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Classification of metallic and non-metallic fractions of e-waste using thermal imaging-based technique

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ABSTRACT

Electronic waste (e-waste) is generated at a rapid pace due to technological advancement and thereby reduced obsolescence age of electrical and electronic equipment (EEE). E-waste comprises of many useful recyclable materials such as metallic fractions (MFs), like aluminum and copper and non-metallic fractions (NMFs), such as plastic, printed circuit boards (PCB) and glass. Classification of MFs and NMFs from e-waste is of great significance from the viewpoint of recycling of materials and resource recovery. In this paper, we focus on the classification of MFs and NMFs from e-waste using thermal imaging-based technique operated in the long-wave infrared range (LWIR) 8–15 μm. We use a feature vector comprising of mean intensity, standard deviation and the image-sharpness extracted from the thermograms of individual materials present in e-waste. We developed a classification model to classify the feature vectors into broad categories of metal, PCB, plastic, and glass. We conducted several experiments on simulated e-waste to validate the developed approach and obtained a classification success rate in the range of 84–96%. We believe that the proposed approach is a viable solution for multi-material classification of e-waste into broad categories and can be scaled up to fit for an e-waste recycling plant.

1. Introduction

Management of e-waste is one of the most rapidly growing problems worldwide because of the quantity and complexity of the waste stream comprising of various end-of-life electrical and electronic equipment (EEE) (Widmer et al., 2005; Wong et al., 2007). Advancement in technology rapidly renders EEE obsolete in a short span leading to the massive generation of e-waste. Around 41.8 Mt of e-waste has been reported to be generated worldwide in the year 2014 (UNU, 2015), and the generation is expected to increase with a growth rate of 4–5% per annum reaching to 49.8 Mt by 2018 (Baldé et al., 2015). Population and wealth have a strong correlation with global e-waste generation. Increase in per capita income will also lead to increase in e-waste production. In general, countries with higher per capita income contribute more e-waste as compared to other low-income countries except for Switzerland shown in Fig. 1 (Priya and Hait, 2017).

The UNU in 2014 classified e-waste into six categories, namely, (i) temperature exchange equipment, (ii) screens/monitors, (iii) lamps, (iv) large equipment, (v) small equipment, and (vi) small IT/telecommunication equipment (Baldé et al., 2015). E-waste comprises of many useful recyclable materials such as MFs like aluminum, copper, lead, zinc, and metal alloys and NMFs such as plastic, PCB, and glass. E-waste contains not only toxic and hazardous contaminants but also valuable and precious metals such as gold, silver, and platinum if adequately managed (Cui and Forssberg, 2003; Huang et al., 2009a; Li et al., 2007; Ongondo et al., 2011; Yang et al., 2009; Zhou and Qiu, 2010). To manage e-waste efficiently a 'take-back system' has been introduced in various developed countries wherein designated organizations collect e-waste in a formal chain for recycling. In the developing countries like India, China, Nigeria, and Brazil, the rag-pickers collect e-waste from door-to-door as well as dump-yards/landfills and sell to recycling shops, middlemen or exporters. These recycling shops and middlemen recycle e-scraps through 'backyard recycling' in an informal manner, which can have a very severe impact not only on the environment but humans too (Schluep, 2012; UNU, 2015; Wang et al., 2013). In recent years, recycling of e-waste informal manner has gained momentum because of the environmental concern and economic benefits. A vast body of literature exists in the area of recovery and reuse of MFs from e-waste (Huang et al., 2009b; Li and Xu, 2010; Ma et al., 2012; Xue et al., 2012; Zhan and Xu, 2009). The NMFs, which take up a significant proportion of e-waste, are

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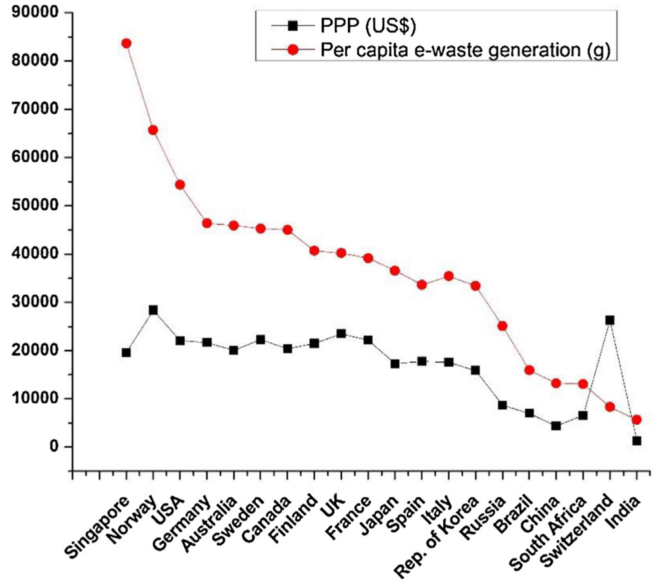

Fig. 1. Per capita e-waste generation versus GDP per capita based on purchasing power parity of various countries.

often managed by incineration or dumping into the landfill (Zhou and Xu, 2012). Most of the studies have focused on the management of either MFs or NMFs from e-waste. This paper focuses on the automated classification of MFs and NMFs together from e-waste into broad categories namely metal, PCB, plastic, and glass.

There has been extensive research on comprehensive understanding of state-of-the-art in the field of automated sorting and recycling of municipal solid waste (MSW) (Gundupalli et al., 2017a,b). Also, different methods have been employed for screening and separation of e-waste materials with varied shape, size, density, electric, and magnetic properties (Cui and Forssberg 2003). Lukka et al., 2014 developed a multi-robot system comprising of manipulator and conveyor system capable of sorting construction and demolition waste (CND). The system involves supervised machine learning approach for material classification and robotic grasping (Kujala et al., 2015; Lukka et al., 2014). Also, there has been extensive research efforts made recently in local invariant feature detection using the RGB camera (Kujala et al. 2015). In learning-based object detection technique, (Viola and Jones, 2001) proposed a robust detection without any restriction in the background. The main limitation of visual object sorting is the requirements for controlled illumination and a confined workspace. In order to resolve the barrier, a robotic manipulator capable of classifying/sorting the recyclables from mixed MSW using a thermographic image has been developed. The classification was performed using support vector machine (SVM) using the extracted keypoint features from recyclable materials via thermal imaging camera (Paulraj et al., 2016). Recently, features like mean and standard deviation were extracted from recyclables present in the thermograms to automatically classify/sort them into broad categories of recyclable groups from MSW stream (Gundupalli et al., 2017a,b). The thermal imaging-based technique can be extended to automatically classify and sort MFs and NMFs together from e-waste. In comparison to automated classification of recyclables present in MSW, there are various technical challenges due to the nature and complexity of e-waste includes: (i) uneven surface and wide range of geometries of the recyclable objects, (ii) a need for rugged/robust sensors so as to handle complex composition of e-waste and (iii) the large computational burden for the classifier. We propose the use of thermal imaging technique as a possible solution to identify/classify MFs and NMFs together from e-waste into broad categories namely metal, PCB, plastic, and glass. Thermal intensity images are single channel yet rich in material information and often have the modest computational requirements.

The paper focuses on identifying/recognizing recyclable materials present in e-waste into broad categories by explicitly estimating the radiation intensity properties. For example, a glass plate which has an emissivity of 0.92 will be opaque and radiate more and thus will appear bright in the thermogram (Holst, 2000). On the other hand, an aluminum plate with an emissivity of 0.04 will not radiate and will appear dark in the thermogram (Incropera et al., 2006; Maldague, 2001). The emissivity values of different metallic and non-metallic materials are available in many references (Holst, 2000; Incropera et al., 2006; Maldague, 2001; Modest, 2003). The broad categories of recyclable materials can be correlated with radiation intensity properties. We introduce a feature descriptor comprising of mean intensity, standard deviation, and image sharpness of thermograms. The paper reports a classification model developed based on a number of thermograms generated in the training stage from which the feature descriptors are extracted. The classification model is subsequently experimented on simulated e-waste during the testing stage to classify the recyclables into broad categories.

2. System overview

The e-waste is usually collected via take-back system by the designated organizations, manufacturers, retailers and the recyclers for the purpose of recycling (see Fig. 2). The collected waste is transported to local dismantling units, where the small, medium and large appliances or equipment are dismantled into MFs and NMFs (see Fig. 2). The final destination of the dismantled e-waste fractions is the material recovery facility where we propose to classify and sort the recyclables using the thermal imaging-based technique.

The schematic shown in Fig. 2 illustrates an overview of the steps employed to classify the recyclables by thermal imaging based approach. In the first step, dismantled e-waste fractions are fed (see Fig. 2(a)) into the sorting system via a conveyor belt. After this, the dismantled e-waste fractions are sent into a hot chamber, which is maintained at a temperature of $55 \pm 03\,^{\circ}$C (see Fig. 2 (b)). Subsequently, the conveyor system carries the e-waste from the hot chamber to the adjacent inspection zone (see Fig. 2(c)). After this, the thermal imaging camera captures the thermograms for material classification inside the inspection zone (see Fig. 2(d)). The camera used in the current setup is a FLIR ORION SC7000 thermal camera with a pixel resolution of 320×256 and placed in a vertical downward-looking configuration at an adjustable height from the conveyor belt and the reflective shield is introduced to prevent the radiation emitted due to heat dissipation by the camera to fall on the samples in the inspection zone. In the next step, the robotic manipulator sorts the identified recyclable materials at the end of the conveyor belt (see Fig. 2(e)). Finally, the manipulator bins the recyclables into respective bins (see Fig. 2 (f)).

A proposed overview of machine vision setup is illustrated in Fig. 3 for classifying the e-waste fractions. Firstly, the thermograms acquired from the thermal imaging camera are normalized according to the workspace dimensions. After this, the captured images are preprocessed and stored in an image database. The objects are segmented using Otsu's thresholding method (Otsu, 1979) to perform feature detection and extraction (see Fig. 3). Based on the type of material the segmentation threshold values are determined. Subsequently, the segmented thermograms are processed to extract features comprising of the mean intensity, standard deviation, and the image sharpness. The extracted features are then presented to the classifier model to recognize the type of recyclable group in the segmented thermograms (see Fig. 3). In the next step, the location of