PENGUIN: Aquatic Plastic Pollution Sensing using AUVs

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ABSTRACT

Underwater plastic pollution is a significant global concern, affecting everything from marine ecosystems to climate change and even human health. Currently, obtaining accurate information about aquatic plastic pollutants at high spatial and temporal resolution is difficult as existing methods are laborious (e.g., dive surveys), restricted to a subset of plastics (e.g., aerial imaging for floating debris), have limited resolution (e.g., beach surveys), or are unsuited for aquatic environments (e.g., wireless sensing or Fourier-transform infrared spectroscopy). We propose PENGUIN, a work-in-progress AUV-based solution for identifying and classifying aquatic plastic pollutants. PENGUIN has been designed as the first system that can both recognize pollutants and classify them according to specifics of the material. We present the overall design of PENGUIN, introducing the different components of the architecture, and presenting current status of development. We also present results of plastic classification experiments using optical sensing, demonstrating that simple PPG sensors provide a low-cost and energy-efficient solution for classifying different plastics. Our solution can easily monitor larger underwater areas than what current techniques offer while at the same time capturing a wider range of pollutants.

CCS CONCEPTS

• **Computer systems organization** → **Robotic autonomy**; **Robotic components**.

KEYWORDS

Autonomous Underwater Vehicles, AUV, Marine Pollution, Plastic Pollution, Pervasive Sensing, Plastic Detection, Plastic Classification, Multi-Drone, Unmanned Vehicles, UAV

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1 INTRODUCTION

Underwater plastic pollution is a significant global problem that affects everything from the health of aquatic ecosystems to weather patterns, climate, and even human health [23, 32]. Most of this pollution results from human activity, with littering, winds and lacking waste management exacerbating the issue. Indeed, already in 2010, between 4.8 to 12.7 million metric tonnes of plastics resulting from manufacturing were estimated to enter aquatic environments [16]. Since plastics are highly durable and not subject to biological decomposition, this has resulted in a steady accumulation of plastics in aquatic environments. For example, estimates in 2014 suggest that over 5 trillion pieces of plastics were drifting in the oceans [6]. Another example is the so-called Great Pacific Garbage Patch [24], which has been shown to steadily increase in size [20].

Counteracting problems resulting from plastic pollution requires both efforts to prevent pollution entering aquatic environments and solutions to clean up existing pollutants. The former is actively pursued by legislative frameworks, which seek to reduce use and to improve handling of polluting materials, with particularly bans or restrictions on single-use plastics being actively pursued [28]. The latter, on the other hand, requires extensive efforts at mapping the extent of pollutants together with costly and laborious cleaning efforts. Currently, obtaining accurate information about the extent of plastic pollutants is difficult as existing measurement solutions are laborious and costly (e.g., dive surveys), limited to specific pollutants (e.g., aerial surveys capture only floating plastics), have limited spatial and temporal resolution (e.g, beach surveys) or operate poorly in underwater environments (e.g., wireless sensing or Fourier-transform infrared spectroscopy); see Sec. 4.

In this paper, we contribute by presenting PENGUIN, a work-in-progress AUV sensing system for monitoring underwater plastic pollutants. PENGUIN has been designed as the first system that can both identify and classify plastic pollutants according to their material characteristics. This enables PENGUIN to monitor much

larger underwater areas with less effort, while at the same time capturing a wide range of pollutants. PENGUIN achieves this using a two-phase sensing process where underwater computer vision techniques are first used to recognize plastic debris. Next, optical sensing is used to classify the plastic type of each detected object to one of six so-called resin identification codes (RIC) – an unified material coding for distinguishing plastic types used in everyday consumer objects. PENGUIN is developed using a commercial-off-the-shelf AUV which is augmented with necessary sensing, computing, and communication components to enable it to achieve its goals. Firstly, to ensure long operational time and efficient debris recognition performance, PENGUIN integrates a small-scale micro-cloud that consists of a small set of containers, each integrating a micro-controller (such as a Raspberry PI or an old smartphone) inside a waterproof container. Secondly, PENGUIN attaches a PPG sensor inside a waterproof container at the front of the AUV to perform plastic classification. We introduce the overall architecture of PENGUIN, describing the main components and the current status of our research and development. We also present feasibility experiments that demonstrate the potential of using PPG sensors for classifying different plastics.

Summary of Contributions:

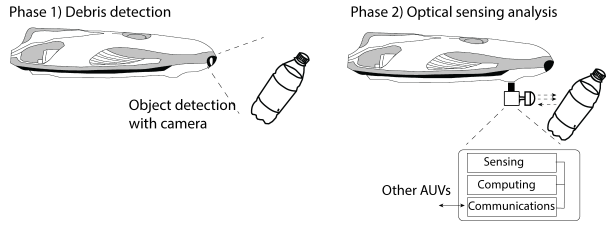
- **New system:** We present the design of PENGUIN, a novel AUV system and architecture for underwater plastic pollution monitoring. PENGUIN augments a commercial-off-the-shelf AUV with modular components to achieve plastic pollutant recognition and classification.
- **New plastic classification approach:** PENGUIN integrates an innovative low-cost and low-power sensing solution that uses commercial-off-the-shelf green light sensor for classifying plastics according to their characteristics.

2 PENGUIN DESIGN AND DEVELOPMENT

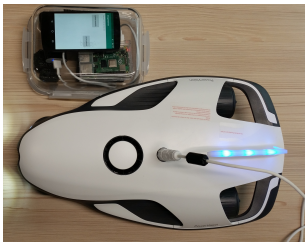
PENGUIN is being designed as a novel AUV-based solution for underwater plastic pollution monitoring. To ensure the collected information is useful in guiding cleaning and other efforts, PENGUIN not only detects plastics, but also classifies them according their material. Plastic types have differing toxicity characteristics and material also affects how the plastics degrade as a result of physical and chemical interactions [1, 31]. This makes capturing the material type of plastics essential for guiding cleaning efforts and other countermeasures, such as bans on plastics. In the following, we first give an overview of the design of PENGUIN, after which we describe the different components of PENGUIN and detail the status of our current proof-of-concept prototype.

2.1 PENGUIN Design

Figure 1a shows an overview of the system design of PENGUIN. At the core is a commercial-off-the-shelf AUV, which is augmented with modular components that offer sensing, communication, computing and other capabilities. These components are only loosely coupled with the AUV, operating as independently as possible to reduce power drain of the AUV. The external components reside inside waterproof containers, which can be attached to the frame of the AUV. Currently, we have designed components for sensing and computing, but we envision also other types of containers, such as custom communication modules, localization modules, or even energy harvesters. Our current prototype relies on off-the-shelf components to ensure flexibility and enable rapid prototyping.



(a) PENGUIN: Architectural overview.



(b) PENGUIN Implementation.

Figure 1: Overview of PENGUIN design and development.

2.2 Components

Where possible, we rely on the existing capabilities of the AUV. Additional functionality is provided by custom modules which are enclosed in waterproof containers, and then attached onto the AUV. The main components of PENGUIN are summarized below.

Sensing: PENGUIN relies on a two-phase sensing process. First, a camera-based solution is used to detect plastic debris. Next, the AUV is directed closer to the detected debris, and an optical sensing approach is used to determine the material of the object. We rely on optical sensing as it has low energy footprint and can operate robustly in underwater environments. Off-the-shelf light sensors and photo-receptors are inexpensive and easy to configure, making it easy to replace the components if needed. Besides the sensors used for material sensing, PENGUIN can also take advantage of sensors available on the AUV. For example, AUVs use accelerometer and gyroscope sensors to stabilize themselves and navigate in water currents. These sensors can be harnessed for estimating current stability [13] which in turn can be used for improving image quality and ensuring the light measurements are not affected by noise.

Computing: Off-the-shelf AUVs tend to have limited computing power as they need to be as lightweight as possible to offer reasonable operational time. PENGUIN overcomes this limitation using custom containers which integrate a separate micro-controller that can be used to support computing operations. By attaching multiple containers into the same AUV – or different AUVs collaborating with each other – it becomes possible to form a small-scale micro cloud that is used to support different computational tasks. For example, deep learning based object recognition can be performed efficiently by using Raspberry PIs or old smartphone models as the computing units [18]. Besides image processing, these computing

devices can be used to support coordination when multiple AUVs participate in monitoring [22].

Communications: PENGUIN requires two types of communication interfaces: short-range communications for intercommunication between components and medium to long-range communications for maintaining contact with remote operators. Unlike their aerial counterparts, AUVs cannot rely on standard wireless interfaces as water heavily absorbs wireless signals. This requires either using other communication mediums or placing the containers sufficiently close so that signal absorption does not become an issue. For long range communications this is not an option, necessitating solutions that can operate robustly in underwater environments, such as audio, optic or electromagnetic communications [2].

Other Components: For enabling large-scale operations, many other components would be required. For example, situational-awareness would require effective localization and ranging solutions, e.g., similarly to LIDARs used on connected vehicles. LIDAR could also replace or supplement the embedded camera and be used as the first source of information about debris [11, 35]. While there are some underwater LIDAR solutions, these are currently costly, bulky and highly energy consuming, which makes them unsuited for pollution monitoring. For collecting actionable and useful information, it is also necessary to have support for suitable sampling protocols. For example, diving surveys rely on transect sampling where information is collected along a delineated strip of the underwater region [19]. To ensure the collected information can be integrated with scientific models, it is necessary to have support for such sampling procedures.

2.3 Implementation

Figure 1b shows our current prototype implementation of the system. The prototype has been build on top of a PowerRay drone[1] which is a reasonably priced (around 2500€) off-the-shelf solution that offers around 4 hours of dive time. The drone was selected for rapid prototyping purposes, and we would expect more advanced drones to be used for large-scale monitoring. In particular, PowerRay does not integrate autonomous operations and is operated by remote commands transmitted through a communication cable. As light sensor, we rely on a PPG sensor from a smartwatch, which provides optical light sensing in the green spectrum. We used smartphones as processing units in the micro-cloud, and we rely on the embedded WiFi interfaces of these devices to provide communication support (See Section 3).

Deployment and autonomous operations: Currently, PENGUIN needs to be deployed by human operators to monitor a specific area, e.g., a river or a lake. However, we envision PENGUIN to be deployed permanently for monitoring continuous water pollution in wider marine areas, including oceans. To achieve continuous operation, PENGUIN can rely on mooring stations and energy harvesting mechanisms to sustain its operations, e.g., tidal harvesting combined with solar cells when the AUV is on the surface. Large-scale deployments of PENGUIN can coordinate operations to detect and classify a diverse range of pollutants and debris. The necessary computational routines for achieving autonomous and coordinated operations are supported by the micro-clouds, which offer additional computational resources without burdening the core functionality of the underlying AUV.

[1] https://www.powervision.me/eu/product/powerray

3 FEASIBILITY EVALUATION

We demonstrate the feasibility of PENGUIN through a controlled benchmark evaluation that focuses on the use of optical sensing for classifying different plastics. The feasibility of underwater debris recognition from video images has been demonstrated in other works, e.g., Valdenegro-Toro show 80.8% performance in binary debris detection using convolutional neural networks on images with a 96×96 resolution [33]. Our previous work [18], in turn has demonstrated that combining $2-4$ low-end computing devices, such as smartphones or Raspberry PIs, would support performing the object detection in real-time for a 30fps video, even if the resolution of the images increases. For these reasons, we focus solely on the second part of the sensing pipeline in our evaluation.

3.1 Experimental Setup

Apparatus: We perform our experiments using the sensing capabilities of the commercial off-the-shelf smartwatch Samsung Gear S3 Frontier, which integrates two green-light LED lights and a photoreceptor. We focus on green light due to its short wavelength, which makes it excellent at penetrating water.

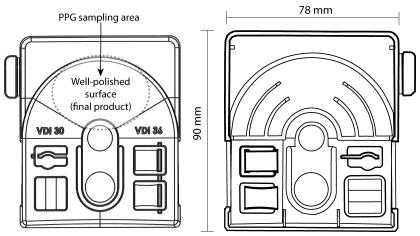
Plastics: We rely on a plastic set of 6 different types of plastics, which correspond to the standard resin identification codes (RIC) used to identify the most common plastic manufactured articles. The tested plastic samples are produced using the same mould cavity and identical manufacturing process[2]. Thus, differences in samples are directly proportional to their inherent material properties, e.g., material shrinkage and stiffness. Figure 2 shows the general specifications of a plastic sample, and the area of plastic that is sampled by the sensor. We measure the polished area of the plastic, which is similar to those used in consumer products. The density of the samples varies between 0.39 and 1.5 g/cm^3 and the weight is between 18 and 30 grams. The thickness of each sample is 2mm, which is similar to plastics used in consumer products (e.g., plastic water bottles are $1-2$mm thick). Table 1 describes each sample along with the categories where it belongs based on its properties. The table contains the RIC, acronym identifier (Acron), plastic name, color, 4 categories to classify the objects (Polymer, Temperature, Performance and Molecular structure) and uses.

Setup: We place each plastic sample in turn inside a glass container covered with a non-reflective (black) lid acting as background for the light measurements. The smartwatch is taped outside the container, directly below the measured object; see Figure 3. Our setup thus emulates detection in underwater environments and assumes the optical sensor is encased in a waterproof container. For each plastic sample, we collect 12 sets of measurements, where each set contains light intensity measurements sampled with 100Hz frequency over a 90 second period. We separately assess effect of luminosity on performance by splitting the measurements into two sets of 6. The first set emulates direct contact between the sensor and the sample, and was achieved by covering the container

[2] https://www.materialsampleshop.com/products/plastics-sample-set

Table 1: Plastic samples considered in the experiments along with their family properties. RIC: Resin identification code.

RIC	Acron.	Plastic name	Color	Polymer	Temperature	Performance	Molecular structure	Uses
01 PET	PET	Polyethylene terephthalate	transparent	polyester	moderate	engineering	semi-crystaline	soft drinks plastic bottles, polyester yarn and fibers, clamshell packaging
02 PE-HD	HDPE	High density polyethylene	blue	polyolefin	low	commodity	semi-crystaline	disposable suits, shampoo bottles shopping bags, playground equipment, food storage containers
03 PVC	PVC	Polyvinyl chloride	gray	polyvinyl chloride	low	commodity	amorphous	vinyl gloves, plastic cards (bank, ids, loyalty), pipes, inflatable products
04 PE-LD	LDPE	Low density polyethylene	red	polyolefin	low	commodity	semi-crystaline	six pack rings, laminated juice and milk cartons, plastic wraps, trays
05 PP	PP	Polypropylene	black	polyolefin	low	commodity	semi-crystaline	respiratory masks filters, sanitary products, diapers, yarns and textiles,suture prolene
06 PS	PS	Polystyrene	yellow	polystyrene	low	commodity	amorphous	foodservice packaging, instrument panels, thermal insulation in walls and roofs



(a) (b)

Figure 2: Plastic sample specifications, a) Front side and highlighted sampling area, b) Back side and dimensions.

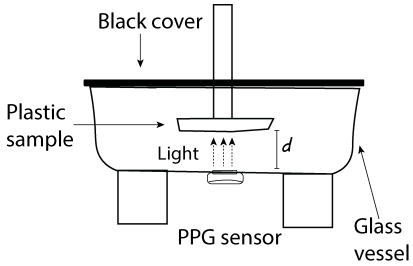
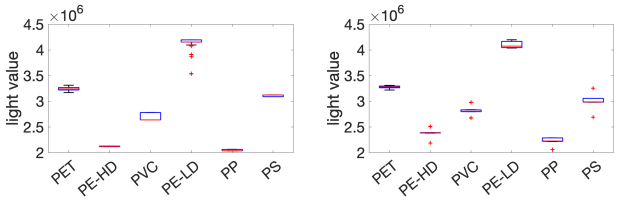


Figure 3: Testbed for plastic recognition underwater.

with a cardboard box. The second set emulates the case where no direct contact can be established, i.e., water and light can enter between the sensor and the sample. This was realized by having the container in a room without covering it. The average strength of ambient light was measured as 15.5lx.

3.2 Results

Figure 4 shows the results of the underwater experiments. We can observe that different materials have different reflectance, and that the relative differences are preserved for both ambient light and darkness conditions. Kruskal-Wallis test using luminosity and plastic type as experimental conditions showed significant differences for ambient ($\chi^2 = 9176$, $\eta^2 = 0.89$, p< .001) and darkness ($\chi^2 = 16562$, $\eta^2 = 0.946$, p< .001). Posthoc comparisons (Dunn-Bonferroni) verified that the differences for objects also were statistically significant. This suggests that light sensors can be used for identification of plastics underwater.



(a) (b)

Figure 4: Reflected light by plastic samples underwater in different conditions, a) Ambient light and b) Darkness.

We next demonstrate that PENGUIN's optical sensing can provide a coarse-grained classification of plastics, even in diverse underwater light intensity conditions. We perform classification tests applying two simple classifiers, a random forest model and a k-nearest neighbor classifier. The use of simple classifiers fulfils the need of having fast, accurate, but energy-efficient models in our AUV deployment. The results of our experiments are shown in Table 2. The classification accuracy for all the test conditions is around 90%. Based on the difference in the reflected light in the plastic materials. The best classification performance in cross-validation is around 96%. We also conduct experiments when using cross-luminosity validation (model → predicted), however, in that case, the classification accuracy drops around 85%. Interestingly, higher accuracy is obtained when we use darkness subset to predict ambient light measurements. This suggest that the darkness subset is sufficient to train the machine learning algorithms. This is a useful advantage for constrained AUVs underwater as reducing processing and battery drain while preserving high accuracy is key for enabling long duration monitoring. Overall, the results demonstrate that PENGUIN's optical sensing approach provides a sufficiently accurate coarse-grained classification of plastic underwater in different luminosity conditions.

4 RELATED WORK

Plastic pollution monitoring: Traditionally plastic pollution has been monitored through visual surveys carried out designated sampling areas [26]. Examples include dive surveys at reefs or other sensitive areas, beach surveys carried out at carefully delineated sections of beach areas, and aerial surveys focusing on areas where

Table 2: Plastic classification accuracy in different experimental conditions. Model data → Predicted

Test	k-NN	Random forest	Average
Cross Validation			
All conditions 6-folds	0.95	0.95	**0.95**
Ambient 6-folds	0.96	0.95	**0.96**
Darkness 6-folds	0.94	0.96	**0.95**
Model data → Predicted			
Ambient → All conditions	0.80	0.80	**0.80**
Ambient → Darkness	0.69	0.68	**0.69**
Darkness → All conditions	0.95	0.95	**0.95**
Darkness → Ambient	0.94	0.92	**0.93**
Average	**89.0**	**88.7**	**88.9**

currents accumulate materials, such as the Great Pacific Garbage Patch [26]. The main issue with these methods is that carrying out the necessary surveys is highly laborious and time-consuming, which limits the scale and resolution of monitoring. Similarly to our approach, these methods are restricted to plastics that can be easily seen. Smaller plastics are typically monitored with the help of water samples collected from multiple areas. The idea is to estimate the number of plastic particles inside the sample and then extrapolate total extent of pollution from the aggregate of all samples. The main issues with water sampling are that the results can be sensitive to locations where the samples were collected, collecting and analysing the samples is laborious and time consuming, and that the methods only capture plastics that have heavily degraded. Indeed, while capturing the extent of micro-plastics is essential for understanding the health of aquatic environments, it is more beneficial if plastics can be detected before they are degraded as cleaning intact plastics is significantly easier than removing micro-plastics [3].

AUV Monitoring: AUV-based underwater monitoring is becoming increasingly common with examples include pipeline and oil spill monitoring [29], fish school estimation [15], debris recognition [36], and underwater surveillance [12]. The application areas have mostly been driven by the restrictions of current AUVs, focusing on domains that can operate using computer vision and where the monitored area is relatively small. There have been also some efforts at underwater pollution monitoring, with particularly chemical plume tracing, i.e., finding the source of chemical contamination, being actively pursued [7]. In terms of plastic pollution, existing AUV solutions mostly focus on surface-based solutions, such as solar powered rafts [27]. Indeed, to our best knowledge, PENGUIN is the first AUV solution for monitoring plastic pollutants and providing detailed information about their characteristics.

Plastic Recognition: Plastic recognition and classification is a special case of material sensing, which has been actively pursued, e.g., for facilitating automatic recycling [30]. For plastics, the most common detection approaches rely on various infrared-based techniques, with Fourier-transform infrared spectroscopy [14], near infrared spectroscopy (NIRS) [34] and hyperspectral imaging being common techniques [17]. Unfortunately, these solutions are difficult to adopt in underwater environments as the required sensors are bulky, expensive, and power hungry. Another challenge with these techniques is that infrared suffers from poor water penetration, making it ill-suited for underwater operations. Recently, there have been efforts at harnessing wireless sensing [5] for material recognition. Similarly to infrared-based techniques, this approach suffers from poor propagation characteristics, which limits its suitability for underwater contexts. PENGUIN relies on sub-infrared optical sensing which has short wavelength and is capable of penetrating water more efficiently than other techniques.

5 DISCUSSION

Remote Interfaces: We envision PENGUIN to be used for large-scale monitoring of wider aquatic areas, such as oceans. Attempting to cover the entire area is clearly infeasible, and instead we expect monitoring to target specific regions, e.g., reefs or areas where currents converge. To support this type of monitoring, there should be support for remote operators who can specify bounds of areas that need to be monitored and inform the AUVs on potential constraints, e.g., maintaining a minimum distance from marine wildlife. Supporting these remote interactions require interfaces to configure, visualize and plan the operations of AUVs.

Room for improvements: Our results demonstrate that an off-the-shelf light sensor (smartwatch PPG sensor) can characterize different types of plastics. While the sensor needs to be in close proximity of the plastic surface to characterize it accurately, it could be possible to rely on other frequencies of optical light to increase the distance to the sensing target. In addition, recognition could be augmented with other modalities to improve detection of plastics, e.g„ thermal imaging [8, 21]. We are also interested in increasing the range of pollutants that can be detected using our proposed system, including detecting the surface type of the materials [9]. Further work is also required to establish cooperation routines between AUVs for performing collaborative tasks [10], such that the burden of individual AUVs is minimized.

Micro and nano plastics: Our work aims at early detection and intervention by recognizing and classifying different pollutants, instead of trying to monitor so-called micro and nano plastic. Degradation of plastics in underwater environments is one of the main contributors of micro and nano plastics, and hence monitoring debris occurrence can help in mitigating their formation. Classification of plastics, in turn, helps with estimating the likelihood and speed of degradation processes [25], and helps in selecting appropriate cleaning measures. Our approach can also help coordinate micro and nano plastic monitoring efforts, e.g., by highlighting areas with significant plastic accumulation and then inform surface-based monitoring solutions to collect water samples from these areas.

Water properties: Water properties can change drastically, e.g., related to temperature or water flow. These changes affect characteristics of light propagation and can affect the accuracy of optical sensing. For instance, plastics can be found stuck in frozen water areas [4]. Thus, further research on ensuring the robustness of the sensing against different water characteristics is required.

Re-purposing optical light sensing: Our work demonstrated that PPG can be used to recognize different types of plastic. This could be used to develop wearable applications that can educate the user about plastics in everyday situations. For instance, a supermarket visitor could use a smartwatch to decide on what kinds of

plastic products to purchase based on how polluting they are to the environment. This implies however, a new design for PPG, such that it can be easily use by users without the need to remove it.

6 SUMMARY AND CONCLUSIONS

We presented our on-going efforts to develop PENGUIN, a system for underwater sensing of plastic pollutants using AUVs. PENGUIN uses off-the-shelf sensing and computing devices to provide identification and classification of plastics at low cost. Our system extends the scope of underwater pollution monitoring solutions by enabling the possibility of not just detecting debris material underwater, but also classifying them according to their material type, e.g., different plastic types. PENGUIN also augments the processing capabilities of the AUVs with waterproof micro-clouds, which can then be used to improve the autonomous decision making mechanisms of AUVs as well as to enhance the planning coordination for better high quality sampling in wider underwater areas.

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