The Internet of Wasted Things (IoWT)

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INTRODUCTION

Office buildings, schools, stores, hotels, restaurants and other commercial, and institutional buildings generate significant amounts of waste. While buildings are becoming increasingly aware of their energy and water usage, the capability to track waste and material use with the same ease has remained beyond the reach of most building facilities managers [1,2]. Studies have focused on the use of sensors for garbage collection at a city level [3]. However, these studies consider waste as bulk and do not itemize and differentiate between their types and amounts [4]. In addition, to achieve the recycling goals, the facilities management offices have to manually or semi-automatically sort through the waste in order to separate the recycle waste apart manually.

As is the case with energy consumption, occupants also have different waste behavior profiles; for instance, it is estimated that 15 to 20 percent of people proactively recycle on regular basis; on the other hand, 15 percent of the population is considered to be the opposite and not consider recycling their waste at all. A major shortcoming in the area of waste management is associated with the lack of awareness and education of the users for separating and managing their own waste. In particular, the following major challenges exist when it comes to waste management at a building and occupant level: (1) automatically separating waste at the origin and (2) assisting and educating occupants on separating waste properly. These problems are further compounded due to limited information available about different waste profiles and whether certain environmental, psychological, or physiological factors may influence recycling behaviors directly or indirectly.

In this position paper, we propose the building blocks for The Internet of Wasted Things (IoWT) - a framework for (1) automatically classifying and tracking different waste items; (2) guiding the user towards the correct trash bin for each waste item; and (3) developing individual waste profile for each user. The following questions are addressed through the implementation of the proposed framework:

- How can trash bins automatically identify waste items and predict an occupant's intent for throwing away a trash?
- Does individual's waste pattern change over time (e.g., times of the day, seasons etc.)?
- Do environmental factors (e.g., lighting, temperature, etc.) as well as social factors (e.g., surrounding people) influence occupants' waste and recycling behaviors?

METHODOLOGY

The schematic view of our proposed platform is depicted in Figure 1. As a person approaches the trash bin, (1) using an RGB camera, video of the person approaching the trash bin will be recorded and fed into an object recognition algorithm

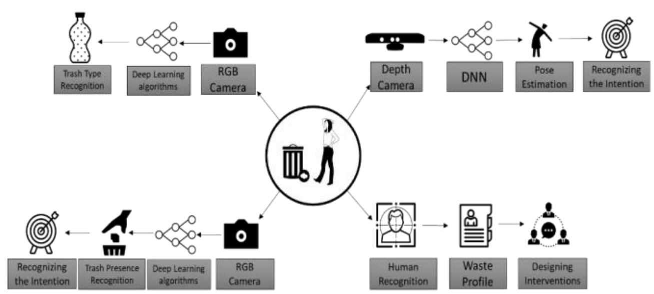

Figure 1. Framework Synopsis

such as existing implementations of deep neural networks (DNNs) [5-9] (i.e. YOLO, AlexNet, etc.). While existing DNN implementations on object data libraries (like ImageNet) are available as starting point, we will build classifiers for a finer granularity of objects relevant to waste management. For example, we may have a pre-trained network that can detect bottles, but it may not distinguish between a plastic and a glass bottle, which may need to be disposed in different manners. Thus, for this specific problem, we need to build a dataset of different types of trash, such as water bottles, soda cans, different color papers, etc. As the DNN recognizes the type of object in a person's hand, the correct trash (object) category will be detected and the correct trash bin will light up (Figure 2 left); (2) using computer vision, we are able to estimate the posture of the person which further helps to determine his/her intention,

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resulting in decreasing the number of false positive triggers in our system; (3) furthermore, by using facial recognition algorithms, we will assign the trash to each person based on his/her face. This correct trash will be recorded in the system for that specific user (for creating user profiles).

As the first stage we have conducted a pilot experimental and observational study. For the experimental study, 4 cameras at different angles were setup to record the surrounding of a set of trash bins (landfill, plastic, paper). Two participants were instructed to throw a number of different objects in the trash bin in their own natural way. The installed cameras covered all the angles that the participant might approach the trash bin. In the observational study, the trash bins were placed in a common area used by many people throughout the day of the building and we observed how people approach a trash bin in a natural situation; for instance, the person's gaze, how a trash was held in hands, and walking trajectory towards the trash bins were observed and analyzed.

PRELIMINARY RESULTS AND DISCUSSION

Our preliminary results using a stock web camera show that it is indeed possible to classify everyday waste objects with significant accuracy, but there is a tremendous room for improvement in these methods (Figure 2 right). For instance, by using a DNN, here we were able to classify three different types of trashes (i.e. water bottle, carton and paper). However, much larger training libraries are required for dynamically and in real-time detecting waste objects.

In addition, analyzing the experimental videos together with the observations revealed some insight into different issues regarding identify and tracking waste. People's intention for throwing a trash can be recognized using multiple factors. First, recognizing an object in their hand that falls in the waste category probably shows the intention of trash disposal. Furthermore, as a person approaches towards a trash bin, his/her gaze may change towards the set of trash bins, although it might not be exactly towards the correct bin (Figure 2 left). In Addition, there is a significant time difference in the body movement and action of the occupant for each type of trash being thrown away. For instance,

Figure 2. Preliminary DNN results (right) and proposed view of the trash bin in space (left)

throwing away a soda can take less time than a cardboard box, which requires smashing before throwing away. This time difference is important for accurately detecting the type of objecting being thrown away (detection). There are multiple times that the trash includes two pieces that require a separation before disposing of it. For instance, some coffee cups have plastic lids. The plastic lid needs to be separated before disposing of the trash. What it means is that the system should understand both materials. In this case, using multiple cameras might be able to help in understanding different objects. In addition, there are situations that people approach the trash box while having the trash concealed in their hand or their pocket (occlusion). In this situation, the detection process takes longer than normal.

Finally, considering the potential issues with this system, as such system incorporates facial and body posture as inputs, there exists privacy issues regarding to potential recording of videos of users. While this is a valid concern during the preliminary study, it will be further addressed by using embedded systems that process the camera feed in real-time without recording videos and causing privacy concerns. Additionally, we will look into how useful information can be collected from different sensors in a smart building (e.g., occupancy sensors) to identify and track waste in an office environment without invading the occupants' privacy.

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