Toward City-Scale Litter Monitoring Using Autonomous Ground Vehicles

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Littering is a significant challenge for environmental sustainability and a major burden for cities and densely populated areas. Current solutions for litter monitoring, such as litter watch campaigns and city-operated litter collection, are costly and challenging to conduct at a large scale. This article presents a vision for using autonomous ground vehicles *(AGVs) for litter monitoring and removal and introduces a mechanism for AGVs that uses thermal dissipation resulting from sunlight to identify and remove litter objects. We identify and highlight key challenges for deploying the envisioned solution on a city scale, and demonstrate the feasibility of the solution through extensive experiments.*

Littering and illegal waste dumping are widespread problems that have several negative consequences to the society.[1] Among others, littering decreases the aesthetic value of environments, damages natural ecosystems, causes harm and risks of injury to animals and citizens, and even can contribute to the spread of diseases. Littering is also a significant economic burden to the society. For example, the Clean Europe Network with estimates suggesting that the costs of land litter cleaning exceed 10 billion euros within the European Union.[2] Litter that persists in the physical environments can also result in indirect long-term impacts. For example, wind and rainfall can transport urban litter into water ecosystems where they can harm organisms and even enter the food chain.[3]

Litter monitoring and removal are essential for reducing litter and mitigating its negative consequences. The most common solution for litter monitoring is to rely on human effort and dedicated cleaning operations, through volunteering, coordinated municipal operations, or litter watch programs that allow reporting litter. Collecting litter can be effective when it is performed regularly but carrying out the effort is costly and logistically challenging. This makes litter collection infeasible as a large-scale and long-term strategy.[4] Litter watch activities, in turn, tend to be limited to systematic and large-scale littering, rather than addressing small-scale littering that gradually accumulates. Besides relying on human effort, there have been some early efforts to develop technologies for litter monitoring, particularly object detection from camera images being a popular approach.[5-7] These can either operate based on pictures taken by citizens or fixed infrastructure, such as smart waste bins, or be mounted on aerial drones.[8] These methods perform best for litter objects that have only recently been discarded and that remain intact as they mostly learn to recognize specific types of objects. Indeed, the accuracy of object detection models can drop up to 69% when presented with discarded litter in new situations.[9] Similarly, the performance of object

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Digital Object Identifier 10.1109/MPRV.2022.3152926

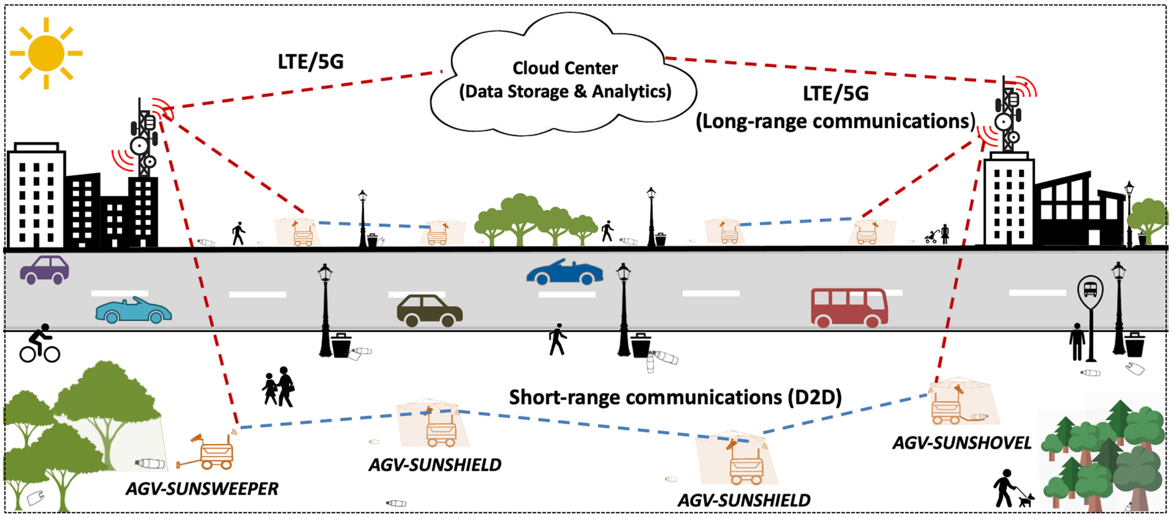


FIGURE 1. Concept of litter pollution monitoring using AGVs. The AGVs exploit shadow areas to analyze litter objects that were exposed to sunlight.

recognition can drop significantly when the objects are partially occluded by the environment.[10] Object detection approaches also require a considerable amount of computational power making them unsuited for large-scale continuous monitoring. Another option is to rely on contact-based sensing, such as optical (laser) sensing[9] or Fourier transform infrared (FTIR) spectroscopy.[11] These solutions require close contact to the objects, e.g., optical sensing requires the sensor to be within 2 cm from the object,[9] which means they are not feasible for practical deployments. FTIR additionally suffers from high power, which makes it ill-suited for autonomous ground vehicles (AGVs). To help mitigate and overcome littering, there is thus a need for new litter monitoring solutions that can operate continuously, increase the scale of monitoring, and operate robustly across environments and different types of litter.

This article contributes a research vision for city-scale litter monitoring using AGVs and develops an innovative solution for using AGVs for litter identification by taking advantage of the thermal dissipation of litter objects. In our vision, as illustrated in Figure 1, AGVs monitor and identify litter objects in the environment and inform relevant stakeholders of the current litter situation with the city. We develop a method for litter identification that uses thermal cameras to piggyback absorption of thermal radiation caused by the sun on the litter objects and use the dissipation characteristics of the resulting radiation to classify the litter objects according to their materials.[9] Thermal imaging has been previously shown to be a promising solution for distinguishing different waste materials in the context of recycling plants, but these solutions require separate heating chambers to induce thermal radiation.[12] In contrast, we rely on sun-induced thermal radiation, which allows us to identify litter materials *in situ* without needing to wait for them to be collected first. Sunlight is a clean and continuous source of energy and using it for sensing purposes can aid AGVs while reducing their computing overhead. Thanks to the increasing adoption of ground AGVs, e.g., for the delivery of goods and services, our envisioned solution can be easily adopted and replicated at a large scale. AGVs also offer new opportunities to collect information rapidly about city-scale litter behaviors of citizens to proactively counteract them, e.g., through targeted campaigns and extra cleaning procedures.

We demonstrate the feasibility and potential benefits of the envisioned approach through extensive controlled experiments that address key challenges in making the vision a reality. First, we demonstrate that sunlight is sufficient for creating thermal fingerprints that can be recognized and analyzed using thermal cameras. Second, we demonstrate the practicability of our solution by integrating an AGV with litter recognition capabilities using our approach. Third, we compare the benefits of our approach against state-of-the-art computer vision techniques for litter monitoring. Finally, we highlight practical challenges emerging from our experiments, discuss the implications of our results for the practical adoption of our solution, and establish direction for future research.

KEY REQUIREMENTS AND CHALLENGES

Municipal waste management strategies increasingly target the premise of circular economy, which prioritizes reduction and reuse of materials instead of disposal.[13] The envisioned city-scale litter monitoring approach seeks to support the implementation of such practices, and hence, it needs to target the entire waste management cycle from identification of waste to cleaning and reuse of the waste materials. In the following, we briefly describe the key challenges, reflect on the current state-of-the-art, and identify future directions for the overall vision. In subsequent sections, we focus specifically on litter identification as that serves as a natural starting point for enabling our vision.

Litter Identification

City-scale litter monitoring requires pipelines that can detect litter robustly and operate in diverse environments. For example, recently disposed litter objects can be more easily detected as they resemble the original manufactured products. Litter that has resided in the environment for a longer period of time, in turn, can be difficult to recognize as the shape of the product changes due to degradation and mixing with the environment, e.g., mud, leaves, or sand. Optimally, the materials of the litter objects should also be identified to facilitate cleaning operations and to produce data that can identify structural problems within the city. Addressing these challenges requires continuous novel sensing modalities that can operate robustly against such diversity. There is also a need for model training to account for the diversity of litter objects and environments, and new types of litter. For example, during the COVID-19 pandemic, urban environments have become littered with used face masks, whereas prior to the pandemic, they were a rare sight. The sensing pipelines also need to be able to operate in different states of degradation, e.g., plastic objects are not subject to decomposition but gradually break down into smaller and smaller constituents.

Cleaning Mechanisms

While the main focus of our vision is on litter monitoring, naturally, there should be mechanisms to remove the litter from the environment. A minimum requirement is to inform litter collectors about the locations where litter is found. A more advanced solution is to integrate the AGVs with robotic parts, such as grabbers or vacuum litter pickers. While integrating these components is technically feasible, there are practical limitations that need to be overcome. First, AGVs have a limited energy supply, which restricts the potential of using robotics parts. Optimally, the energy needed for cleaning could be harvested from sunlight, motion, or a combination of modalities, but currently, this is not yet feasible. Another challenge with robotic parts is to ensure they can work as intended in different terrain types and environments without damaging or getting damaged by the environment. In practice, we would expect to see a combination of different solutions ranging from manual cleaning to partially autonomous cleaning where AGVs are responsible for removing some litter objects and informing collectors about the ones left in the environment.

Litter Separation and Coordination

Removing litter from the environment is only the starting point for mitigating the negative effects of the litter as the collected litter objects also need to be stored (e.g., at landfills), recycled, or reused in a meaningful way. New ways to reuse litter are steadily emerging, e.g., plastic litter has been used as a material to build roads.[14] Both recycling and reuse require separating the litter according to the material of the objects and this requires coordination among the entities responsible for collecting the objects. In the simplest case, litter collection schedules need to link with waste sorting facilities that are responsible for separating the different materials, whereas a more advanced solution would be to have dedicated AGVs responsible for certain types of litter, e.g., separate for glass and plastic objects. Having dedicated AGVs requires intercommunication and coordination among the AGVs to ensure all of the potentially hazardous litter is removed.

Litter Tracking

Litter is rarely stationary but is transported in the environment as a result of wind, human activity, and other factors. For example, curbside collection of waste bins can result in excess waste dropping on the ground and then gradually being transported around the city.[15] Covering every nook and cranny of the city is naturally infeasible and, hence, there is a need to design movement plans that attempt to predict the most likely trajectories for waste transportation using weather, human mobility, and other variables as input. Some of these models could run on the AGVs and help coordinate their movement patterns in response to changes in weather, whereas large-scale coordination would require interacting with designated coordination centers. Beyond the algorithmic and system-related challenges, this also

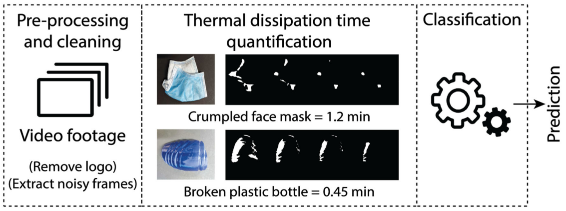


FIGURE 2. Sensing pipeline used for litter identification.

requires usable interfaces for human operators so that they can interact with the AGVs remotely. Waste transportation also means that there is a need to support coordinated movement plans, e.g., litter removal operations in sensitive environments tend to follow predefined transects, which help to maximize the coverage of the region that is monitored.

LITTER IDENTIFICATION USING SUNLIGHT

Accurate and lightweight litter identification is the starting point for enabling city-scale litter monitoring and, thus, solving this challenge is the first step in enabling our vision. The identification methods should also be cost-effective and able to operate autonomously without human effort. Our solution achieves these goals by integrating AGVs with sensing capability that relies on thermal dissipation characteristics of materials to identify and classify the materials of litter objects. The basic premise is to piggyback the thermal radiation that the sun induces on the litter objects. We temporarily block the sunlight using a sun-shield and monitor the dissipation of the thermal radiation on the surface of the object to establish a *fingerprint* that can then be used as input to machine learning algorithms to determine the material of the object.[9] The main benefit of harnessing sunlight is that it is freely available, thus reducing the energy drain of the AGV and even offering an opportunity to power—or at least charge—some of the components used by the AGV. Indeed, minimizing energy consumption is essential for ensuring the cost-effectiveness of the litter monitoring and for helping the AGVs to cover as large an area as possible. Note that the basic principle is not limited to using sunlight as an artificial heat source can similarly be used to create thermal radiation close to the object (see the "Discussion" section). Similarly, if the AGV cannot be integrated with a sun-shield, the object can first be taken to a location with a shade before the measurements are taken.

We have implemented a proof-of-concept pipeline that has been integrated with a commercial-off-the-shelf AGV. The processing pipeline of our implementation is shown in Figure 2. Video footage is recorded from an object until no temperature is visible in the thermal image. Raw video is preprocessed and cleaned by removing artifacts from the video and by dropping all frames that correspond to internal recalibration and heating up of the camera. The video footage is then converted into an ordered sequence of images, which are transformed into gray-scale (0–255) for easy manipulation. The overall dissipation time of an object's thermal fingerprint is calculated from the reduction in the (white) area of thermal fingerprint until it disappears (turns black). After this, feature vectors are produced to train classification algorithms. These vectors comprise the total dissipation time, shade area temperature, and the temperature under the sun area. As classification algorithms, we consider lightweight classifiers, including support vector machine (SVM), random forest (RF), and multilayer perceptron (MLPC).

EXPERIMENTS

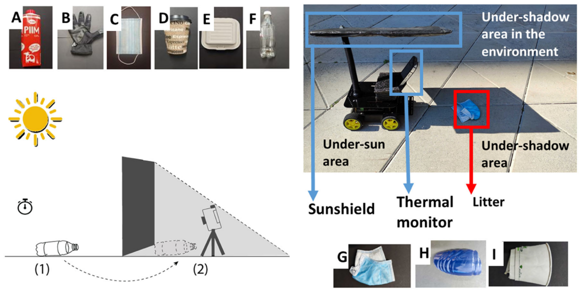
The feasibility of the vision is intrinsically linked with the capability of using sunlight and thermal cameras for identifying litter objects and the potential of integrating the proposed technology into ground drones. We next demonstrate the feasibility of these tasks by conducting several experiments on the use of sunlight-induced thermal radiation for classifying litter objects. We also assess the practicability of our approach by evaluating three different designs for integrating the monitoring onto ground drones. Finally, we demonstrate that our solution can operate in different environments and support litter objects that have already been degraded. We next describe our experiments.

Apparatus

Thermal dissipation measurements are collected using a CAT S60 smartphone with an integrated FLIR thermal camera. The device is mounted, pointing toward the ground, on top of a DFRobot Romeo V2 drone. Cardboard designs parallel to the ground are installed on top of the AGV to create a simple sun-shield for the thermal camera and the vision area [see Figure 3(a)].

Sunlight Characterization

To evaluate whether thermal dissipation time serves to recognize litter objects using sunlight, we first conduct an experiment to demonstrate that (i) sunlight can heat up litter objects enough to characterize them using the thermal dissipation fingerprint and (ii) it is possible to estimate thermal dissipation time in an open environment just by moving the object from an area of direct



(a) (b)

FIGURE 3. Experimental setup. (a) Characterization of litter objects with sunlight. (b) Integration of thermal dissipation fingerprinting into ground AGVs.

sunlight exposure (*under sun*) to a shadow area (*under shadow*). To do this, we first exposed each litter object to sunlight for about 15 min [see Figure 3(a), step 1]. Thermal dissipation time can be measured from quick exposures to thermal radiation,[9] however, we chose 15 min to ensure that thermal radiation was absorbed by the object and emulate real situations in which litter is disposed—in general for longer time periods. When the exposure time was completed, we moved the litter material to a shadow area and measure the thermal dissipation time using the thermal phone [see Figure 3(a), step 2]. The sunlight intensity to which each object was exposed was measured using the Lux Light Meter app for Android. The experiments were conducted in a public park between 12:00 a.m. and 15:00 p.m., twice per day, during three separate days. Six litter objects representative of different discarded solid waste were considered for the experiments, including A: Milk pack (tetra pack, low-density polyethylene—LDPE), B: Hand glove (Rubber), C: Face mask (polypropylene—PP), D: Coffee cup (wax-coated paper), E: Takeaway box (polystyrene–PS); and F: Plastic bottle (polyethylene terephthalate—PET).

AGV Designs

As part of the experiments, we assess the sensitivity of our solution to the design of the thermal dissipation monitoring. Specifically, our approach requires having the objects first exposed to sunlight and then measuring the objects in a shadow area and we assess the robustness of our sensing pipeline for different designs for achieving this. Indeed, AGVs can either create their own shadow using integrated components or piggyback existing shadow areas available in the environment, e.g., below a tree. To evaluate the most effective solution for thermal dissipation monitoring, we consider three different AGV designs that use different principles for creating the shadows. The three AGV designs are shown in Figure 1 and are referred to as *Sunsweeper*, *Sunshield*, and *Sunshovel*. Sunsweeper is equipped with a sweeper to move litter objects to a shadow area. Sunshield integrates an umbrella or other cover that blocks the sunlight to produce a temporal shadow over the litter object. Sunshovel combines these designs by having an umbrella to block sunlight but also integrating a shovel to have a constant background for the shadow area. Besides evaluating the different designs, the experiment has also been designed to provide insights into the situations where different AGV designs are best-suited. Indeed, it would be possible to allocate different AGV designs to different areas of the city depending on their characteristics.

Environments

The characteristics of the ground where litter resides can also affect the thermal fingerprint, and consequently the performance of the litter identification. To demonstrate the robustness of our solution, we conduct a follow-up experiment where we evaluate our solution in four different locations: pedestrian area (concrete), park (grass), harbor (wood), and paved road (stone). As part of this experiment, we also consider litter objects that are realistic and representative of those occurring in the wild. We achieve this using three objects whose shape, color, and other characteristics have changed as a result of degradation. The objects are shown in Figure 3(b) and comprise (G) a crumpled face mask, (H) a broken plastic bottle, and (I) a piece of a coffee cup. Experiments were conducted during a span of 10 days, three times per day (morning, midday, and afternoon). This translates to 85 trials, of which 12 are analyzed separately as spontaneous cloud formation resulted in reduced thermal fingerprints for the experiments. The former is used to analyze the performance of our method under ideal conditions, whereas the latter is used to analyze performance during partial and intermittent sunlight absorption. Ground truth temperature information is collected using DR CHECK FC500 from the location in which the litter is analyzed. In each location, we separately measured the temperature in the sun, under a shadow, and under the shadow produced by the AGV.

RESULTS

Characterization With Sunlight

Figure 4 presents the results of using sunlight to characterize litter objects. The average temperature during the whole experiment was about $18\,^{\circ}\mathrm{C}$ and objects

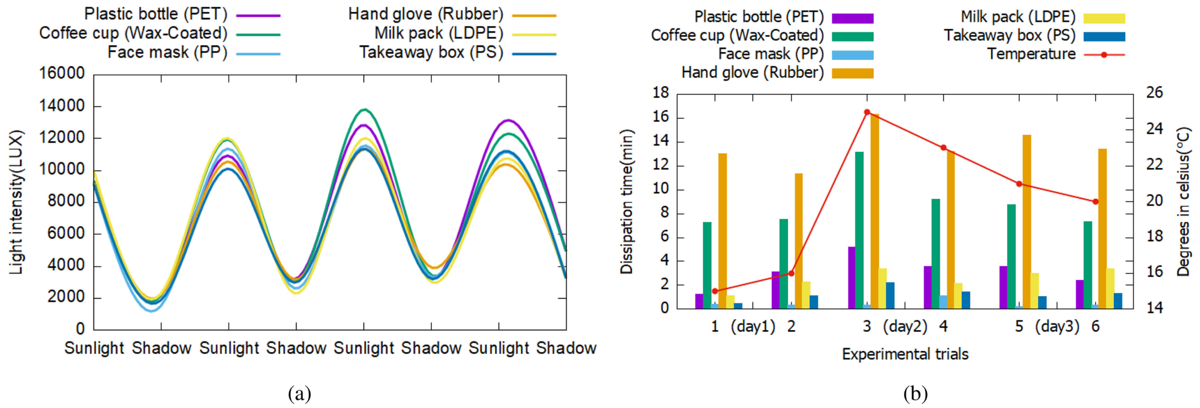


FIGURE 4. Thermal dissipation fingerprint using sunlight. (a) Light (thermal) exposure. (b) Dissipation values.

were exposed to sufficient sunlight. As shown in Figure 4(a), on average each object is exposed to an environmental light of intensity 12000 lx (under the sun). In the shadow, the light intensity reduces to an average of 3500 lx (under shadow). Figure 4(b) shows the thermal dissipation time for each litter object. From the figure, we can observe that different objects clearly have different fingerprints. Repeated-measures ANOVA test using thermal dissipation time as experimental conditions showed significant differences between objects $(F(1.86, 9.28) = 165.49,\quad p < .05,$ $\eta_g^2 = 0.94)$, demonstrating that thermal radiation can characterize different object materials. Pairwise post-hoc comparisons using t-test (with Bonferroni correction for multiple comparisons) confirmed that the differences in dissipation times are statistically significant for all the object pairs ($p < .01$), except for milk pack and plastic bottle ($p > .01$). Generally, the dissipation characteristics depend on the material's emissivity and thermal conductance, with the former referring to the fraction of thermal radiation that can be captured by the thermal camera and the latter referring to the speed at which heat is transferred to the outside. Polyethylene (PE) products (both low-density LDPE and high-density HDPE), such as the milk pack, have low emissivity but average thermal conductivity, i.e., they transfer heat to the outside well but only reflect a small amount of the transferred heat, whereas PET products have high emissivity but low conductivity, i.e., they insulate heat well but reflect large proportions of the transferred heat. These factors combine to make the dissipation times of PET and LDPE similar in the experiments. As shown in Figure 4, the intensity values of the materials are clearly different, and thus, a potential way to overcome this issue would be to use the light intensity as an additional feature when the dissipation times are similar. From the results, we can also observe that the relative differences in fingerprints are preserved for the objects when data are collected across different days. When considering the 12 trials where objects were exposed to partial and intermittent sunlight due to spontaneous cloud formation, repeated-measures ANOVA test using thermal dissipation time as experimental conditions showed no significant differences between objects $(F(1.11, 12.16) = 0.374,\quad p > .05)$, demonstrating that thermal radiation cannot characterize different object materials when there is only intermittent sunlight exposure. Note that it is possible to extend our solution to operate also during cloudy conditions by using an artificial source of sunlight; see the "Discussion" section.

Effectiveness of AGV Designs

We next evaluate the performance of the three different AGV designs (sun-sweeper, sun-shield, and sun-shovel) for thermal dissipation fingerprinting. We first quantify the difference in temperature between having the litter exposed to sunlight or having it under a shadow. The correlation coefficient (Kendall) indicates a positive correlation between thermal dissipation time and difference in temperature (τ=0.419, $p < .05$). Thus, the temperature difference is an important feature for obtaining a representative fingerprint of an object and we can compare the designs by assessing the temperature difference they produce.

Figure 5 presents the differences in temperatures that can be obtained with the different AGV designs. Generally, the higher the difference in temperature, the higher the variance in thermal dissipation (σ^2=0.273 cf. σ^2=0.454 for measurements below/above the median), which suggests the thermal properties of the materials are adequately captured. Indeed, the higher the thermal

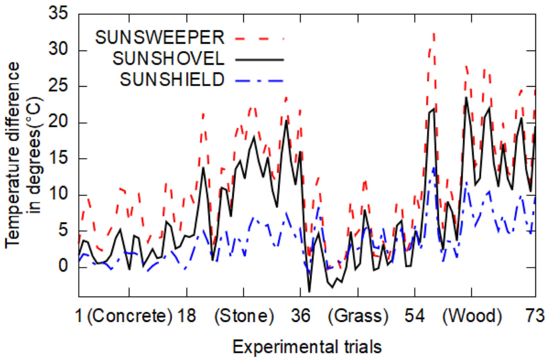


FIGURE 5. Temperature differences achieved by each ground AGV design to estimate thermal dissipation time of litter objects.

conductivity and emissivity of a material, the more variation we expect to see as a result of environmental variations. Of the different designs, sun-sweeper has the largest difference in temperature as it also needs to transport the objects to a shadow. The sunshield design, in contrast, shows stable performance when the background is fixed, but the performance decreases as the background changes. Specifically, when the litter is located on grass, the performance is highest, whereas stone and wood result in a drop in performance. Another limitation of the sun-shield is that the background where the litter resides starts to cool down also when the object is covered, which further weakens the thermal dissipation fingerprint. The sun-shovel overcomes this limitation and generally has a similar performance to the sun-sweeper. Specifically, the sun-shovel design is able to provide a consistent background, which improves the dissipation characterization.

Finally, we used the sun-shovel design to compare the *relative* thermal dissipation characterization of degraded litter objects in the park and in a controlled laboratory testbed (i.e., objects G, H, and I in Figure 3). Dissipation times in the park are 1.04 min for the crumpled face mask, 0.54 min for the broken bottle, and 1.02 min for the piece of a coffee cup, whereas the corresponding times in the laboratory are 1.27 min for the crumpled face mask, 1.05 min for the broken bottle, and 1.51 min for the piece of a coffee cup. Thus, the relative pattern between the different objects is preserved when the characterization is integrated with the AGV. As these objects represent litter objects found in real environments, the result also highlights the robustness of our solution and suggests it can be used for litter monitoring in the wild. Naturally, there are cases where our solution may struggle, e.g., objects that contain a mixture of multiple different materials or that are heavily contaminated by soil may result in unstable thermal fingerprints.

Litter Classification Accuracy

We next consider the potential of using machine learning to classify the objects according to their material. As described in the "Litter Identification Using Sunlight" section, we consider three common machine learning models: SVM, RF, and MLPC. When only dissipation time is considered, the average estimation accuracy is 59.1% across all the classifiers. This corresponds to a generic model where no information about the context is given. Once we include more parameters about the environment, i.e., the temperature and humidity of the environment, the temperature under the sunlight, the temperature in the shadow area, and period of the day, the accuracy is significantly improved to an average of 90.1% (90, 9% RF, 88.6% SVM, and 90.9% MLPC). Thus, simple features and classifiers are sufficient for classifying the materials of the objects, but measurements need to be taken in two diverse environments (i.e., under the sun and in the shadow) to ensure robust performance. In terms of accuracy, our results are comparable to those obtained using state-of-the-art object recognition.[16] However, as discussed, object recognition is sensitive to the state of the litter object. Indeed, the performance of object recognition decreases significantly when the litter objects are degraded or their shape has changed[9,10] as the model effectively learns to distinguish specific kinds of objects instead of what is litter. Our solution also requires less training data and processing than the object recognition approach.

DISCUSSION

The vision proposed in this article strives to offer a new way to monitor litter on a city scale that provides a cost-effective solution that can significantly increase the scale of monitoring, provide detailed insights into the litter situation in the city, and pave the way toward better environmental sustainability. Compared to state-of-the-art solutions, our proposed approach is more lightweight and flexible for identification of object litter objects using AGVs. Naturally, there are further challenges and limitations that must be addressed before our vision can fully be realized on a city scale. We discuss few of these points in the following.

Stakeholders

The main stakeholders for our solution would be municipalities and municipal waste collectors as our solution aims at increasing the scale and coverage of litter monitoring. However, we expect there to be also other beneficiaries and stakeholders. For example, as the imaging capabilities improve, we could expect to see the sensing pipeline being integrated into smartphones and wearables and offer people feedback on their behavior and information about the correct recycling practices. Similarly, recycling plants can integrate thermal dissipation sensing as a mechanism to support waste sorting. Indeed, the feasibility of thermal sensing has already been demonstrated in recycling context[12] and our work further extends this to using dissipation instead of measuring the objects in constant heat. Manufacturing industries may also become stakeholders as environmental regulations increasingly aim at making the industries responsible to contributing to waste management, and thus they could indirectly support the uptake of solution through payments to municipal actors. Finally, companies operating delivery services and goods could be piggybacked to carry sensors and collect information about the state of the environment.

Educating the User

Achieving long-term change in environmental sustainability requires besides identifying and removing litter, also educating and motivating the citizen to litter less and to recycle better. Thermal dissipation monitoring can be integrated into smartphones that are equipped with thermal cameras to help educate individual citizens or AGVs can be trained to recognize when someone drops litter and notify the person about the environmental consequences of their littering.

Regulations and Other Challenges

Drone usage is increasingly becoming regulated, even if currently it would seem that smaller ground AGVs will face fewer restrictions than other types of autonomous vehicles. AGVs are also generally more energy-efficient than other types of autonomous vehicles.[17] As such, we expect that in the near future, it would be possible to piggyback AGV operations for litter monitoring needs also. For example, delivery drones already operate in certain limited areas, e.g., university campuses, and there are autonomous street sweepers being deployed. Any upcoming regulations are likely to be influenced also by the size of the vehicles and, hence, there are design challenges in making the design as small and non-intrusive as possible. For example, having large sun-shields may be infeasible for public use and instead, there may be a need for retractable barriers that do not significantly increase the size of the vehicles.

Sunlight Intensity

Our experiments demonstrated that sunlight can be used as the source of thermal radiation to recognize material using thermal dissipation fingerprints. We conducted experiments in the morning and afternoon where adequate sunlight was available. We expect our solution to work also when sunlight intensity is lower, e.g., during the early morning or evening times, or when there is partial cloud cover. Winter conditions are another potential challenge as ice and snow may encapsulate the litter and cause the AGV issues to navigate. In case, when there is no sunlight, an artificial source of thermal radiation can be used to induce the thermal radiation. Alternatively, it may be possible to link the radiation with other environmental sensors. For example, air quality monitoring often uses metal-oxide sensors for capturing gas concentrations. These sensors need to be heated up prior to sampling the air and the resulting heat could potentially be channeled onto the objects being tested.

Micro- and Macrolitter

Off-the-shelf thermal cameras tend to have limited resolution, which means that our solution is better at recognizing larger litter objects (macrolitter) rather than smaller pieces or particles that also blend with the ground (microlitter). Comprehensively addressing litter thus requires combining our approach with other technologies that can also identify smaller particles. For instance, a combination of light reflectivity and thermal imaging[12] could potentially improve the extent of litter that can be recognized. Light reflectivity similarly has low energy footprint and, thus, it is well-suited for AGVs and the main research challenge is to ensure robust recognition performance.

Power Consumption

Operating litter monitoring in cities requires sufficiently small power consumption. AGVs generally have a longer-lasting operational time than other vehicular modalities,[17] yet the time is typically in the order of few hours. Our solution can operate using a smartphone or similar IoT-device that is integrated with the AGV and contains its own battery or another power source. Thus, the main impact on an AGV is a minor increase in payload, which does not significantly affect the operational time of the AGV. Even if an artificial source of light or heat is needed, this can be accomplished by piggybacking on other components, e.g., metal-oxide sensors used for air quality monitoring require heating and could be used to induce thermal fingerprints. As our solution relies on sunlight, it can also take advantage of energy harvesting, e.g., a solar panel could be integrated with the sun-shield to provide energy for the sensing as well as the AGV.

SUMMARY AND CONCLUSIONS

We presented a research vision of large-scale litter monitoring using ground AGVs that are equipped with thermal cameras and sun-shields. We presented proof-of-concept implementation and three different design prototypes, which were tested in controlled real-world experiments. Our vision seeks to increase the scale of litter monitoring by developing a solution that can operate at a larger scale than what is currently possible and overcome the need for human effort. The key to our solution is the idea of harnessing sunlight as a sensing modality and taking advantage of the fact that litter objects have different thermal properties that sunlight can expose. We identified key requirements and challenges for our vision and demonstrated the feasibility of the vision. Our results showed that over 90% litter classification performance can be achieved and that our solution can operate robustly against environmental variations. Our research paves the way toward new city-scale monitoring solutions that can address environmental issues and ultimately help improve the quality of life for citizens.

ACKNOWLEDGMENTS

This work was supported by the European Social Fund via the IT Academy Programme and the Academy of Finland Project 339614.

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