UNIVERSITY OF TARTU
FACULTY OF SCIENCE AND TECHNOLOGY
Material Science and Technology Curriculum

Mayowa Olapade O

Autonomous Monitoring of Litter using Sunlight

Master Thesis (30 EAP)

Supervisor: Huber Flores

TARTU, 2021

Abstract

Litter has become a major concern worldwide due to human overpopulation, deficient human practices and poor garbage collection systems. Existing methods to overcome the problem of litter are mostly manual and require human intervention. More sophisticated automated methods have also been designed, but they have limited coverage and are difficult to scale and deploy at large-scale. Indeed, automated approaches to identify litter automatically require continuous supply and access to battery resources. In this work, we develop LIZARD, a new innovative sensing approach that exploits sunlight to recognize litter materials. LIZARD piggybacks sunlight radiation absorbed by materials when lying on open areas. By analyzing the thermal characteristics of these materials using off-the-shelf thermal cameras, it is possible to identify and classify different types of litter materials. We validate our approach through extensive empirical benchmarks, demonstrating that LIZARD can recognize different materials sizes and shapes using sunlight. In addition, we integrate LIZARD with terrestrial unmanned autonomous vehicles (UAVs) to demonstrate that our approach is lightweight and easy to scale. Our solution paves the way towards new efficient and green solutions to monitor litter in open areas, e.g., public spaces in a city.

CERCS: P170 Computer science, numerical analysis, systems, control

Keywords: thermal imaging, waste management, mobile computing, pervasive computing, recycling solutions, IoT

Inimesest eraldunud soojusliku kiirguse kasutamine

kokkuvõte: Tulenevalt ülerahvastusest, puudulikest käitumisharjumustest ja viletsatest prügi kogumis- ja ladustamissüsteemidest on risustamisest saanud tähtis globaalne probleem. Olemasolevad risuga tegelemise meetodid vajavad enamjaolt inimeste käsitsi sekkumist. On olemas ka peenemaid automatiseeritud meetodeid, kuid need on alaliselt piiratud ulatusega ja suuremõõtmeliselt on neid keeruline rakendada. Näiteks vajavad automaatsed lähenemised risu tuvastamisele pidevat ligipääsu akulaadimisvõrkudele. Käesolevas töös kirjeldame LIZARD süsteemi arendust, mis on innovatiivne lähenemine risu tuvastamisele kasutades ära päikesevalgust. LIZARD kasutab ära risu materjalide UV-radiatsiooni imandumist valguse käes oleva prügi materjalis. Analüüsides erinevate materjalide termilisi omadusi olemasolevate termokaameratega on võimalik tuvastada ja liigitada erinevaid prügi liike. Kontrollime oma lähenemist ulatuslike empiiriliste võrdlustega ja demonstreerime, et LIZARD suudab ära tunda erinevaid materjale, suuruseid ja kujusid päikesevalguse abil. Sellele lisaks integreerime LIZARD süsteemi maapealsete mehitamata autonoomsete sõidukitega (UAV-d) demonstreerimaks meie lahenduse lihtsust ja skaleeritavust. Loodud lahendus sillutab teed uutele tõhusatele ja jätkusuutlikele lahendustele risu jälgimiseks avalikus ruumis nagu näiteks linnaruumis.

CERCS: P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine

Märksõnad: termopildistamine, jäätmekäitlus, mobiilne andmetöötlus, kõikehõlmav andmetöötlus, ringlussevõtu lahendused, IoT

Contents

List of Figures

List of Tables

LIST OF TABLES

Acknowledgements

A very big thank you to my family with whom have provided me with the support to write this work. I would like to appreciate Prof. Dr. Huber Flores for giving me the opportunity to learn under his tutelage and his outstanding contributions during every phase of the project. My gratitude would not be complete without special mentions to Mohan Liyanage and Zhigang Yin for their relentless efforts during the experiments; their support cannot be overestimated on completing this work. Finally, huge thanks to my program coordinator, Hele Simon who is ever willing to listen and help and special mention to Aivar Pere for his encouraging words always.

1

Introduction

1.1 Introduction

Litter has become a major concern worldwide due to human overpopulation, deficient human practices and poor garbage collection systems (1). The main problem of human littering is that it causes pollution in natural ecosystems (2, 3). It also can be understood as a social problem, whose behavior is easily spread out and cultivated into others but rather difficult to eradicate - litter in public spaces causes more litter (4, 5). Litter can easily persist into any environment once is introduced in it. Litter is problematic as it blends in with the environment as the time goes by (6, 7). Indeed, as part of the decomposition process of any litter object, either caused due to exposure to environmental factors, e.g., sunlight; and urban induced degradation, e.g., damaged by human activity; litter objects break apart over time into smaller pieces that are difficult to extract from the environment. Moreover, litter as former end products are manufactured from materials that have long lifespan, e.g., plastics can last up to 50 years (8). As a result, litter can be easily accumulated over time, aggravating the problem of pollution silently.

Existing methods to remove litter from the environment rely mostly on volunteers and human cleaning activities through visual and manual inspections. These activities can be effective when performed regularly (before litter breaks). However, these activities are costly, require strong planning and logistics, e.g., campaigns. Thus, they are not a long term solution (9, 10). In contrast, automated methods mostly rely on object detection techniques to spot litter, such that it can be removed (11, 12). For instance, mounting a camera in an aerial drone to identify litter in a location (13). While these techniques can aid to overcome the problem of litter, they are difficult to scale and to adopt for continuous monitoring. Indeed, object detection techniques are resource intensive applications with low discriminatory power. Similarly, other available solutions provide better recognition accuracy, but they have lower spatial coverage and cannot be applied continuously over long time periods due to constrained resources, e.g., laser-based classification (14). This suggests that a rich infrastructure ecosystem needs to be also in place to support these applications. For instance, proximal computing support though edge deployments and charging stations to power up batteries (15).

In this master thesis work, we propose LIZARD, an autonomous pervasive sensing system that can sense and monitor litter though sunlight. LIZARD uses the fact that litter in public spaces is exposed to sunlight over long periods of time. By piggybacking the absorption of sunlight by the litter object, it is possible then to identify its type and recognize its material. To achieve this, LIZARD analyzes the dissipation time of absorbed thermal radiation using a thermal camera. In addition, when the litter object is not clearly identifiable though its thermal dissipation, LIZARD also implements a light-based mechanism to investigate further the characteristics of the object. This mechanism obtains exploration instructions from the thermal analysis, such that the area to analysis is reduced. We conduct rigorous evaluation to analyze the performance of LIZARD to detect and identify litter of different sizes.

1.2 Contributions

The following sums up the contributions:

- **Novel method:** We develop LIZARD as a novel sensing approach for monitoring litters using thermal dissipation footprints from sunlight.
- **Novel insights:** We demonstrate through extensive benchmarks that enough thermal radiation (from sunlight) can be absorbed by materials, such that it is possible to piggyback that absorption for recognizing materials of different sizes and shapes (from plastics to micro-plastics).
- **Improved performance:** We conduct a rigorous evaluation that demonstrates that our proposed approach is more efficient in terms of cost when compared with existing state-of-the-art approaches that are based on light reflectivity.

1.3 Outline

This thesis is structured as follows:

- Chapter 2 reviews the state-of-the-art about infrared thermal imaging, its limitations as well as its application in computer systems. Also, we review different material recognition technologies and sustainable solutions for litter pollution.
- Chapter 3 presents a feasibility analysis of using thermal radiation to recognize different litter materials
- Chapter 4 demonstrates that thermal radiation can be used to recognize litter materials of different sizes and shapes.
- Chapter 5 presents our overall LIZARD system evaluated in the wild. It also demonstrates that thermal radiation that is absorbed by materials from sunlight can be piggybacked to recognize materials.
- Chapter 6 discusses the implications and limitations of our work
- Chapter 7 presents the summary and conclusion of our work

2

State of the Art

This Chapter is a review on thermal imaging technology and other material sensing applications, these broad concepts will be the foundation of this thesis. Some of recent research advancements useful for our study will be reviewed. A background knowledge on different sensory technologies will be highlighted, however the focus will be on thermal sensing used in computer systems. We then review previous knowledge based on material sensing and how they have been used to address litter pollution in the past. We will also look to improve the studies that have shown little uniformity in litter detection for subsequent extraction, and quantification (16).

2.1 Sensor devices

The purpose of a sensor is to respond to an input physical property (stimulus) and to convert it into an electrical signal that is compatible with electronic circuits. All sensors may be of two kinds: passive and active. A passive sensor does not need any additional energy source and directly generates an electric signal in response to an external stimulus. The active sensors require external power for their operation, which is called an excitation signal. Examples of passive sensors include thermocouple, photodiode, and infrared thermal imaging (17).

2.2 Thermal imaging

Infrared thermography is the science of detecting infrared energy emitted from an object, converting it to an apparent temperature, and displaying the result as an infrared image that is captured by a thermal camera. It is a very rapidly evolving field in science as well as industry owing to the enormous progress made in the last two decades in microsystem technologies of IR detector design, electronics, and computer science (18). These cameras involved work in an environment without ambient light and can penetrate thick fog such as smoke and haze. Thermal cameras record thermal infrared radiation (TIR) unlike the digital photograghic cameras. Since all objects emit infrared radiation in the long-range spectrum it becomes possible to capture images even at night with no visible light (19). The visible light is defined by the sensitive range of the light receptors in our eyes, only covers a very small range within this spectrum, with wavelengths from 380 to 780 nm. There is an adjacent spectral region with wavelengths from 780 up to 1 mm which represents the infrared, followed by microwaves, RADAR, and all electro-magnetic waves that are used for radio, TV, and so on (20). This range of wavelengths corresponds to a frequency range of approximately 430 THz down to 300 GHz (21). Infrared waves are given off by all objects at temperature above absolute zero. Thermal imaging determines an image temperature based on the absolute temperature of the object. The image formed is based on the object's heat signature and records the items' current signatures based on their heat pattern. When image analysis is going on, the thermal infrared camera heats-up, therefore creating a thermal radiation source. Radiometric calibration is performed by the inbuilt thermometer at regular time intervals to leverage on the heat. During calibration, frames are recovered due to a plate of known temperature is attached in front of the sensor. However, machine learning applied to thermal imaging camera calibration allowed the recognition of its digital information with high accuracy for the classification of individual temperature values (22).

2.2.1 Thermal detection types

Thermal detection works on a principle that changes some of a material's measurable properties due to the rise in temperature of that material caused by electromagnetic radiation absorption (23). The resistive bolometric effect, the pyroelectric effect, and its modification (known as either the bias enhanced pyroelectric effect or the ferroelectric bolometer) and the thermoelectric effect (23) are widely applicable. However, there are several thermal detection mechanisms. Uncooled microbolometer is a common type of thermal detector made of a metal or semiconductor material sensitive to temperature primarily developed with thermal and ferroelectric microbolometer detectors (using Barium Strontium Titanate (BST) as detector material, which suffers from halo effect) (24). Due to their advantages over ferroelectric detectors, microbolometers have more economic value.

2.2.2 Advantages and limitations of thermal imaging

Thermal imaging does not require any additional lighting unlike visible light cameras. This means that thermal cameras can be installed very discreetly while remaining highly effective. This makes thermal cameras the ideal choice for surveillance and defense applications. Again, unlike visible-light cameras, thermal cameras generate virtually no maintenance costs. While the initial purchase price is often higher, over time, thermal cameras are a more cost-effective. Fog and outdoor lighting do not affect the images. In other words, performance is guaranteed in a variety of conditions. However, unlike visible light, infrared radiation cannot go through water or glass. Infrared radiation is reflected off glass, with the glass acting like a mirror. This is a major disadvantage for uses like capturing images of individuals in cars. It can be used in detecting people without identifying them, making sure privacy is intact. Also, another limitation is their viewing angles cannot be easily avoided unlike other point-based methods(24).

2.2.3 Thermal imaging application in computer systems

With the growing influence of thermal imaging, this section briefly discusses thermography as an applicable technology in different fields. It helps us to apply scientific principles in a transparent way and to assess the performance results This detection technique is used in computer systems, which uses sophisticated image analysis algorithms and a computer to reconstruct the images to show heat patterns.

Medical thermography: Thermal imaging is presented as a diagnostic method, which can detect thermal anomalies in medical analysis. Computer systems are being used for image processing and monitoring of changes in thermal radiation. Thermography based computer-assisted detection/diagnosis (CAD) systems help to screen for fever patients in areas with a high influx of people, such as airports and border crossings (25, 26). The early detection of the diabetic foot, specifically, CAD systems for diabetic foot

(27), help prevent complications and amputation. Early stage of tumors also has been revealed, most notably breast cancer (28). Medical issues such as the behavior of ciliary muscle of the human eye (29), the periodic fluctuation in skin temperature (30) or blood flow rate measurement in superficial veins (31), and the assessment of environmental conditions of detected corpses can be studied from thermal images(32).

Facial analysis: Faces of individuals are a biometric trait that can be used in an automated computer-based security system for authentication purposes. Investigating and developing methods for the improvement of face recognition by experts in this field (33). Using the information gotten by face heat radiation, humans' stress levels can be detected using thermal imaging. The thermal facial analysis was used for deception detection (34). Pavlidis et al. (35) also proposed how the technique can be used to capture anxiety.

Fire detection and military: It is popularly used by the army and navy for border surveillance and law enforcement. It is also used in ship collision avoidance and guidance systems. In the aviation industry it has greatly mitigated the risks of flying in low light and night conditions. They are widely used in military aviation to identify, locate, and target the enemy forces. Recently, they are also being incorporated in civil aviation for health monitoring of aircrafts (36). Mobile robots can be used for fire detection systems (37) by locating the hot spots, the robot is placed in the direction of the fire source. Arrue et al. (38) proposed an alternative real-time infrared-visual system for forest fire detection, composed of both visual and thermal cameras coupled with meteorological and geographical information. In the military, Price et al. (39) worked on the Gunfire Detection and Location (GDL) system for military applications to detect gunfire. Gunfire validated by acoustic events is detected in Mid-Wave IR (MWIR) imager.

Aerial thermography: Recent advances in the sophistication of thermal cameras, the reliability of commercial drones, and the growing power of photogrammetric software packages can collect, process, and analyze aerial thermal imagery. Various studies have investigated methods of using drones for problem-solving, be it in the delivery service industry(40), video surveillance(41), rescue(42), which can produce the output with increasing levels of complexity which is sometimes beyond the scope of danger to humans. Thermal sensors have been coupled into some UAVs for tracking and supervising the behavior of certain physical property and temperature changes over time.

Remote sensing in Unmanned aerial vehicle (UAV) which aids data collection has developed rapidly from a researching stage to a more practical approach, which is applied in various fields(43). The authors in(44), used aerial thermography to perform dense crowd detection effectively. They proposed region of interest (ROI) extraction and a two-stage blob-based approach for pedestrian detection, by first extracting pedestrian blobs using the regional gradient feature and geometric constraints. The detected blobs are classified utilizing Support vector machine (SVM) technique with a hybrid descriptor. Furthermore, in archaeology, UAVs collect aerial imagery from specific altitudes at different weather conditions at any given time. In energy conservation, it can be used to locate sources of energy losses and wasteful energy management practices. The map outlines the key environmental conditions conductive to obtaining reliable aerial thermography. The map is developed from defined visual and heat loss discrimination criteria which are quantized based on flat roof heat transfer calculations(45).

2.3 Material recognition

Recognizing material properties of surfaces and objects is a fundamental aspect of visual perception (46). Automatic material recognition can be useful in a variety of applications, including robotics, product search, and image editing for interior design (47). The use of different light spectrum parts and measuring either reflection or absorption at different frequencies is quite a common material sensing approach. A good example is the use of green light sensing to detect plastic waste (14). Also, proposed deep learning approaches for detecting different material types from reflection patterns at different wavelengths have been tried (48). Other works have used smartphone cameras to identify liquids' (49, 50).

Laser technology: Laser is an artificial light source obtained by the amplification of light by radiation emitted by activating the elements of a corresponding physical medium (51).The nature of the active substance in each set up is used for their classification(52).We have solid state, gas, liquid, semiconductor and fiber lasers(53), Laser Diode (LD) is a semiconductor device with p-n junction which emit laser radiation (range from infra-red to the UV spectrum) by applying a current in a stimulated emission process compared to LEDs. This technique allows measurement and profile of transparent materials like glass, lenses, and liquids(54). With the improvement in laser sensor technology, the size and cost of sensors have decreased, which has led to the robust use of laser sensors in many areas. Aerial laser scanning requires, receiving and registration of a signal (pulse) reflected from the object's surface, determination of the distance from the reflection point and coordinates setting computation of the reflection point laser scanning point. In addition to traditional manufacturing industry applications, laser sensors are increasingly used in robotics, surveillance, autonomous driving and biomedical areas(55, 56). It has also been found that laser's light can be modified in anticipation of the way it will travel through the disordered environment so that it hits its target on the other side with sufficient coherence for making accurate measurements(57).

Electrostatic sensing technology: This is purely based on electrostatic signal on any contact material to be identified, compared to the existing recognition methods, It is not influenced by light, electromagnetic, pressure and other factors(58). The difference of surface resistivity of different materials leads to different degrees of inhomogeneity of electrostatic charge distribution on the surface of materials(59). The conductivity of the material with low resistivity is good indicating distribution of the electrostatic charge on the surface is not uniform, while high resistivity is poor means the distribution of electrostatic charge on the surface is higher.

Hyperspectral imaging: This imaging technology is based on collecting and processing information from across the electromagnetic spectrum(60). The purpose of hyperspectral imaging is to obtain the spectrum for each pixel in the image of a scene, with the purpose of detection and identification different objects(61). Hyperspectral imaging (HSI), combined with chemometrics, was recently and successfully applied to the microplastics characterization(62). The primary advantage to hyperspectral imaging is that an entire spectrum can be acquired at each point while disadvantages are the cost and complexity.

RGB model: True color sensors are based the common RGB model (red, green, blue). A large percentage of the visible spectrum can be created using these three primary colors. Many color sensors can sense more than one color for multiple color sorting applications(63). Depending on the difficulty of the sensor, it can be programmed to know only one color, or multiple color types or shades for categorization and identification operations. They are widely used in applications in displays, photography, scanning and electronics.

Computer vision: Computer vision tasks include methods for acquiring, processing, analyzing and understanding digital images, and extraction of high-dimensional data from the real world in order to produce numerical or symbolic information(64, 65). It involves the development of a theoretical and algorithmic basis to achieve automatic visual understanding(66). For example, It is the most common IoT-based approach in waste management (67, 68). The fact that it can be trained with numerous convolutional neural networks (CNNs) makes it a valuable material recognition technology in different fields(69).

FTIR and raman microscopy: The combination of both technologies is believed to best when detecting microplastics and their respective polymer. This is best described by Kappler et al. (70). both spectroscopic methods in combination with optical particle recognition. The Gepard Enabled Particle Detection (GEPARD) program package was developed for this combination of methods to be able to carry out the measurements largely automatically(71). The program first determines all particles on a filter optically and segments not isolated particles with different algorithms. The coordinates (x,y,z), the optical image and the size of each particle are recorded. The coordinates are automatically transferred to the FTIR and/or Raman microscope, where all particles are automatically measured and identified using spectra databases. All results can be transferred to national and international databases (e.g., the “Marine Plastic Data Base”) and comfortably output by the GEPARD program.

2.4 Sustainable solutions to litter monitoring

Litter pollution is a huge problem which threatens to get bigger with waste accumulation in different landfills and oceans every year(72). There have been various techniques proposed and currently in use to mitigate the litter issue especially in the marine which has posed the greatest threat(73). Also, standards for the collection, storing and processing of observations of plastics at different environments are lacking. Some of these techniques include manual sorting, density separation, electrostatic processes, and various optical systems, including optical inspection using photodiodes or charge-coupled device (CCD) machine vision, near infrared (NIR), ultraviolet (UV), X-ray analysis, and fluorescent light or laser radiation(74). Density separation systems are used to separate particles with higher densities than water from buoyant ones. Here, the density of particles must significantly differ(74, 75). Electrostatic separation systems are used to separate a mixture of debris that can acquire different charges through triboelectrification. It is not suitable for sorting complex mixtures and the particles must be clean and dry(74, 76). Beach litter monitoring practices like Marlin and OSPAR have been used in the Baltic because of it cost effectiveness and seasonal variation data capturing(77). Remote sensing methods have been considered for detection using both passive and active sensing approaches(78). The passive method using the near infrared and short-wave infrared spectrum while the active method involved laser induced optical features or radar. However, these methods are limited to the upper ocean layer monitoring (79). The most used technique for plastic litter monitoring depend extensively on in-situ visual census approach(80). In situ research infrastructures (RIs) currently have the potential to ensure autonomous long-term monitoring, which would also provide crucial data along with the manual systems already in place. The advancement in optical sensing technology could see optical monitoring as one of the primary tools in terms of microplastic monitoring in different environment(81). Specific requirements for any technique deployed in our environment include calibration, operation and maintenance and power.

High spatial resolution imaging: Generally, this technique is applied to the visible spectrum (400–700 nm) by making true color RGB composite images. Visible images have been used, for example, to study the dynamics of rafts of marine debris(82). Litters are monitored using high-resolution cameras on fixed platforms, ship-borne, airborne and satellites(82, 83, 84). With a low-cost RGB camera onboard an unmanned aerial system (UAS), very low altitude images can be captured which are used in characterizing litters on a sandy beach(85). This is very efficient for macro litters alone(86). While military satellite technology can provide higher resolution, commercial products are limited to 25 – 50 cm, restricting their utility to several meters-sized objects. True color RGB images provide crucial information about the apparent color and shape of litter that can be used to, for example, discriminate man-made objects from marine organisms, such as kelp or whales. However, the RGB images do not provide information on the physical and chemical composition of the litter(87).

Optical spectro-radiometric techniques: The Spectro-radiometric analysis from ultraviolet to distant infrared spectrum has opened new ways of detecting and characterizing of plastic and other types of marine debris(88). The absorption features of the near and short-wave infrared spectrum show apparent color or polymer type of plastic particles, suggesting that these features have potential applications in remote detection of ocean plastics under various backgrounds, including vegetation. The technique shows the possibility to detect the reflectance of floating ocean plastics, depending on sensor capability(88, 89). A more in-depth technique to observe submerged debris is using a light detection and ranging system (LIDAR) that can measure the onboard laser lights backscattered from the ocean. Other applications are based on fluorescence and Raman spectroscopy although the latter utilizes a low signal which is presently challenging to detect from current satellites missions(87).

Unmanned autonomous vehicles (UAV) and litter monitoring: UAV (Unmanned Aerial Vehicle) and Deep neural network was proposed to overcome the disadvantage of the thresholding method that requires applying threshold to images captured using a webcam(90).The detection process of the beach litter using the method is composed of 3 steps (Image acquisition and preprocessing, detection using neural network and postprocessing)(91). The camera on the UAV was a 1-inch CMOS with a resolution of 20MP. The images obtained through UAV are produced as orthoimages and input into a pre-trained neural network algorithm. The Deep Neural Network used for Beach litter detection removed the fully connected layer from the convolutional neural network for semantic segmentation(90). Similarly, a novel method, APLASTIC-Q algorithm which is based on CNN technology has also been developed which outperforms many systems with respect to various classification performance metric(92). It is quite easy to adapt for fast and automated detection as well as quantification of floating or washed ashore plastic litter from aerial, high-altitude pseudo satellites and space missions using APLASTIC-Q (90, 92).

2.5 Summary

In this Chapter, we discussed several views of past authors on state-of-the-art infrared thermal imaging, sustainable solutions to marine litter and material recognition methods. Thermal cameras were introduced, also their detection types and modes were discussed. Thermal cameras with thermal and quantum detectors, where the uncooled microbolometers are the most common types. Although thermal cameras have little disadvantages, compared to their strengths, one of which is their ability to see in dark or foggy conditions. Night vision systems, where they can be used to identify and greatly magnify tiny quantities of visible light. Some breakthrough solutions to marine litter problems were discussed involving mostly optical and visual technologies. Furthermore, we explored how existing methods have been used for material recognition. Most techniques are applicable for characterizing and sorting materials in different environment. Developing a standard procedure and application for plastic at beaches and in the environment could rapidly increase the information available on global scale. Using drone or aerial surveys would require large costs and should be an option in priority areas. There is a need to develop templates and tools for the collection of information on beach debris. It is important to apply intelligent algorithms to identify and quantify plastics in images are needed, and artificial intelligence (AI) approaches to pattern recognition are the latest ventures. However, techniques like FTIR and Raman microscopy have been used widely to further characterization due to their noninvasive nature and can be applied directly on the filter holding the extracted particles in different environment. The common initiative in most techniques is different physical and chemical characterization can be made due to method sophistication. Finally, to intensify our research work on material sensing, we explore and evaluate whether our state-of-the-art thermal imaging or the ability of any other material recognition technology to travel through disordered environment can be used to detect litters autonomously, in the next Chapter, we introduce the feasibility of this approach.

3

Feasibility Analysis

Previous work has demonstrated that thermal imaging can be used to characterize different objects materials. Indeed, thermal radiation can be transferred from humans to objects as a person interacts with objects (through touch) (93). In this Chapter, we demonstrate further that thermal imaging can be used to characterize materials from the same type. In particular, we show that thermal imaging can be used to distinguish between a large number of different plastics. In addition, we also show that thermal imaging provides better performance when compared with existing state-of-the-art approaches based on light reflectivity.

3.1 Materials selection

We next describe the selected object materials for our experiment. We focus on plastics materials primarily as recent studies have shown that urban spaces can be polluted by them from different sources, e.g., atmospheric micro-plastic (3). We rely on a plastic set with 20 different types of plastics[1]. Each plastic in the set is manufactured using the same mold and the same process. Thus, differences between plastics are mainly based on their inherent material characteristics. Figure 3.1 shows the overall plastic set. In addition, Table 3.1 shows the overall characteristics of the plastics.

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

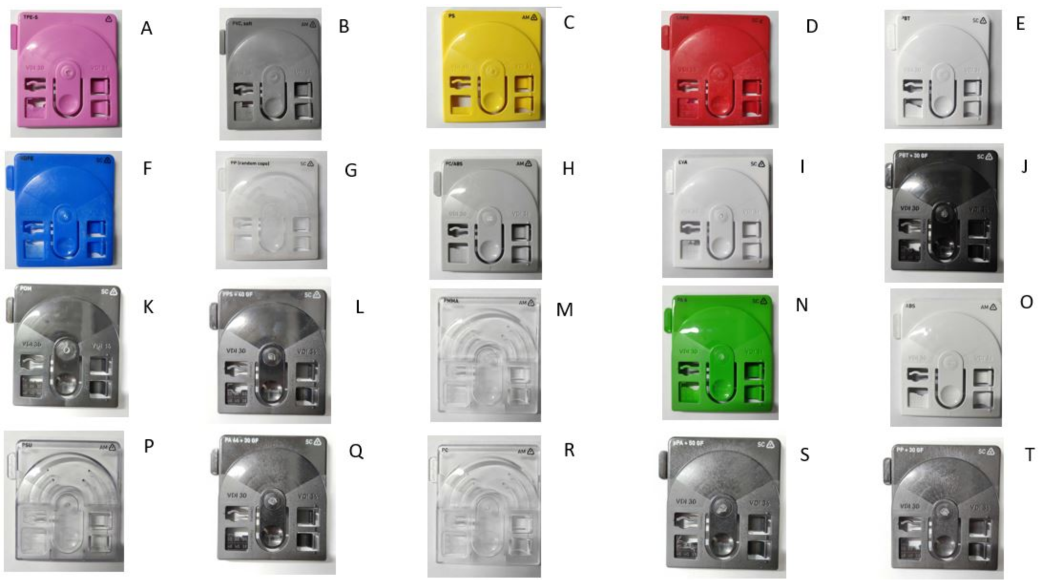


Figure 3.1: Different types of plastic materials A- TPE-S, B- PVC soft, C- PS, D- LDPE, E- PBT, F- HDPE, G- PP random, H- PC/ABS, I- EVA, J- PBT+ 30GF, K- POM, L- PPS+ 40GF, M- PPMA, N- PA 6, O- ABS, P- PSU, Q- PA66+ 30GF, R- PC, S- pPA+ 50GF, T- PP+ 30GF

3.2 Light reflectivity characterization (Baseline)

We proceed to use state-of-the-art techniques based on light reflectivity to characterize plastics. We use this approach as baseline to compare the performance of our proposed approach based on thermal imaging.

Experimental setup: We next characterize plastic materials using light reflectivity. We rely on a a photoresistor connected to the analog input pin of an Arduino MEGA ADK. The photoresistor captures light changes based on its resistance exposure to the light intensity of the reflected material. As a light source, we rely on a red laser diode (wavelength 650 nm). The object was located 2 cm and 5 *cm* away from the light source, depicting a practical usage of the sensor in transport belts and smart bins (67). We took measurements during 1 min from the polish part of the plastic sample, which depict the end result of the material when used in an end-product.

Results: Figure 3.2 shows the results of the characterization with light. From the result, we can observe that the distance between the photoresistor and the target material influences the overall characterization process. This means that the limitation of this

Id	Acron.	Plastic name	Color	Common Eng.	Polyolefins	Polyamides	Polyesters	High temperature	Common Hous.	Semi crystaline	Amorphous	TPE
1	POM	Polyoxymethylene	black	✓								
2	pPA+GF	Polyamides	black			✓				✓		
3	PPS+GF	Glass-reinforced polyphenylene sulfide	black					✓		✓		
4	PP+GF	Polypropylene	black		✓					✓		
5	PBT+GF	Glass-reinforced polybutylene terephthalate	black	✓			✓			✓		
6	PA66+GF	Glass-reinforced polyamide	black	✓		✓				✓		
7	PMMA	Polymethyl methacrylate	transparent								✓	
8	PC	Polycarbonate	transparent						✓		✓	
9	PSU	Polysulfone	transparent					✓				
10	PP(copo)	Polypropylene	transparent		✓					✓		
11	PBT	Polybutylene terephthalate	white	✓			✓			✓		
12	EVA	Ethylene vinyl acetate	white		✓					✓		
13	ABS	Acrylonitrile butadiene styrene	white						✓		✓	
14	PC/ABS	Blend polycarbonate	white						✓		✓	
15	PS	Polystyrene	yellow						✓		✓	
16	LDPE	Low density polyethylene	red		✓					✓		
17	PVC,soft	Polyvinyl chloride	gray								✓	
18	PA6	polyamide	green	✓		✓				✓		
19	HDPE	High density polyethylene	blue		✓					✓		
20	TPE-S	Thermoplastic elastomer	pink									✓

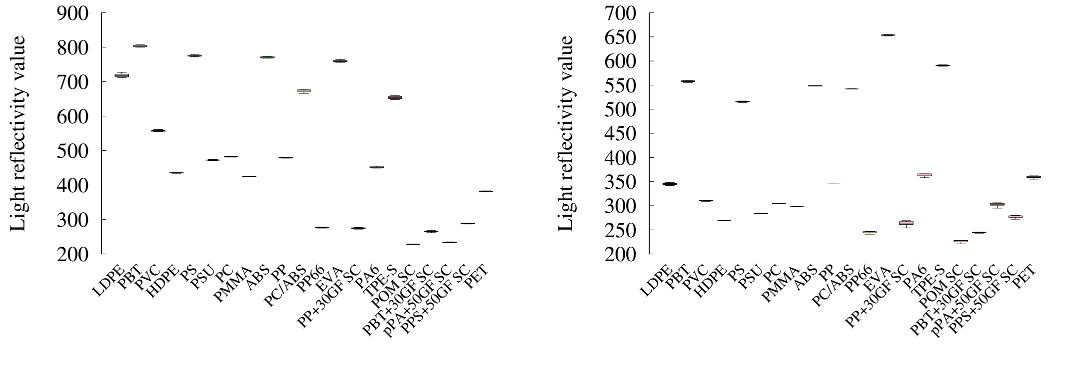
Table 3.1: Plastic samples considered in the experiments along with their family properties.

approach is that it requires a short distance between material and sensor for accurate classification.

3.3 Thermal imaging characterization

We then analyze the performance of thermal imaging for characterizing plastics of different types. Besides relying on the most common plastics defined by their RIC (Resin Identification Code), we also rely on variations of different plastics.

Experimental setup: We measure the dissipation time of a thermal footprint in different plastic materials. Thermal dissipation time can be defined as the time that it takes for an object to reach thermal equilibrium with the temperature of the environment. We then correlate this thermal dissipation information with the emissivity coefficient of plastics. Plastics have well known emissivity coefficients ranging from ϵ=0.90 to 0.97. In the experiments, we first place the plastic sample inside a fridge with a constant temperature of 5 °C, to obtain a baseline temperature for comparison. To measure different temperatures, we use a constant heat source (lamp bulb of 60 W) to heat the plastic samples. The lamp is placed at a fixed distance of 10 cm from the samples to



(a) Distance = 2cm

(b) Distance = 5cm

Figure 3.2: Light reflectivity values of different plastic samples according to RIC.

avoid burn damage while ensuring they are exposed to sufficient amounts of thermal radiation. We consider different heating periods (1, 2, 3 and 4 minutes) to correspond to differing initial temperatures and measure the dissipation of the thermal footprint. We selected up to 4 minutes as previous work as shown that four minutes is enough to correlate materials with their emissivity coefficient (93) During the experiments, ambient temperature oscillated from 22 °C to 24 °C. We estimate the thermal footprint dissipation time using a CAT S60 (video footage was also recorded). The device was located $30 - 35$ cm away from each sample.

Results: The results in Figure 3.3 show that the thermal footprint dissipation varies across the plastics materials. The (Spearman) correlation between dissipation time and emissivity coefficient of the materials was found statistically significant ($\rho = 0.66$, $p < .05$), indicating that the dissipation characteristics indeed provide information about the material of the object. This also have been reported by previous works (93).

3.4 Thermal dissipation characterization with sunlight

In the previous section, we demonstrate that heat from a bulb can be used to transfer thermal radiation to plastics. In this section, we analyze further whether the plastic samples can rely on heat from sunlight to characterize their type.

Experimental setup: For this experiment, we rely on seven plastics samples representing the most common types of plastics used in end-products. Specifically, we rely

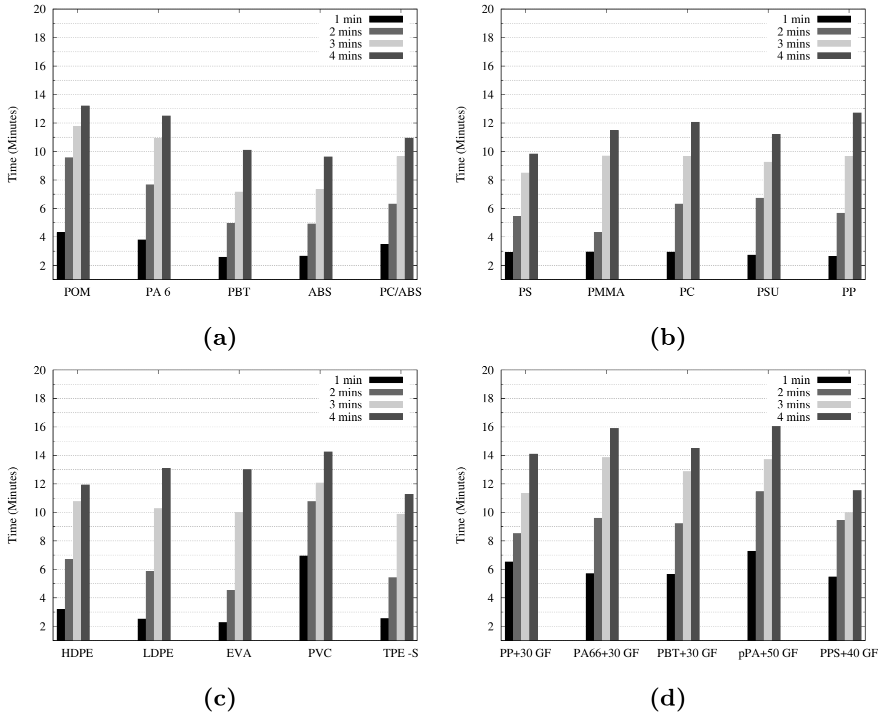


Figure 3.3: Characterization of plastics using thermal imaging and a light bulb as a source of heat radiation.

on high density polyethylene (HDPE), low density polyethylene (LDPE), Polystyrene (PS), soft Polyvinyl chloride (PVC), Polypropylene (PP), Polybutylene terephthalate (PBT), and Polyethylene terephthalate PET (bottle form). These selected materials were exposed to sunlight for 15 minutes. Once the exposure time is completed, we then locate a sunshield to block the sunlight and measure the thermal dissipation time. We placed the thermal camera at a fixed distance of 20 cm in each experiment. In addition, ambient temperature of environment was taken into consideration to determine the effect they have on dissipation times.

Results: Figure 3.4 shows the results of dissipation time when each plastic sample is exposed to sunlight. From the results, we can observe that the plastic samples can absorb enough heat from sunlight, such that it is possible to characterize their type via thermal dissipation analysis. Also, we observe that ambient temperature of the environment affects thermal dissipation time, at higher temperatures, the thermal dissipation time takes longer.

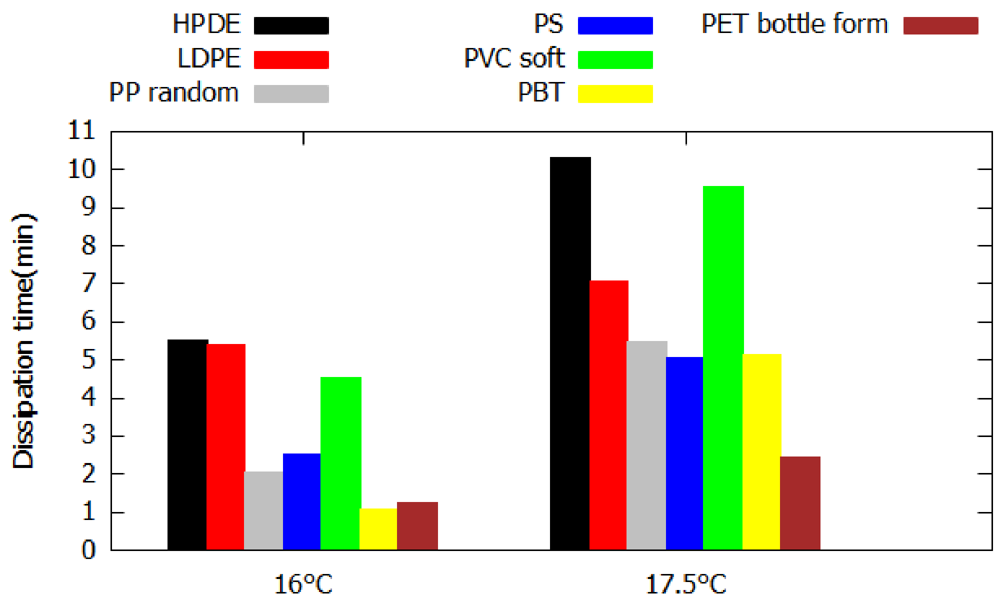


Figure 3.4: Thermal dissipation time of selected materials under sunlight at two different ambient temperatures

3.5 Summary

In this Chapter, we showed the feasibility study of the thermal imaging analysis and light reflectivity analysis on characterizing plastic materials. We analysis both methods using a plastic set of twenty (20) different plastic types. The result showed both methods can be used effectively. Light reflectivity analysis shows that light can characterize plastic materials of different physical and chemical properties, but it is noteworthy to point that for reliable results, the distance between the sensor and the plastic material must be small. We conduct controlled thermal experiments for the plastic materials and results showed different behaviors of materials on exposure different heating periods (1, 2, 3 and 4 minutes). Moreover, we selected seven plastic materials from the plastic set and determine their thermal dissipation in sunlight for more real result analysis. The result showed that different plastic materials had different average dissipation times. This enough gives us further proof that thermal radiation can be used to classify different type of plastic materials.

4

Characterization of litter materials using sunlight

In previous Chapter, we demonstrated that sunlight can be used to characterize different types of plastics. In this Chapter, we explore further how shape and size influence this characterization process. Moreover, since the background area, where the material is located is also exposed to sunlight. We also analyze the influence of this area in the characterization process. To achieve this, we conduct controlled experiments where sand is incrementally added in the background, where the material is placed.

4.1 Apparatus

We simulated the heat energy source from the sun with an incubator (JANOEL 18S) to provide the heat required. The incubator has an adjustable thermostat which can be set to different temperature in the range of 30 °C to 42 °C in the incubator, depending on the time deviation required on preset. We rely on a caterpillar smartphone (s60) with integrated thermal imaging cameras. The device is capable of measuring thermal temperature directly from the surface of materials. The CAT s60 main features are thermal Resolution (Pixels) 60×80 pixels, temperature Range -20°C to 120°C, thermal sensitivity (MRDT) 150mk, accuracy typically ±5°C or ±5% of the difference between ambient and scene temperature, thermal sensor $17\mu m$ pixel size, $8 - 14\mu m$ spectral range. The CAT s60 camera was placed on a tripod at a distance of $30 - 35$ cm from the object and calibrated after thermal equilibrium has been attained when exposing to the room temperature of $22-23.5$℃. Video footage was recorded with the CAT s60 and before start of experiments, room's ambient temperature was collected using a Netatmo weather station (`https://www.netatmo.com`). We also collect the dissipation time of the thermal footprint manually using a stopwatch timer.

Testbed: We designed a testbed to obtain clean measurement of thermal dissipation. We also designed a sample container of unique dimension to have a concise area of analysis. The sample container is made of black color to material to avoid reflection of light. The weight of the sample container bed was 2 grams with a surface area of 64 cm2. One gram of plastic samples was weighed and added to the container for each experiment using a professional scale device. We measured the dissipation time of thermal footprint in different plastic sizes under varying conditions to obtain the results of thermal dissipation.

4.2 Procedure

The procedure of thermal radiation transferred from heat energy from incubator and our plastic samples is illustrated in Figure 4.1. In the experiments, we first placed each different type sizes of plastics inside the incubator with a constant temperature of ranging $36-38$℃, in order to achieve baseline temperature (also to simulate sunny day conditions). We set a time of exposure between 14-16 minutes to give samples enough time to absorb thermal radiation. We then located the thermal phone in a vertical fixed distance ($15-18$ cm) using a tripod stand ranging and proceed to measure thermal dissipation time. Ambient temperature during experiments varied around 22-24℃. Once a period is completed, the researcher removes the heat source and measure each sample's thermal footprint dissipation using the CAT s60 to record. The fixed distance from the samples to the camera was maintained by marker drawn on the table. Also the background of the table was designed to be black to obtain clean thermal footage and reduce light interference from the surface as shown in Figure 4.2.

4.3 Material selection

Litter consists of waste products that have been disposed improperly, thereby constitute environmental nuisance. They vary in size, shape, nature and unique properties.

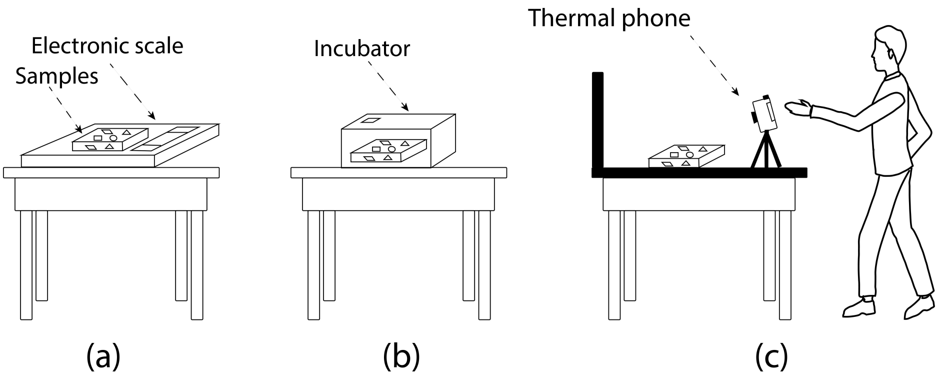


Figure 4.1: The simple procedure of experiment from A, weighing of samples to B, heating of samples in incubator to C, observing the dissipation time

Figure 4.2: Researcher using the experimental tesbed

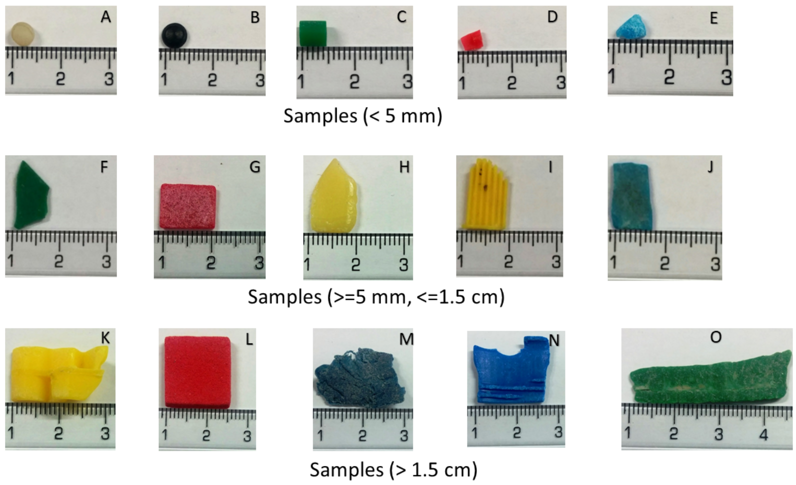


Figure 4.3: Micro-plastic types

Moreover, given the fast rate of production and single use advantage, plastic materials have been found to be the most littered materials. As a result, in our study, we focus on analyzing plastics.

Size selection of plastics: To analyze whether thermal imaging can be used further to characterize materials of different sizes, we obtained real samples of micro-plastics and proceed to analyze them rigorously[1]. We used these samples as they depict the real condition sizes of materials that can be found in real situations. Available sizes ranged from the smallest Type I (less than 0.5cm), to Type II (less than 1.5cm) and Type III (greater than 1.5cm). Figure 4.3 shows the samples.

4.4 Light reflectivity of micro-plastics (Baseline)

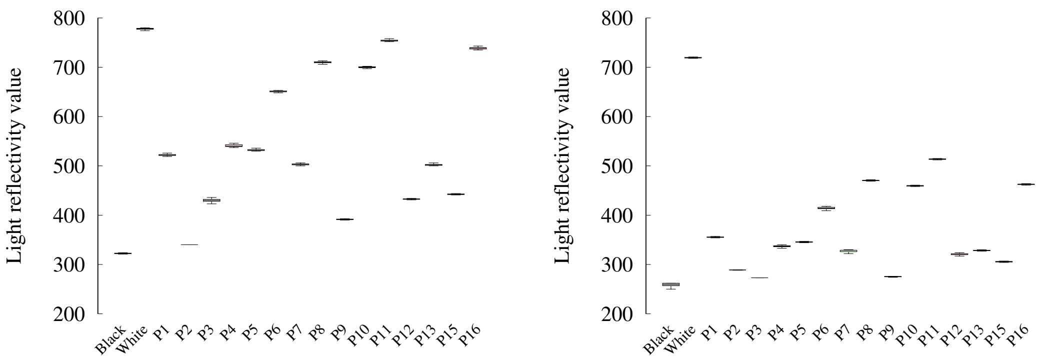
Analysis done based on light reflectivity is a highly adopted technique used in the characterization of different materials. We proceed with analysis of our available micro-plastics to have an idea of what is obtainable in relation to thermal imaging technique.

Experiment setup: The setup was similar to the characterization with the plastic set. The photoresistor decreases resistance with respect to receiving light signals on the micro-plastic surfaces. The red laser diode was our light source, and each micro-plastic

[1]These samples were obtained with special instruments by our collaborators in Italy

was placed at 2 cm and 5 cm away from the light source. Measurement was made during 1 min from the larger surface area of each micro-plastics.

Results: Figure 4.4 shows the results for both analysis based of the two different distances to the surface of the micro-plastics. We can observe that light can be used to characterize these plastics with their small sizes. Although it becomes difficult for accurate analysis as the distance from sensor gets farther away (as in the case of 5 cm distance). Some of the micro-plastics did not show enough distinction in their analysis at distance of 5 cm away. This suggests that the light reflectivity requires to take measurements from materials very closely.



(a) Distance = 2cm **(b)** Distance = 5cm

Figure 4.4: Light reflectivity values of different Micro-plastics of different sizes.

4.5 Thermal dissipation of micro-plastics

We next demonstrate that thermal radiation can be used to characterize plastics materials of different sizes. To achieve this, we first rely on a controlled experiment with fixed levels of temperature. In addition, we also analyze in a controlled experiment how background materials influence the overall identification of small size plastics.

Experiment design: We analyze the amount of thermal radiation transferred to small size materials using an incubator. We used an incubator to set fixed levels of temperature in our analysis, and to make results comparable in different conditions. To study how small size materials absorbed thermal radiation, we consider two conditions. Each condition analyzes different arrangements of plastics. The first conditions considers

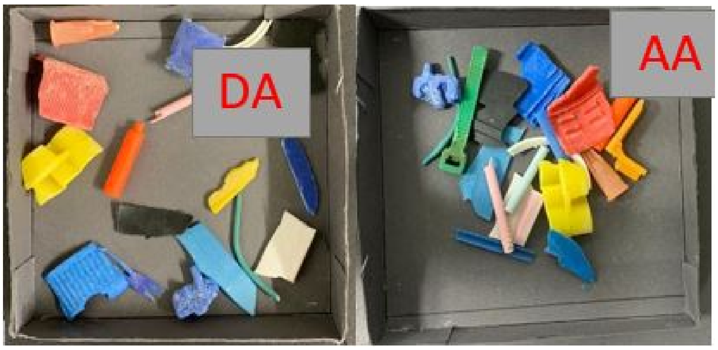


Figure 4.5: The two different arrangement of the samples, agglomerated arrangement AA and dispersed arrangement DA

when small plastics are agglomerated (Agglomerated arrangement), whereas the second conditions considers when small plastics are distributed (Dispersed arrangement). Figure 4.5 shows the two conditions. Overall, the controlled experiment follows a 2×3 within-subject design with thermal radiation transfer type and object type as independent variables. Thermal radiation types had two (2) variables; Dispersed arrangement (DA) and Agglomerated arrangement (AA) while for the objects we had 3 variables Type I (less than 0.5cm in size), Type II (less than 1.5cm) and Type III (greater than 1.5cm). This resulted in six experimental conditions: TYPE I-DA, TYPE II-DA, TYPE III-DA, TYPE I-AA, TYPE II-AA, TYPE III-AA. Figure 4.6 shows the six experimental conditions.

Results: Figure 4.7 shows the results. From the figures, we can observe that a thermal footprint dissipates differently in different sample types and arrangement. The bigger the sizes the more the dissipation time, type III recorded highest dissipation time. It was observed that longer dissipation times were also recorded for the agglomerated arrangement compared to the dispersed arrangement. Average time found in each trial is shown in Figure 4.8.

4.5.1 Thermal dissipation of micro-plastics in sand

After observing the dissipation time of different samples using the incubator testbed, we then analyze how the background area influences the dissipation thermal footprint of small size samples. Thus, this this experiment demonstrates further the effectiveness of our method in a real-life scenario.

Figure 4.6: Available sizes of samples in different arrangement type I-AA, type II-AA, type III-AA, type I-DA, type II-DA and type III-DA

Experimental design: Beach sand was gradually introduced into our controlled arrangement conditions described previously. The sand was added to our conditions in an incremental rate from 1 gram up to 5 grams for each plastic types (as shown in Figure 4.9). Thermal dissipation time was measured after sand was added. Five experiments were conducted for each gram.

Results: From the Figure 4.10, we can observe the average dissipation time for different sample types and arrangement. This illustrates that with increase in sand in different sample types, dissipation time reduces. However, the biggest effect was seen on the type I plastics which account for very low dissipation time when sand was introduced. This can be attributed to the influence of sand being heated up rather than the samples, due to their smaller sizes.

4.6 Comparison of the state of art thermal imaging approach to baseline approach

This section compares both approaches that have been used for sensing litter. We investigate the baseline approach of light reflectivity and our approach of thermal imaging

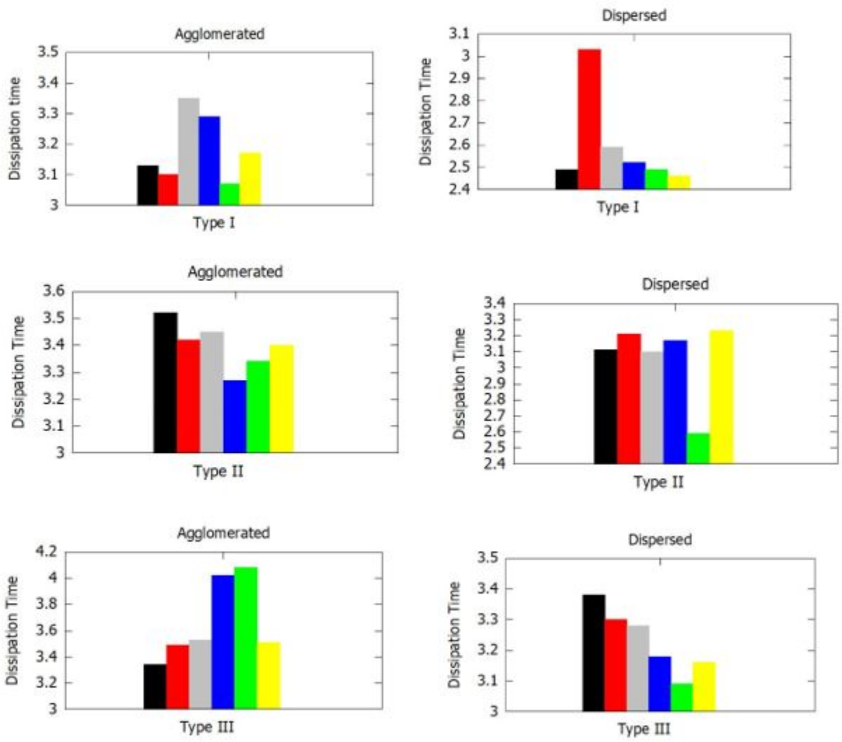


Figure 4.7: Different dissipation time recorded for agglomerated and dispersed samples for Type I-AA, Type I-DA, Type II-AA, Type II-DA, Type III-AA and Type III-DA

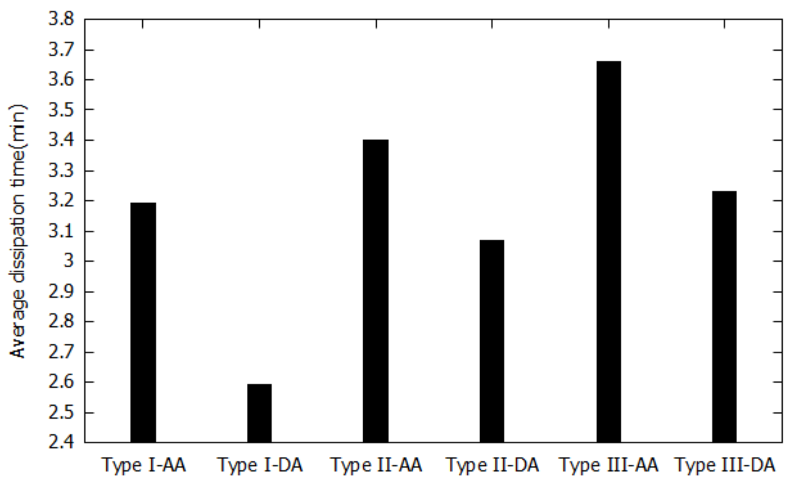


Figure 4.8: Average dissipation times recorded for agglomerated and dispersed samples for Type I-AA, Type I-DA, Type II-AA, Type II-DA, Type III-AA and Type III-DA

Figure 4.9: Type I sample with the addition of some grams sand

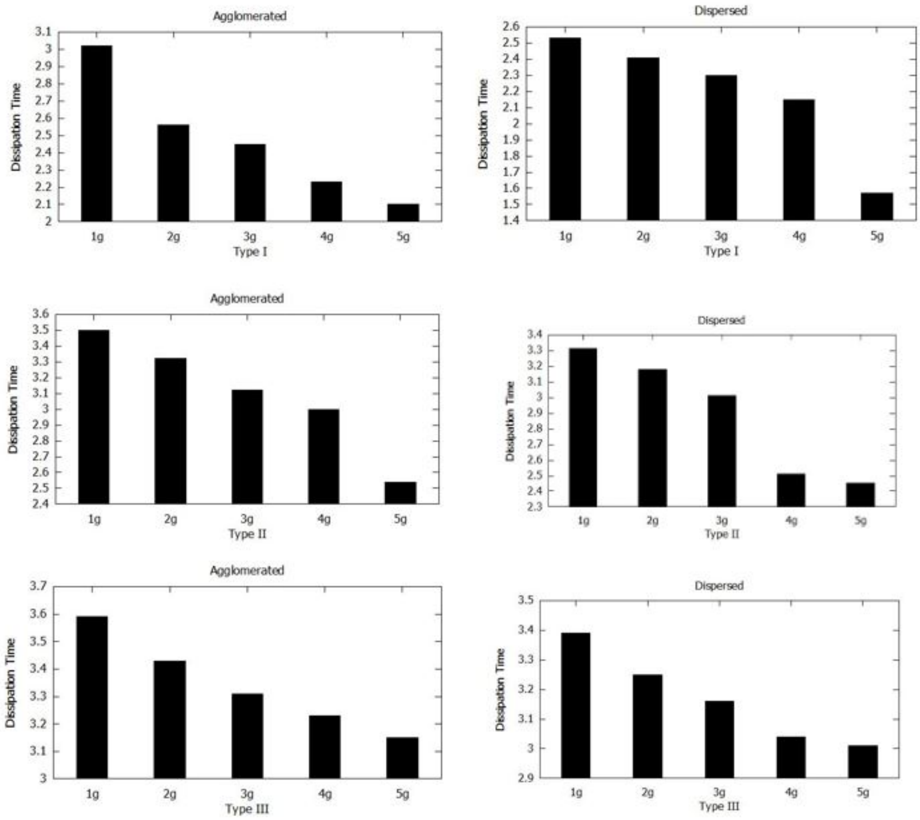


Figure 4.10: Average dissipation times in minutes and respective behavior to addition of different grams of sand

to consolidate the effectiveness of both. The results from both approaches have shown advantages that thermal imaging has over light reflectivity in the terms of the following.

Distance between sensor and material: From chapter 3 and figure 4.4, we showed results from light reflectivity analysis of materials, it shows the approach requires a short distance between material and sensor for accurate classification. However, the thermal footprint videos can be captured at longer distances as detailed in the experimental designs.

Energy requirement: Energy can be measured either in different forms e.g., thermal or electromagnetic. It is defined by the amount of work that can be done by a force per unit time. In our work we have been able to demonstrate the use light reflectivity using a laser diode and also thermal imaging to characterize different plastic litter. We consider a specified surface area containing litter. Using the light reflectivity method, energy density of approach is modelled such that the residence time is a function of the beam diameter and scanning speed of the laser. These two quantities will be responsible for the amount of energy required to finish a scanning area. For a large surface area filled with microplastics, it means the sensor regardless of its power is largely dependent on beam diameter which will be quite small and tedious. But for thermal imaging approach, energy density is modelled only from the thermal dissipation footprint video footage that utilizes a very limited amount of time.

4.7 Summary

This Chapter presented a preliminary analysis of the thermal dissipation of different sample types of plastics using heat radiation from an incubator and also dissipation time of selected materials on field using sun radiation. We measured the dissipation time of a thermal footprint in various sample types when placed in the incubator for a period. The controlled experiment was done using a thermal phone CAT S60. The samples are then placed 15cm away from thermal camera vertically. The sample types were type I (less than 0.5cm in size), type II (less than 1.5cm in size) and type III (greater than 1.5cm in size). Measurements were also done in two different arrangements: agglomerated arrangement AA and dispersed arrangement DA. The result of the experiment shows that a thermal footprint dissipates differently in different sample types and arrangement. Furthermore, the feasibility analysis adding varying sand weights to different sample types was also done. The procedure for this followed the same for experiments for without sand. The only difference is the carefully weighted sand in samples and results showed drastic reduction in thermal dissipation time for type I sample due to sand being heated up and taking off energy off the samples largely due to their smaller sizes. Our findings continue to show that various samples can be distinguished by thermal radiation regardless of sizes and shapes. We compare thermal imaging technique with existing baseline approach of light reflectivity and observed thermal imaging is more economical in terms of energy and more accurate results can be gotten regardless of the distance between materials and sensor.

5

LIZARD: Development and Evaluation

In previous Chapter, we demonstrate that sunlight can be used to identify materials of different sizes. We showed that thermal dissipation can be measured from materials - even in the cases where materials have micro-plastics size level. However, we also showed that there are several issues to overcome as the materials get smaller. Thus, our approach is more effective with litter of bigger sizes. In this Chapter, we introduce the applicability of our approach. We envision our approach to monitor early stages of litter mostly. We conduct experiments to demonstrate the potential of our approach when combined with unmanned autonomous vehicles (UAVs).

5.1 Overview of LIZARD

We developed LIZARD as a combination of three major components, a land UAV, a sunshield and a thermal camera device in a special arrangement. Figure 5.1 shows the overall representation of the LIZARD system.

5.1.1 Apparatus

To build LIZARD, we rely on a thermal phone CAT s60 and a terrestrial land drone, DFRobot Romeo V2. We also designed a sunshield made of cardboard, which is also covered with a black surface (like the one in our controlled testbed), such that it is possible to reduce the reflectance of light from surface. The sunshield of LIZARD is

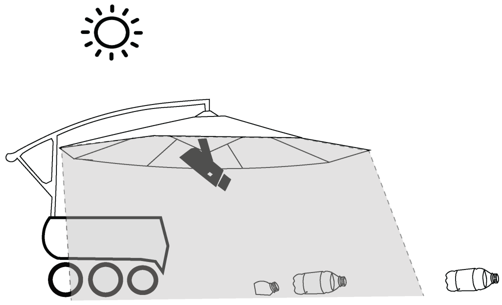


Figure 5.1: LIZARD overview.

Figure 5.2: Different angles of the LIZARD system taken under the sun

also designed in such a way that the shield is flexible enough to be turned against the sun radiation while in operation. Our thermal camera s60 CAT, is in an enclosed plate on the land UAV. Figure 5.2 shows the LIZARD prototype in action from different angles.

5.1.2 Material selection

We thus far have demonstrated that thermal radiation can be used to characterize different materials and even materials of different sizes. However, best performance is obtained when using bigger size materials (litter in early stages). As a result, we next explore how our LIZARD prototype can be used to recognize different big size litter in the wild[1]. Asides the plastic materials that have been discussed earlier, we will highlight a few other types of materials including rubber and cotton materials which are seen as common litters in the environment.

Rubber material: Natural rubber is used extensively in many applications and products, either alone or in combination with other materials. In most of its useful forms, it has a large stretch ratio and high resilience, and also is waterproof. Due its versatility in function, it has contributed to a high volume of waste in the environment. Some of waste generated by rubber include balloons, rubber gloves, condoms, etc.

Cotton material: Cotton is used to make several textile products. This ranges from terrycloth for highly absorbent bath towels and robes; denim for blue jeans and so on. They are produced in several millions of tonnes per year and however add to the growing list of waste materials in the world. A good example now will be face masks which have been mandatory in most part of the world to fight against the current COVID-19 pandemic.

5.1.3 LIZARD evaluation

Baseline experiment: Before evaluating LIZARD, we measure the dissipation time of some of the common litters in the environment. We consider materials that often account for waste in the environment as described previously. They include a transparent plastic bottle (A), coffee cup (B), face mask (C), hand gloves (D), Milk pack (E) and a takeaway box (F) are shown in the Figure 5.3

We then followed the similar steps we used for the plastic sample types to capture the video footage of thermal footprints of the different materials. We exposed these materials into sunlight for 15 minutes each and shielded from the sun afterwards we capture the residual thermal radiation left in each material using our smartphone camera CAT S60 for this purpose. Ambient temperature was also recorded for each experiment. However, to determine the extent of light intensity available from the sun for each material, we recorded values of light intensity using a smartphone LUX application on another smartphone device. We recorded these values for each material when exposed to sunlight and when shielded away from the sun. A detailed description of set up is provided in Figures 5.4 and 5.5.

[1] light reflectivity techniques could be integrated to recognize smaller materials and generalized our approach

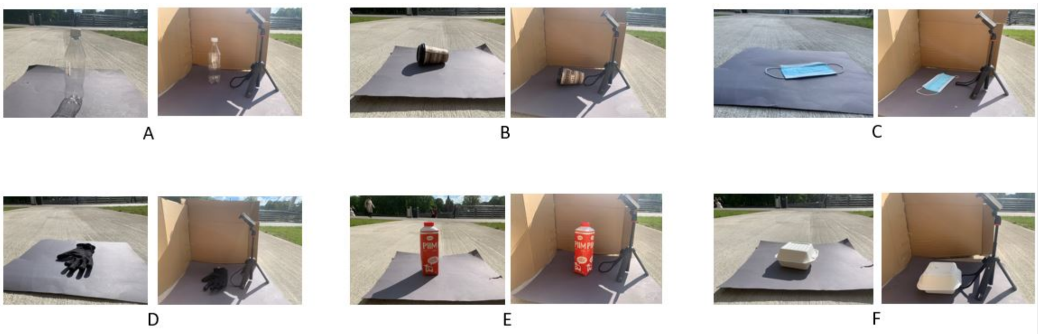


Figure 5.3: Selected litters for experiment when exposed to sunlight and under shield; Plastic bottle A, Coffee cup B, Face mask C, Hand gloves D, Milk pack E and Takeway box F

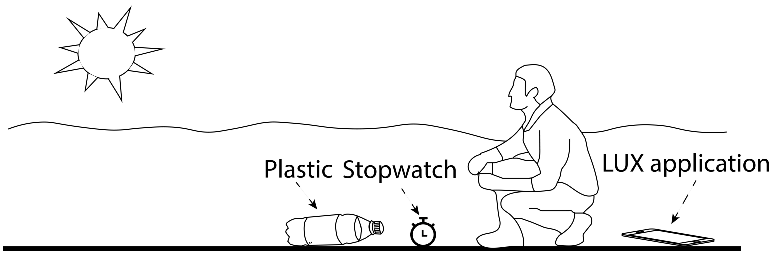


Figure 5.4: Procedure for experiment when exposed to sunlight

This experiment was carried out six different times for each material. This was achieved by changing the positions of the materials for different experiments and getting a variance of data for each.

LIZARD results: Baseline results mirror the performance of LIZARD when identifying materials. Overall, Figure 5.6 shows the result of the dissipation time for each material, with some materials like the hand gloves and coffee cup having high dissipa-

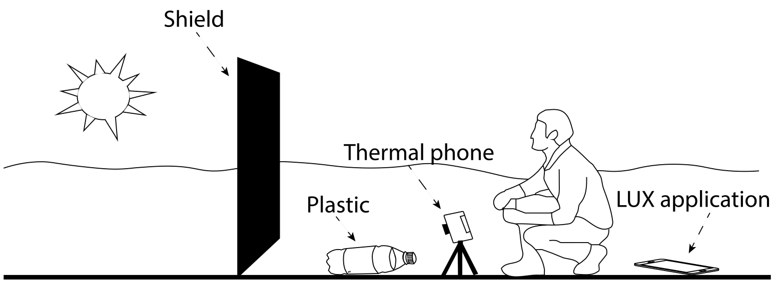


Figure 5.5: Procedure for experiment when shield from sunlight

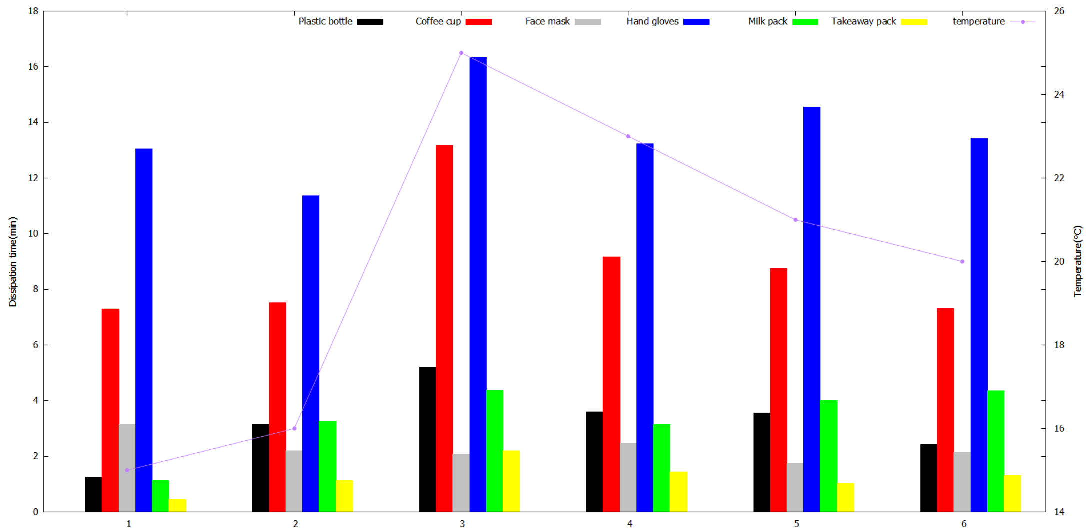


Figure 5.6: Dissipation time in minutes of the selected materials in six different positions in relation to ambient temperatures

tion times due to their material intrinsic properties. Also the light intensity pattern and values with respect to ambient temperatures for different materials is shown in Figure 5.7 and Figure 5.8 with an SI unit of lux. It is also observed that at higher ambient temperatures, thermal dissipation times are longer for all materials.

5.2 Summary

In this Chapter, we introduced a LIZARD system for autonomous monitoring of different litter materials. We selected six different material types and conducted experiments on thermal radiation response. Thermal footprints of different materials were monitored and recorded using the smartphone s60 CAT thermal camera. Materials were exposed in the sun for a period of 15 minutes, while temperature of the environment and light intensity of the sunlight was recorded when exposed and under shield. The fixed distance from the surface of the ground and camera was 20 cm which was due to coverage for large materials. There is also an indication that temperature and light intensity values of the environment have a linear relationship with the dissipation time of each material. All in all, our finding indicates that autonomous solutions for monitoring litter can be easily created by exploiting sunlight.

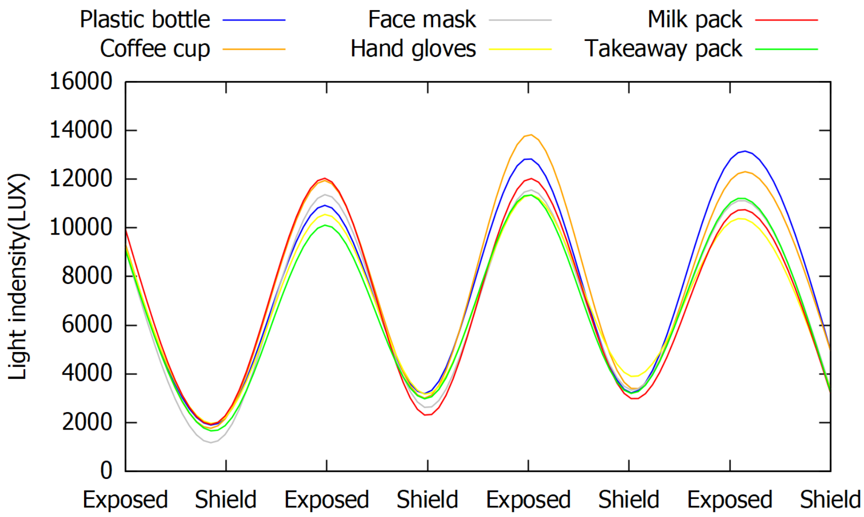


Figure 5.7: Light intensity value pattern for different materials

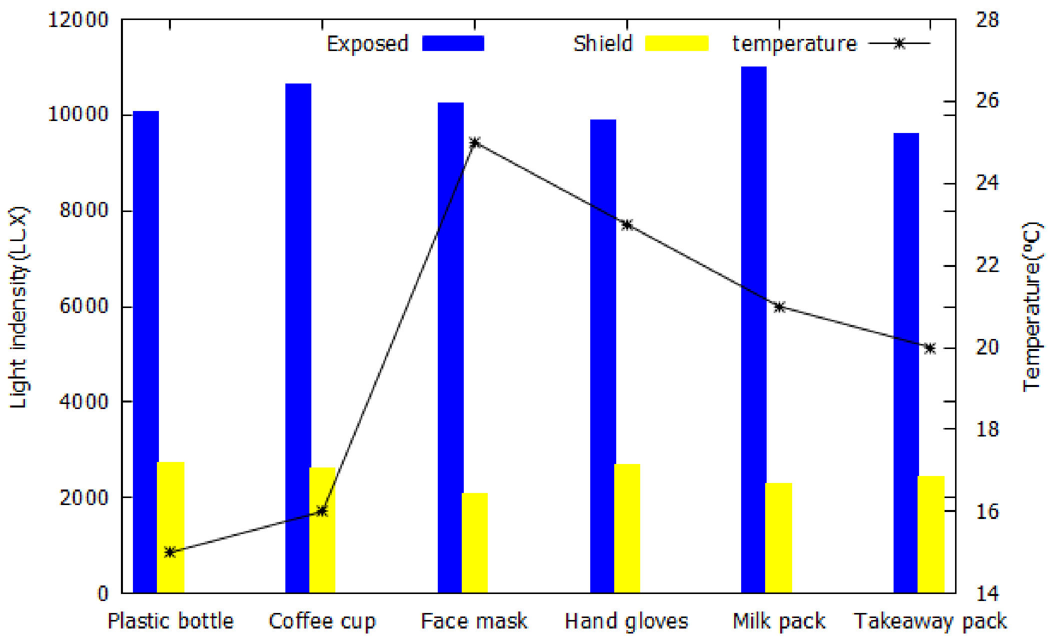


Figure 5.8: Light intensity values with respect to ambient temperatures for different materials

6

Discussion

This Chapter will give insights on the implications and limitations of our work.

6.1 From big to micro size materials

While we demonstrate that our approach can be used to identify materials of bigger sizes (litter that has just being disposed), it could be possible to generalize our approach to different sizes by integrating light reflectivity techniques. In this context, thermal imaging can provide information about the areas that were not monitored accurately, such that light reflectivity can be used instead. While we showed that both approaches can be used in our experiments, this integration is not explored in this work. Thus, we are interested to explore further their integration.

6.2 Energy conservation

Energy is always conserved by improving efficiency through technological innovation and improved operation. Several methods are also being used to classify litter materials. In this work we took a closer look on how light reflectivity is used in monitoring litter materials. It proved to be an effective method but it requires substantial energy to power a laser diode over a large surface area. We are able to demonstrate that by piggybacking on the free energy of sunlight we can cover large surface areas, with lesser energy through thermal imaging.

6.3 Improving recycling efforts

Existing methods of recycling plastic materials start from manual evacuation of plastics such as handpicking and suction devices. With our LIZARD system, thermal radiation analysis of plastics can be carried out to determine and characterize plastic materials to ease the recycling process of plastic materials. Humans involved in evacuation can easily sort these materials on the spot during evacuation with this approach. This increases the economic security by reducing the length of chain events involved in recycling.

6.4 Room for improvement

With the massive growth of the drone Internet of Things (IoT) (94), we demonstrated how UAVs equipped with commercial and off-the-shelf (COTS) thermal cameras can be used to implement the service of characterizing litter materials in open areas. The trajectory planning which coordinates the optimal road path of the device between the starting point and the ending point (95) is not covered in the scope of our work. The major constraint is usually to establish a path directory with the optimal cost function value (95). Also, there are certain materials and environments that will be difficult to evaluate through thermal footprints. We intend to analyze different environmental medium of where litter exist on terrestrial surfaces with increased sophistication by adding other sensors.

6.5 Waste reduction

Climatic conditions are not constant, and our functional ecosystem needs to be sustained for long periods. By effective characterization of litters with sunlight powered by thermal imaging, we reduce the enormous quantity in landfills. We then lessen their impact on our agriculture and freshwater locations. With the global pattern of microplastics in commercial food-grade salts (96), human ingestion of microplastics-type litter can also be reduced.

6.6 Pervasive solution to testing methods

Testing and investigation methods of materials involves to searching and examining the properties of materials in an attempt to learn the facts about them for development and design. Our thermal dissipation approach from sunlight can be used by manufacturing industries to finding properties of composite material. For example, a composite plastic material can be characterized just by exposure to sunlight for a period. Investigation of other materials can be done with corresponding algorithm designs.

6.7 Influence of weather and climate

The little amount of the average sunlight per year in countries like Estonia impacts the use of our LIZARD system. Since our method exploits sunlight as our provider of energy, it proved to be a limitation to the use of the device when the weather is mostly humid. Extreme winter weather which brings about precipitation in the form of ice crystals (snow) prevents the workability of this approach. Also, the presence of occasional strong winds during warmer periods affects the stability of litters being monitored.

7

Summary and conclusions

In this work, we presented LIZARD, a novel innovative sensing approach that uses sunlight to recognize litter materials in public open areas. LIZARD exploits the fact that litter is exposed to sunlight when is located in open areas. By analyzing the absorption of sunlight radiation by covering the material with a sunshield and using a thermal camera, it is possible to identify the type and characteristics of the litter material through its thermal dissipation fingerprint. We conducted rigorous experiments that demonstrate the feasibility of our approach. Moreover, we also compared our approach against existing state-of-the art approach based on light reflectivity, demonstrating that our approach not just has higher coverage, but also is more efficient in terms of energy consumption.

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Appendix

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