marine environmental monitoring.

To better understand the potential dependence of the transmittance on the colour of the sample, the response of the first category was separately analysed: samples with the same material and thickness but different colours. In Figure 7, the transmittance of samples 1A, 1B, and 1C is plotted. The three samples considered here are made of LDPE with a thickness of 40 µm ± 5 µm and are coloured orange, yellow, and blue, respectively. As can be seen from Figure 7, the transmittance for the blue sample is higher in the blue region of the spectrum. On the other hand, samples 1B and 1C are characterized by a maximum transmittance value in the yellow/orange region. This provides clear evidence of the possible dependence of the transmittance on the material colour.

Furthermore, to better highlight the potential dependence of the transmittance values on the samples material, the response of the second category of samples was studied: samples with the same colour and thickness but different materials. In this case, samples 5, 6, and 7 were taken into account. They are transparent with a thickness of 315 µm ± 15 µm and are made of PET, PP, and PC, respectively. In such a situation, as shown in Figure 8, except for the different amplitude of the transmittance values, there is not a clear discriminant among the selected samples. This may be attributed to a not high enough sensitivity of the used measurement system.

Finally, samples belonging to the third category are analysed: samples with the same material, same colour, and different thickness. In this case, the samples come from a PET plastic bottle. It is worth noting that since the samples come from the same plastic object, the plastic composition can be reasonably considered the same among the samples, and all the samples have roughly undergone the same aging process. This allows for visualization in terms of transmittance of the effect of the samples thickness only. The samples 4A, 4B, and 4C are characterized by a thickness of 120 µm ± 15 µm, 460 µm ± 15 µm, and 910 µm ± 15 µm, respectively. The transmittance of these samples as a function of the selected colour sequence is reported in Figure 9. In this case, a clear trend is visible between

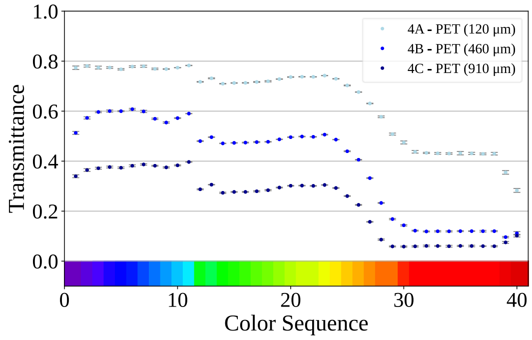

Figure 9. Transmittance of samples made with the same material and colour, but different thickness. The error bars represent the experimental measurement repeatability. Each point on the graph represents an individual measurement, with labels in the legend indicating the corresponding sample number and material type.

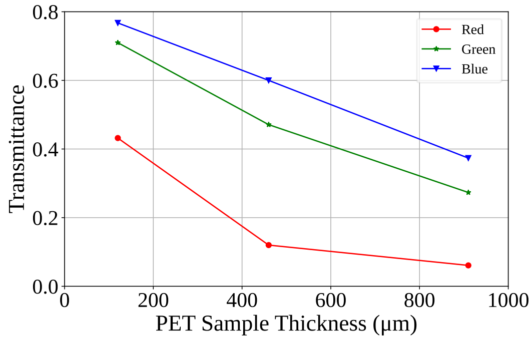

Figure 10. Transmittance as a function of the PET samples thickness at red, green, and blue colours.

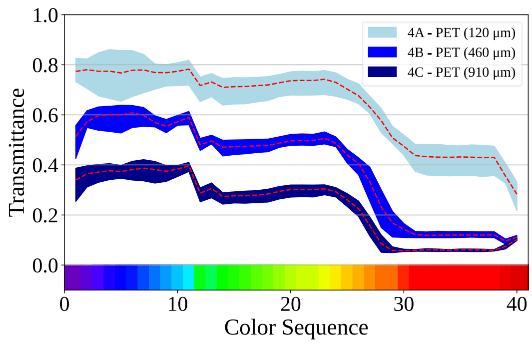

Figure 11. Transmittance of the samples made with the same material and colour, but different thickness. The bands represent the experimental measurement reproducibility.

the transmittance and the SUTs thickness. This dependence is better represented in Figure 10, where the transmittance values at the three colours red (255,0,0), green (0,255,0), and blue (0,0,255) are plotted as a function of the samples thickness.

To assess the metrological performance of the proposed system, the measurement repeatability and reproducibility have been evaluated. In the first case, multiple measurements were acquired on the same samples under the same measurement conditions, and the deviations in terms of standard deviations are reported in Figure 11 as error bars. The average bar length is 0.003, which is a small value, demonstrating the high measurement repeatability of the proposed system. On the other

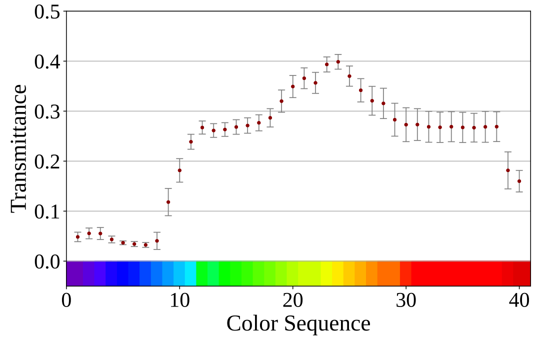

Figure 12. Transmittance of polyimide samples. Measurements were carried out on a total of 30 fragments derived from a commercial Kapton sheet with a nominal thickness of 127 µm. The red points indicate the average transmittance value for each colour. The error bars represent the standard deviation.

hand, reproducibility was evaluated by replacing the plastic samples at each measurement and considering different ROIs each time. In this case, the deviations are represented in Figure 11 as coloured bands. The achieved average band thickness is 0.1 which highlights the good measurement reproducibility of the system.

Finally, in order to provide a more comprehensive investigation, measurements were carried out considering multiple fragments of the same plastic materials with similar nominal specifications. Specifically, a total of 30 fragments of polyimide were extracted form a commercial Kapton substrate with a nominal thickness of 127 µm. This enabled further testing of the measurement performance of the system when considering plastic samples with similar characteristics (e.g., in terms of material, colour, and thickness). The results of this investigation are presented in Figure 12. Here, for each colour in the sequence, the average value of the transmittance and the standard deviation from measurements of 30 different polyimide samples are displayed.

6. DISCUSSION AND CONCLUSIONS

The proposed measurement system represents a valuable tool for identifying microplastics in marine environments by providing a low-cost and compact solution for straightforwardly identifying and quantifying microplastics. The system uses a 2.4-inch LCD panel as a programmable light source and a digital microscope as a detector. The results of this study are promising and indicate that the system could be a useful tool for further research on microplastics in marine environments. The system was able to discriminate samples based on their material properties, with the transmittance values of the samples being different for different materials and colours. The organic samples, in particular, showed distinct transmittance values compared to the plastic samples, which can be used to distinguish between organic and inorganic materials. The software used for system management has been empowered to include a script for the automatic selection of the ROIs using an image-processing algorithm that is able to recognize the shape and contours of the SUTs. The script employs the python OpenCV library, which reduces the need for manual selection of ROIs, thus increasing the efficiency of the measurement process. Furthermore, the quad-core single-board computer allows for the implementation of machine learning-based classification algorithms, enabling even more accurate and reliable results. The metrological performance of the proposed system in terms of measurement repeatability and reproducibility was also evaluated, with values of 0.003 and 0.1, respectively.

Although the developed prototype has shown very promising results in identifying microplastics in laboratory settings, it is important to acknowledge some inherent limitations of the proposed measurement system. A significant challenge arises from the diverse nature of plastic materials, particularly in terms of their optical properties, that can be found in real-world application scenarios. For example, plastics with high opacity pose a significant challenge as they have inherently low light transmittance, making their detection and analysis via transmittance measurements less reliable. To overcome this, the present system can be further improved by adding the capability of reflectance measurements [31], [41], which would provide a more comprehensive description of the SUTs. This addition would allow the system to analyse a wider range of plastic materials, especially those with higher opacity, thereby increasing its applicability in different marine conditions. Moreover, the addition of reflectance measurements and the use of machine learning-based classification algorithms will further improve the accuracy and reliability of the system. Another critical aspect to consider is the inherent limitation of the light source used in the system. The 2.4" LCD panel used to illuminate the samples generates colours through a weighted combination of red, green, and blue light. While this approach is effective for general colour representation, it does not provide the pure spectral output found in more advanced spectrometers. However, this choice is a strategic compromise to maintain affordability. The LCD panel, while limited in spectral resolution, significantly reduces the overall cost of the system, making it a viable option for widespread use in marine environmental monitoring. Furthermore, the choice of using an LCD panel as a light source, despite its limited spectral resolution, aligns well with the use of a low-cost camera (i.e., the USB digital microscope) as a detector instead of a more expensive multispectral camera [17], [29], [30], [42]. The primary advantages of the proposed system over other competing technologies, such as hyperspectral imaging and conventional spectroscopy, lie in its affordability and ease of implementation. These features make it an attractive and accessible solution for marine environmental monitoring.

In conclusion, this research provides some first results and opens up opportunities for further development and implementation in marine environment monitoring. Microplastics are a significant environmental issue, and, then, effective tools for identifying and quantifying them are vital for understanding and addressing this critical and challenging problem. The proposed measurement system has the potential to make a significant contribution to the ongoing efforts to understand and combat the effects of microplastics on marine life and ecosystems.

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