

Plastic Pellets on Riverbanks: Combining Smartphone Imaging and SWIR Hyperspectral Unmixing

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Keywords: marine litter, plastic pellets, hyperspectral unmixing, smartphone imaging, feature detection.

Abstract

Plastic pellets (2-5 mm industrial feedstock granules) are an increasingly important component of plastic pollution in aquatic environments. Their small size, variable weathering state, and similarity to natural substrates such as sand and gravel make their detection and characterization challenging. This study, conducted within the SSPIRIT project, investigates a complementary remote sensing approach for detecting and mapping plastic pellets on riverbanks and coastal environments.

Two detection strategies are explored. First, very high spatial resolution RGB imagery acquired by drones and smartphones is used to detect individual pellets and estimate their abundance and spatial distribution. Second, SWIR hyperspectral imaging is employed to exploit the distinctive spectral signatures of common polymers such as polyethylene, polypropylene, polystyrene, and PVC. This enables both discrimination of pellets from natural background materials and identification of dominant polymer types.

A dedicated spectral library is being developed by combining existing open-access measurements with new laboratory spectra of virgin and weathered pellets, including bio fouled samples. Field acquisitions using a VNIR-SWIR hyperspectral imaging system will support the evaluation of sparse spectral unmixing techniques for estimating pellet abundances within mixed pixels. Initial RGB and multispectral datasets have already been acquired, while spectral measurements and field campaigns are ongoing. Preliminary results will be presented, together with an assessment of how high-resolution feature detection and hyperspectral unmixing can be combined to improve plastic pellet monitoring in riverine and coastal environments.

1. Introduction

Plastic litter, especially in marine environments, is widely recognized as a worldwide problem with large ecological impact. In recent years, major efforts and advancements have been reported to establish large scale detection and monitoring using remote sensing. However, challenges remain because plastic pollution in aquatic environments is very heterogeneous in shape, size, colour and density.

In this work, we focus on one specific type of litter: plastic pellets (also called nurdles). These are small, bead-like granules (2–5 mm in diameter) with uniform sizes and shapes that serve as raw material for manufacturing plastic products. They are generally made of common polymers like polyethylene (PE), polypropylene (PP), polystyrene (PS), and PVC.

Pellets are spilled at industrial sites during production, handling and processing, and during transport both on land and at sea. Often through harbours, they enter estuaries, seas and oceans and end up massively in coastal habitats (as shown in Figure 1-1) and in food chains of fish and birds. Since cleaning efforts only yield limited benefits, prevention of loss the preferred mitigation solution. Since loss can take place at many locations, mapping of plastic pellet distributions and identification of critical points is important.

Yet detecting pellets in natural environments like beaches and riverbanks is challenging because they are very small and look very similar to other items like sand grains, and because they are mixed with other debris or entangled in tidal deposits and vegetation. An example of pellet in a natural environment is shown in Figure 1-1. Detailed spectral signatures can help

distinguish pellets from natural backgrounds and potentially also recognize specific types of polymers.



Figure 1-1 Pellets in a natural environment

The work described is part of the SSPIRIT project, funded by VLAIO (Flemish Agency for Innovation and Entrepreneurship). The SSPIRIT project proposes an integrated remote sensing approach that combines aerial, underwater, and satellite observations to monitor plastics of all sizes throughout the water column. The approach uses direct detection whenever possible and complements this with proxy indicators where direct observation is not feasible. In addition, geomorphological indicators are investigated as indirect proxies for the presence of plastic pellets.

2. Methodology

To detect pellets in their natural environments, we investigate two complementary approaches. The first approach is based on the geometrical properties of the pellets as round objects with a specific size range. The second approach uses the spectral signatures of the pellets as polymers which are different from the spectra belonging to the other items in natural environments.

Note that for both approaches, the spatial resolution is a dominant parameter: directly since a very high resolution is needed to capture the shape of individual items, or indirectly because a high resolution is needed to capture a sufficient contribution to the spectral signal from items vs background.

2.1 Geometric Detection

2.1.1 Spatial Resolution

The first approach aims to detect pellets based on the geometry of individual items. This implies that the imaging of the areas on which pellets will be detected is performed with a spatial resolution which is detailed enough to resolve the shape of the pellets. Recalling the typical size of pellets (2-5 mm), the images need to resolve at sub-mm level.

This requirement may seem very stringent. For drone imaging, it requires a combination of a very high-resolution imager and flying at low altitude. However, when we consider taking images handheld with a regular consumer smartphone, the requirement is easily fulfilled. The typical convenient height above the ground is small, and present-day smartphones offer imaging at least with 3000x4000 pixels, and offer much higher pixel counts. In our experiments, we used 6112x6112 pixel images.

Our initial acquisitions (an example is shown in Figure 2-2-1) revealed that the resolution of the images was indeed sufficient so that individual pellets can be detected and counted by a human. Such a manual process is however prone to human errors, and prohibitively tedious and time consuming to be used in practice.

2.1.2 AI model for automatic detection

Thus, our goal is to establish reliable automatic detection and high precision counting of individual pellets starting from similar imagery. The specific shape and sizes of pellet make this a well constrained object detection problem, for which the major challenge lies in the variability of the backgrounds and acquisition parameters.

In the last decade, major progress has been made in creating general purpose object detection models using neural networks. The YOLO framework is particularly widely used for many different tasks because it allows to rapidly build performant systems. Within the framework, we selected a modestly sized implementation: the YOLO 11 model ((Khanam, 2024)



Figure 2-2-1 original smartphone RGB image, showing pellets within a wooden quadrant of 50cm by 50cm at a natural site in the port of Antwerp.

2.1.3 Adaptation of the model

The YOLO 11 model is a convolutional neural network, which does not contain a transformer. It has been designed for rapid real-time inference. It is a so-called nano-model, containing a modest number of parameters. Computer vision models like YOLO often struggle with two aspects. Firstly, very high pixel count imagery causes it to reach memory constraints. Secondly, the amount of labelled data is often quite small to perform the learning. We made specific adaptations to address these limitations.

To process the native high-resolution images without down-sampling, we utilized a **tiled inference strategy**. Images were subdivided into a grid of discrete tiles for prediction. These local predictions were then mapped back to the global coordinate system to reconstruct the full-frame count.

We optimized the YOLO model for small datasets through **contrastive learning**. By fine-tuning a pretrained backbone to maximize feature similarity between augmented views of target objects, we improved the model's discriminative power despite a limited pool of manually labeled images.

2.2 Spectral detection

Pellets are made of polymers which exhibit distinct spectral characteristics, esp. absorption peaks in the SWIR spectral range. (Castagna, 2023). This should allow not only to detect them against other materials and backgrounds but also distinguish between different plastic types.

The detection can be performed using spectral unmixing techniques. They are very well suited to estimate abundances of a set of materials with distinct spectral signatures from imagery which contains mixed spectra. Within the SSPIRIT project, a well-tailored spectral unmixing approach has been implemented and tested for spectral determination of macro litter. This method will be reused for the pellet detection using the specific spectral library.

Spectral unmixing methods require a spectral library containing reference spectra of the different materials and backgrounds expected to contribute to the spectral signals. The success of spectral unmixing depends critically on the quality of the spectral library. Therefore we concentrate our efforts on building a good spectral library for pellet detection.

We create a spectral library containing spectral reflectance measurements of pellets, as well as a representative set of background materials e.g. concrete and sand. We maximally incorporate existing measurements from open databases to represent a wide range of background and materials. For the pellets however, only limited measurements exist. Therefore, we will perform systematic spectroscopic measurements of different types of pellets in a controlled lab environment, including pellets with various degrees of weathering (including degradation and biofouling).

The resulting images will be used as input to perform spectral unmixing, with the spectral library (or a relevant subset) acting as the reference library of spectral endmembers. A sparse unmixing approach will be used, which favours outputs which are a combination of a limited number of endmembers, thus focusing on creating abundance estimates of the main constituents.

Spectral measurements were performed in 2 independent ways: Single point spectral measurements were carried out using an ASD handheld point spectrometer, covering the full 400nm to 2500nm spectral range. To measure different types of pellets, a pile of them was placed in a small bowl, ensuring that the whole field of view of the spectrometer was filled with pellet material.

The second method uses a Specim FX17 900–1700nm imaging spectrometer, mounted above a translation stage. The translation stage provides the necessary forward movement to allow scanning of an area. The areas used were flat backgrounds (white and black have been tested) with individual pellets of different types (different polymers, virgin and weathered, ...)

In future we will also perform hyperspectral acquisitions over a selected site, using a high-end VNIR–SWIR hyperspectral camera (covering ~900–2500 nm) mounted on a tripod for controlled site imaging. Later campaigns may use drone platforms for aerial coverage.

3. Results and discussion

3.1 Geometric Detection results

Ground truth is first collected by using traditional field sampling using 50x50 cm wooden quadrats laid out in a natural environment, at locations near the waterline. Most of them abundantly contained pellets, but also some background images were included. For each of the quadrats, a smartphone image was made that fully contains the quadrat frame. For selected frames, the top layer of sand, pellets and other debris was collected to allow offsite analysis after imaging.

We collected a total of 531 images, for each of the images was cropped to the area inside the quadrat. 383 images were used for training the YOLO model, while the remaining 148 images were used for validation. During the training phase the whole data set (with each image split in tiles) is presented to the model and the weights of the model are optimized. This process is repeated iteratively in epochs. We monitored the loss functions

on the training and validation data to track the evolution of the learning process.

When 100 epochs are executed (a process that takes only a few minutes to complete) we see following behaviour. After about 10 epochs, the output has already become quite stable. Results improve slowly until at least 50 epochs, after which the results stabilize. To avoid overfitting, which is when the model tailors to the specific examples in the training dataset, losing the general ability to also detect the pellets in new, unseen examples, the model after 50 epochs was taken as final result.

The results depend on the choice of the confidence threshold. If we choose the threshold at 0.5; we achieve a precision mean Average Precision (mAP) of 90–95% and a recall of 85%. The confusion matrix is shown in Figure 3-1.

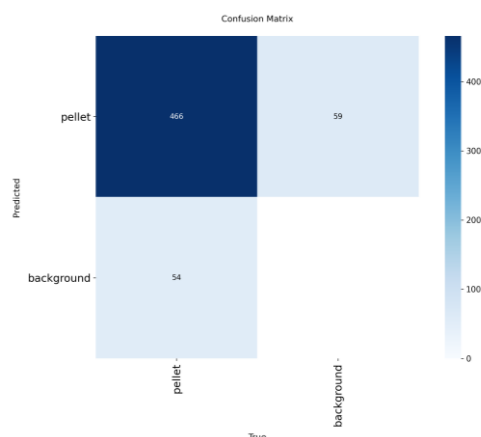


Figure 3-1 confusion matrix

To assess if the results obtained correspond to what is expected, it is instructive to inspect the results of individual pellets detected by the method. We show a representative example of the detection of pellets in a quadrant in Figure 3-2. The blue boxes drawn around every detected correspond well to what a human would indicate as pellets.

The results demonstrate that contrastive learning is a highly effective regularizer for object counting in low-data regimes. Robust detection from compact training set using a small and fast YOLO model is demonstrated, enabling to quantify the spatial distribution of pellets and identify hotspots.

In our experiments, images were subdivided into tiles, as a practical approach to deal with very large images. A simple tiling scheme with no overlap between the tiles was used, which inevitably causes edge effects at the edge of the tiles. In a future refinement of the method, the tiling approach will be modified to include a sliding-window, which can mitigate boundary-related loss.



Figure 3-2 Top: object detections via a YOLO Computer Vision model over the whole quadrant; Bottom: one part of the RGB image with pellet detections denoted as blue boxes around individual items.

To test the capacity of the model to generalize, it was also used to detect pellets in 2 unseen environments. The first environment is a setting with concrete pavement tiles as used on roads. An example is shown in Figure 3-3, where the top image gives a detailed view of the concrete tiles, with some pellets present. For a human, the pellets are difficult to see because the background looks quite similar. Still, as shown in the bottom part of Figure 3-3, the model manages to detect many of them.

Encouraged by this, but also because we wanted to rule out that this was an outlier result, we performed a similar test for a second unseen environment: terrace ceramic tiles which have a more even surface with much less structure, and a glossier appearance.



Figure 3-3 Pellets on pavement. Top: zoomed in on small area. Bottom: complete smartphone image, with detected pellets indicated with blue boxes.

An example is shown in Figure 3-4. Again, the zoomed in top image shows pellets on the terrace tiles and on the joints between them. The bottom image shows detection results on a larger area. Also this example shows decent detection of many pellets for this new environment.

In the experiments above, the environment did not naturally contain any pellets. Therefore, small numbers of pellets were sprinkled over the areas. The pellets were counted before applying them onto the areas, so their numbers were known, providing a reliable reference. By comparing the reference number to the number of pellets found in the images we can get a quantitative assessment of the accuracies that can be reached.

We show overview results in Figure 3-5. They show that while the method fail to detect some pellets, and may falsely find some others, the overall numbers of pellets found correspond well with the ground truth numbers. This demonstrated that the model is also useful for unseen environments



Figure 3-4 Terrace tiles Top: zoomed in on small area. Bottom: complete smartphone image, with detected pellets indicated with blue boxes.

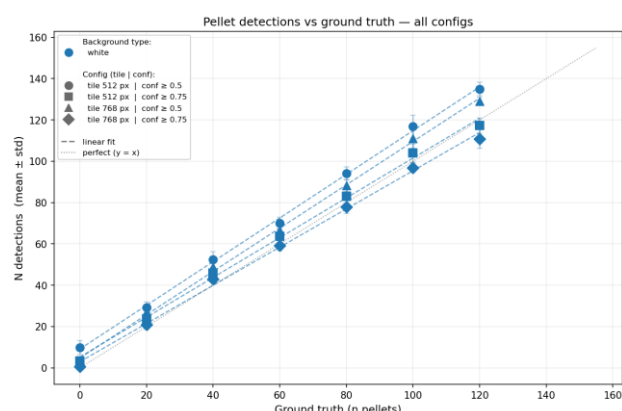


Figure 3-5 estimates of number of pellets detected vs ground truth

3.1 Spectral Detection results

We present example results of spectral measurements of piles of pellets using the ASD spectrometer (selected for demonstration purposes from a much larger set). We select 5 types of pellets, obtained from a pellet manufacturer: polypropylene (PP), amorph virgin, amorph FRH, unlabelled darker grey and unlabelled lighter grey. The resulting spectral measurements are shown in Figure 3-6.

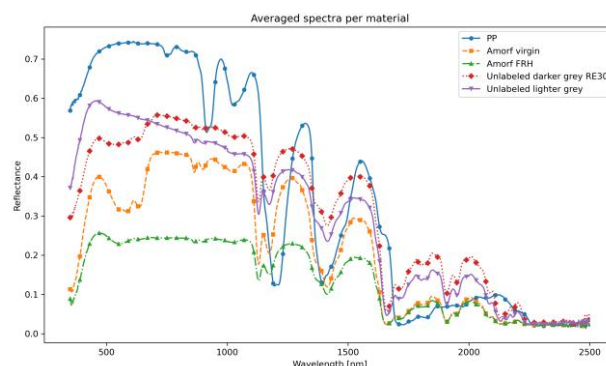


Figure 3-6 example spectra: measured for point spectrometer. Figure 3-6

The second measurement method using an imaging spectrometer produces hyperspectral images in which individual pellets as visible, giving detailed spectral information at a very high spatial resolution. Individual pellets were laid out on a background as shown in Figure 3-7, top. An RGB rendering of the resulting hyperspectral image is shown in Figure 3-7, bottom, demonstrating the level of spatial detail at which the spectral information is captured.

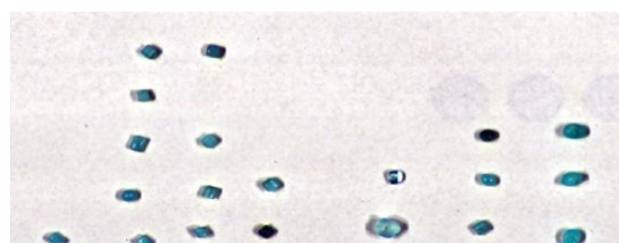
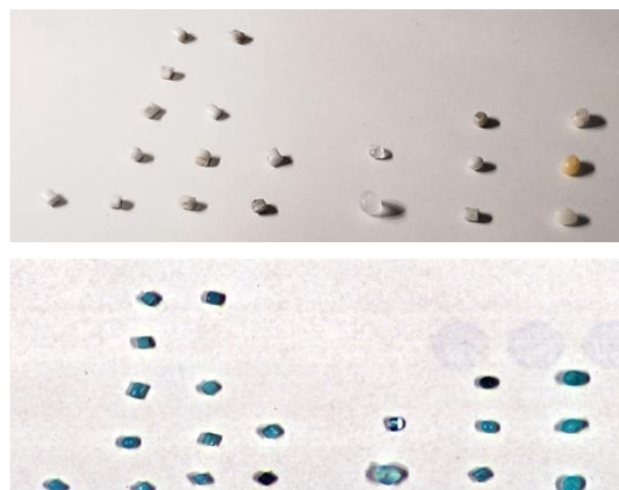


Figure 3-7 top: oblique visual image of placement of plastic pellets. bottom: RGB rendering of hyperspectral image of the same area

To compare the two sets of measurements, we collected the sets of per pixel spectra per pellet and calculated the mean and standard deviation of each spectral reading. This results in a set of spectra representing the different pellets. We show results for the same set of 5 pellet types as shown before. The resulting spectra (including standard deviations) are shown in Figure 3-8.

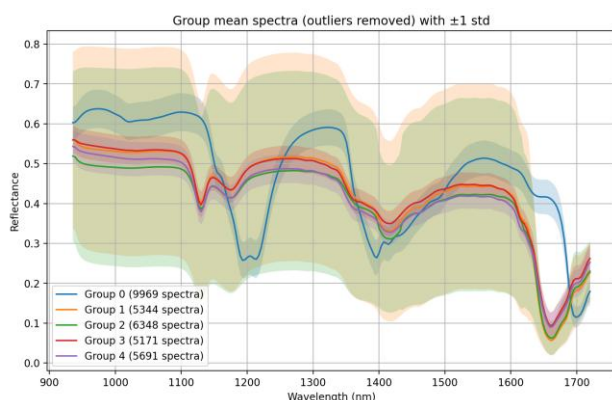


Figure 3-8 spectra of individual pellets compiled from hyperspectral images.

When comparing them to the spectra measured with the point spectrometer, we see good correspondence in spectral shape & features. However there are large variations in absolute reflectances, which we suspect can be contributed to difference in illumination. This indicates that hyperspectral acquisitions, while at lower spectral resolution, can yield complementary information on the major types of pellets in an area, which links to the sources of the pellets.

4. Conclusion

We have proposed two complementary approaches for the detection of plastic pellets.

In the geometric approach, the goal is to provide direct estimate of pellet abundance based on geometric features. In the experiments, we have shown that reliable estimates can be obtained based on a neural network based YOLO model using contrastive learning with tile-based inference, using a relatively modest input data set. It provides a scalable foundation for high-precision field data collection using ubiquitous mobile devices.

For the spectral approach. A spectral library has been established. Spectral measurements have been performed in the lab in two distinct ways. First single point spectral measurements have been carried out. They provide accurate spectral information for the pellet materials. Secondly, an imaging spectroscopy setup using a translation stage allowed to create hyperspectral imagery of pellets at very high resolution, resolving individual pellets. This gives valuable information on the spectral variations occurring in pellets, mainly due to the interaction of their 3D structure with the illumination.

In the next phase, hyperspectral field acquisitions will be performed. The resulting hyperspectral imagery will then be analysed using the unmixing approach as described, using the spectral library. This should allow to identify the different material types.

The geometric and spectral approaches constitute complementary sources of information. The results obtained can give a basis to advance plastic pellet detection. Currently, we are exploring the combined use of both approaches. Such combined use can lead to both accurate localisation and material identification of plastic pellets.

The integration of high-resolution detection and hyperspectral analysis supports the objectives of the SSPIRIT project. Its expected added value lies in the fact that it offers prospects for

scalable monitoring of pellet pollution along riverbanks, in ports and in coastal areas, and can support future operational monitoring campaigns.

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