A Novel Integration of Hyper-spectral Imaging and Neural Networks to Process Waste Electrical and Electronic Plastics

Alimohammad Tehrani and Hamidreza Karbasi
School of Engineering
Conestoga College Institute of Technology and Advanced Learning
Cambridge, Ontario, Canada
atehrani@conestogac.on.ca
hkarbasi@conestogac.on.ca

***Abstract*— In this study, a technique which combines hyper-spectral imaging technology and a neural networks-based algorithm has been introduced for identification and separation of different types of e-waste plastics (e-plastics). Although recent technological developments in computing power allows for the handling of big data in a relatively reasonable time, a manageable number of neurons must be utilized in order to realize real-time sorting applications for plastic recycling. A successful result to identify three different common types of e-plastics with a very high rate of accuracy has been presented. The result has been achieved using a special designed Artificial Neural Networks (ANN) algorithm and hyper-spectral signature of those plastics. The promising result will pave a road to address the shortcomings of current e-plastic sorting technologies in terms of efficiency and reliability.**

Keywords*— Solid Waste Management; Plastic Recycling; Electronic Waste Recycling; Optical Sorting; IR hyper-spectral Imaging; Neural Networks; Machine Learning; Spectroscopy; System Integration; e-waste; WEEE.

I. INTRODUCTION

Consumer electronics have revolutionized the way in which we communicate and transfer information. Key segments of resource recovery and waste management processes and strategies for Waste Electrical and Electronic Equipment (WEEE) or "e-waste" include material sorting, chemical separation and treatment, decontamination, logistics, and material recovery. The recovery of metals and plastics that are contained within WEEE contributes to both economic and environmental sustainability [1].

The fastest-growing sector of solid waste, Waste Electrical and Electronic Equipment (WEEE), generates 40-50 million tonnes globally, each year. It is estimated that 80-85% of WEEE is not properly recycled, where it is either exported to Third World countries where precious metals are liberated via incineration, or ends up in landfills, deserts, or on riverbeds. In the U.S. alone, 2.2 million tonnes of e-waste is disposed annually [2].

One of the challenges for current recycling technologies is in identifying and classifying waste [3]. Distinguishable data streams provided for classifying waste is another challenge encountered by recycling technologies.

There are many applications of ANNs for classification problems currently being utilized by companies and universities. Recycling applications are not excluded in this case, although applying ANNs to recycling classification problems is quite new [4]. Using image and colour as the input data to the ANN has been used in some of the approaches in solving the recycling classification problems in academia and industry [4, 5]. In cases where we cannot distinguish the inputs using a visible-range image, we need to find a type of input that makes the classification problem feasible. In this paper, we are introducing the application of Hyper-Spectral Imaging in recycling material classification with a low and tolerable error rate.

II. HYPER-SPECTRAL IMAGING AND ARTIFICIAL NEURAL NETWORKS

Different types of plastics, such as Polystyrene (PS), Polycarbonate (PC), Polypropylene (PP), Acrylonitrile Butadiene Styrene (ABS), and High Impact Polystyrene Sheet (HIPS), dominate the materials which comprise the WEEE stream [6]. These materials are "ground-up" into flakes in order to be able to process and sort them into high-purity "bins of material". In this paper, a novel technique for processing WEEE plastics using hyper-spectral imaging and neural networks is introduced.

Hyper-spectral imaging [7] has been extensively used in the identification of objects within various fields of science and engineering, including, but not limited to, remote sensing [8], food processing [9], and recycling. In e-waste recycling, distinguishing between different types of plastics that are used in electronic devices, so-called "e-plastics", is the first step in the recycling process. Due to the fact that different types of plastic can share the same colour, isolating them by visible range image processing techniques is not possible. These different types of plastic, however, show different spectral signatures within infrared range [10], and it is therefore possible to rely on their spectrum for identification. Inherently, acquiring the spectral signatures of materials is a slow process, as it includes scanning through both space and frequency. Recent developments in sensor technologies have enabled us to capture spectral information at a rate sufficient for real-time identification of materials moving at a high rate of speed.

In an e-waste recycling facility, thrashed pieces of plastics enter a sorting system on a high-speed conveyor belt. The sorting system should first identify the type of plastic and then segregate them into separate bins of material. To realize this task, three major subsystems are needed: high-speed sensors to capture the spectral information, a high-speed intelligent algorithm to identify material types based on the spectral information, and high-speed mechanical actuators to separate the different types of materials into their designated bins. Materials entering the sorting systems are usually dirty, and the surrounding environment is also contaminated with dust that is caused by processing these dirty materials. As such, the intelligent system needs to be able to recognize the same material under various conditions in the presence of dirt and other tainting agents. This environment necessitates the use of algorithms that have learning and generalization capabilities. They need to learn from actual material samples and be able to generalize when they encounter a material that is not exactly in the same condition as the material that they had been trained with. Artificial Intelligence (AI) algorithms seem to be the best candidates as they have both learning and generalization capabilities. Most AI algorithms, however, are computationally expensive, which makes them unsuitable for high-speed, real-time decision-making applications. Among them, neural networks seem promising, assuming the number of neurons can be limited in order to minimize computation time.

In this paper, we explain the design and development of a high-speed identification system that is used to classify three types of plastic: PC, ABS, and HIPS based on their spectral signatures.

III. PROCEDURE

A. Imaging and Acquiring Spectral Data

The sensor used in this system is a short-wave infrared (SWIR) hyper-spectral line scan camera which is utilized to acquire the spectral signature of the plastic objects. The SWIR camera scans lines in 384 pixels. For each pixel, the camera captures the intensity in a wavelength range between 1,000-2,500 nm, which is divided into 288 bands; these bands are referred herein as spectral bins. The intensity in each bin is a 2-byte value in the range of 0-65,535. Figure 1 shows the spectral signature of a piece of white HIPS plastic. The camera sends spectral information of the scanned object in bit interleaved (BIT) format to the computer through a serial link. A single data frame is 211,184 bytes in size, which corresponds with 2 bytes per pixel, for an image that is 384 x 288 (spatial x spectral).

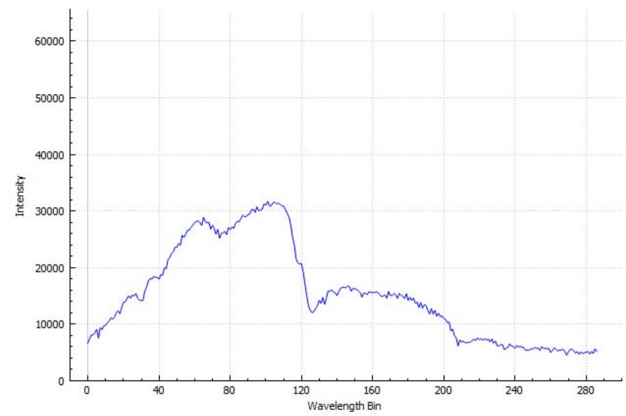

Figure 1: Spectral signature of a piece of white HIPS plastic

A full image of the objects on the moving bed is constructed by stitching frames together. In this experiment we stitched together 30 frames to get a narrow strip for image processing, and then used 36 strips to produce a full image similar to that shown in Figure 8. The maximum frame rate that can be achieved depends upon the number of spectral bins that are acquired. To acquire all 288 bins of spectrum, the maximum rate we were able to use was 250 frames per second.

B. Data Analysis and Preparation

Since different shades of the same material show different signatures due to the change in the intensity of reflection, the spectral data needs to be normalized so that objects can be distinguished solely based on their spectral details, and not based on the intensity level. Figure 2 shows the normalized spectral signatures of the three types of plastic mentioned above.

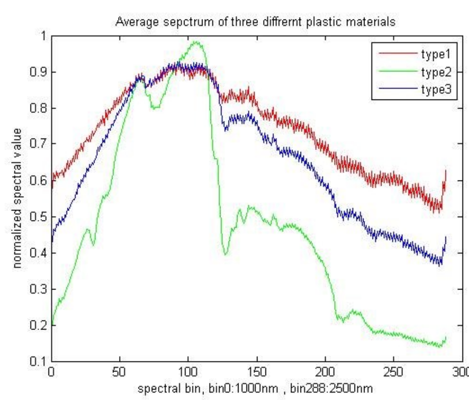

Figure 2: Spectral signatures of three plastic types:
type1 – dark grey PC, type2 – light grey ABS, type3 – white HIPS

To determine if these plastic types can be distinguished based on their spectral data, we completed a principal component analysis. Figure 3 shows the two principal components with the highest variances. As can be seen, even with only two principal components, the spectral data seems to be easily distinguishable. However, computing principal components is too expensive for use in real-time applications, so rather than processing all 288 bins of spectral data, we chose a selected number of bins that, based on the report from the camera manufacturer, display distinctive features for the three plastic types with which we are experimenting. The selected bins are: bin78 (1412nm), bin125 (1680nm), bin 165 (1901nm), bin172 (1944nm), and bin 225 (2238nm). The normalized values of these spectral bins for the three plastic types can be seen in Figure 4.

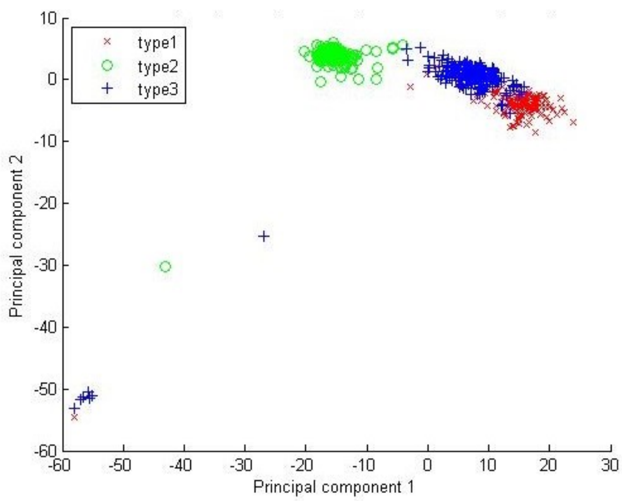

Figure 3: Distribution of two principal components of spectral data of three types of plastics

The fluctuation of data from sample to sample is the source of noise and sharp spikes in Figure 4. To train any kind of classifier, this noisy data can disturb the learning process. Therefore, this data is first smoothed out by a moving average smoother with a window size of 10. Figure 5 shows the bins' values after filtering.

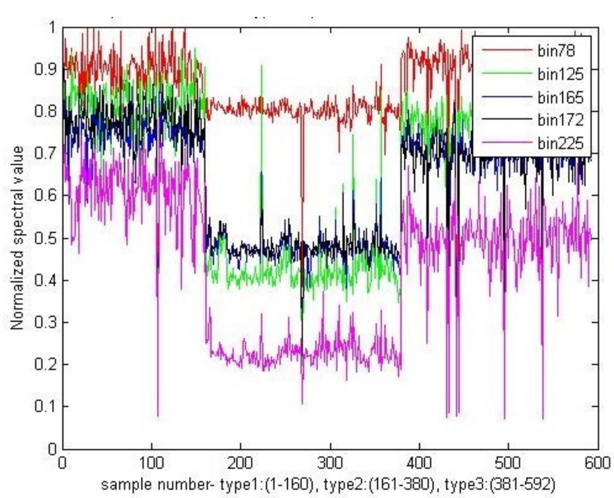

Figure 4: Normalized values of five spectral bins for three types of plastic. The three sections of the graph belong to the three types of plastic.

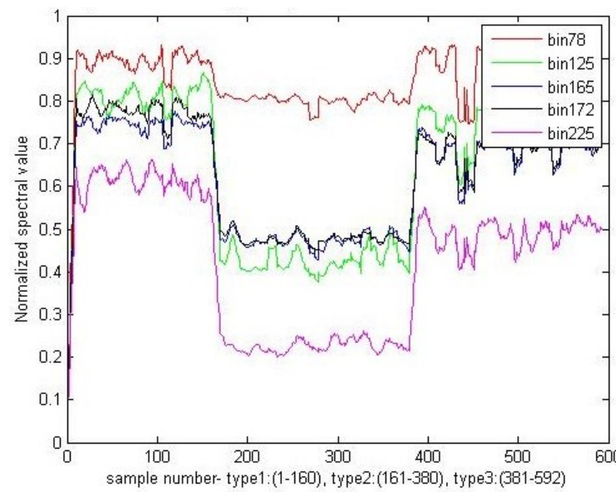

Figure 5: Normalized values of five spectral bins for three types of plastic after filtering.

C. Data processing and the Neural Network

To identify objects based on their spectral data, we require a classifier. In this work, we used a multi-layer ANN. Figure 6 shows the ANN with five input neurons, four hidden neurons, and three output neurons. Inputs to this ANN are normalized spectral values of the five bins mentioned in Section B, and the three outputs represent the three types of plastic that are being classified.

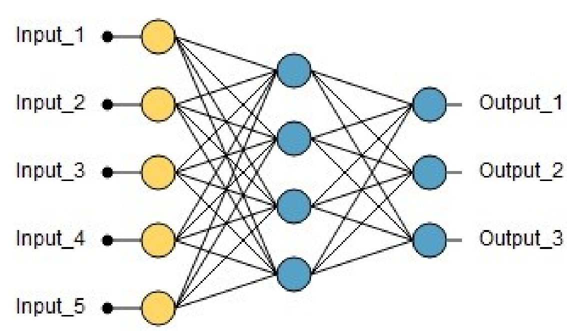

Figure 6: Three-layer ANN with five inputs for five spectral bins' values, four hidden neurons, and three output neurons for three types of plastic

1) Training Phase

Before this ANN can be used to identify plastic types, it should be trained. The network is trained in a supervised manner by presenting the input data, and identifying the proper output that it should generate. To facilitate this, the conveyor belt is loaded with one type of plastic, and is then scanned. This process is to be completed for each type of plastic. In each scan, the system finds the spectrum of each piece at the specific wavelengths described previously. These spectral values are fed through the neural network as training data. In an ideal scenario, input data from plastic type1 should result in a value of 1.0 at the first output, and 0 at the other two outputs. This would mean that type1 is the winner in this competition. Therefore, when training the network, the input values with ideal output values are used [Figure 7]. The same process is then repeated for the other types of plastics, until the network is trained for all three types of plastic.

1	0.375586	0.234974	0.258778	0.251484	0.114397	1	0	0
2	0.432425	0.221927	0.263066	0.258946	0.129290	1	0	0
3	0.420279	0.200229	0.233310	0.243503	0.118685	1	0	0
4	0.445502	0.218067	0.254124	0.264256	0.129213	1	0	0
5	0.420890	0.200519	0.234379	0.244953	0.119356	1	0	0
6	0.412604	0.189578	0.231754	0.227283	0.110826	1	0	0
7	0.424475	0.266346	0.270558	0.260441	0.136034	1	0	0
8	0.427344	0.192767	0.241993	0.237690	0.098512	1	0	0
9	0.448966	0.213687	0.250629	0.247715	0.118013	1	0	0
10	0.419028	0.209079	0.247410	0.243580	0.109483	1	0	0
11	0.417227	0.224796	0.244282	0.248768	0.095888	1	0	0
12	0.456306	0.225879	0.270268	0.263264	0.126436	1	0	0
13	0.440772	0.212589	0.251652	0.255940	0.132036	1	0	0
14	0.417044	0.207843	0.249561	0.245563	0.124239	1	0	0
15	0.370871	0.185092	0.211780	0.219837	0.110124	1	0	0
16	0.416190	0.201282	0.235752	0.239368	0.112474	1	0	0
17	0.397681	0.194369	0.225177	0.218769	0.107744	1	0	0

Figure 7: Training data. Each row belongs to one sample of Plastic No. 1. Columns 1-5 in each row show the input spectral values, and Columns 6-8 show the ideal output for Plastic No. 1

To simulate the ANN before implementing it in the actual setting, we used Neural Designer, which is a free software to design and test neural networks. The advantage of Neural Designer is that is uses openNN C++ library, which is the same library that we used to implement our neural network.

Table 1 shows the confusion matrix of the network after being trained. It indicates that the network has learned the data without any confusion, so it can determine the type of plastic based on the input data.

2) Identification Phase

The trained neural network can then be used as a classifier. Now, a mixture of plastic pieces of different types will be placed on the conveyor belt and be scanned [Figure 8]. The spectral information of each piece is fed through the neural network and the output with the higher value will identify the plastic type. Our results have shown that with the five spectral bins, and a neural network with five input neurons, four hidden neurons, and three output neurons, we could classify three different types of plastic at a conveyor belt speed of 1 m/s, with 99% accuracy.

TABLE 1: CONFUSION MATRIX OF THE ANN CLASSIFIER

	Predicted type1	Predicted type2	Predicted type3
Actual type1	160	0	0
Actual type2	0	220	0
Actual type3	0	0	192

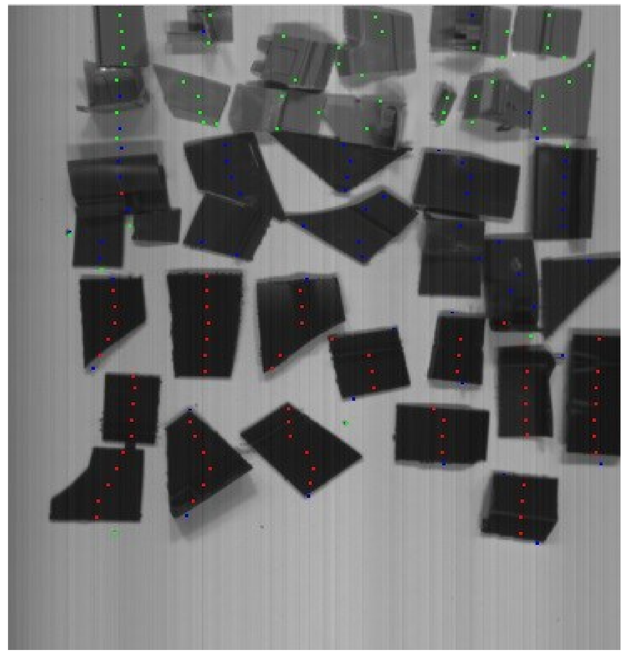

Figure 8: Stitched image of the conveyor belt loaded with 38 pieces of plastics from three different types, where each piece is scanned multiple times. The dots show the location of sampling during the line scan, and the colour represents the predicted type.
Red – type1, Green – type2, Blue – type3

IV. DISCUSSION

In this paper, we have explained the process of using ANN to identify three types of plastic. At first, properly identified and labelled pieces of plastic were shown to the network for training purpose. In the next step, the trained network was used to identify unknown objects. Due to separation of spectral data in the feature space, ANN was a suitable choice for classification. Although neural networks have been used for classification for many years, due to the high-speed of material processing in e-waste recycling, they can be computationally expensive. For use in high-speed, real-time applications, the size of the neural network should be small, otherwise, the speed of computation cannot keep pace with the speed of the materials that are passing in front of the camera sensors. To shrink the size of a neural network, the number of inputs should be reduced. In this work, we have shown that a selection of a small number of features from the full spectrum of the object is sufficient to feed a neural network and obtain accurate results.

At this stage of experimentation, the sample plastic pieces that were used were in a better and cleaner condition than that of the materials that would typically be found within a recycling facility. The next phase of this research includes the repetition of these experiments with materials that are tainted and more accurately reflect the condition of typical materials found in a recycling facility. It is expected that the presence of dirt will not impact the spectrum of the plastic but this will need to be examined in order to prove this assumption.

To continue this work, we plan to apply the same technology in the MWIR range to identify black plastics. Black plastic materials, due to their high-carbon content, absorb the SWIR energy and do not reflect anything to the camera. Using Medium-Wave Infrared (MWIR) allows us to get meaningful spectral signatures for black plastics.

As part of future research, and based on the promising results from this work, we have been encouraged to apply the ANN algorithms on hyper-spectral signatures of different plastics to study the possibility of identifying flame-retardant plastics in the waste stream. If realized, it will address a growing concern of toxic substances that are present in recycled plastics.

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