Identification of Plastic Types Using Discrete Near Infrared Reflectance Spectroscopy

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Abstract - This paper presents a low-cost and handheld system for the identification of plastic types based on discrete near infrared (NIR) reflectance spectroscopy. For identification among different types, a method based on machine learning is introduced. The current capability of the system includes differentiation between polyethylene terephthalate (PET), high density polyethylene (HDPE), polypropylene (PP) and polystyrene (PS). Accurate detections of the machine learning model are demonstrated within the constraints of the current solution. Finally, improvements to the setup are suggested.

I. INTRODUCTION

With the worldwide plastic production historically growing 9% p.a., packaging being the single biggest source of plastic waste [1] and its impact on climate change being proven [2], recycling plastic is one of the main challenges of this century. The recycling process gets threatened predominantly by the following four factors: polymer cross contamination, additives, non-polymer impurities, and degradation [3], which is why much of the municipal plastic waste still can't be recycled. To reduce polymer cross contamination and non-polymer impurities proper sorting before disposal is mandatory.
This paper aims to introduce one possible solution by proposing the use of a discrete spectrometer for differentiating common kinds of plastic. Such a solution is cheap to manufacture even at low volume and can be realized in a handheld form.

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It makes the capability of easily sorting plastics available to individuals as well as public institutions. The authors of this paper suggest the application of such a device primarily in education, in environmental projects, and in developing countries.

II. SYSTEM

The system used to collect measurement samples consists of a custom made discrete spectrometer and a computer running the machine learning model.

A. System Properties and Dimensions

The developed system is displayed in Figure 1. A 3D printed case is used for enclosure and to ensure more constant lighting conditions for each individual measurement. It has the overall dimensions of 65 x 35 mm with a 15 mm diameter window as interface to the plastic item under test.

Figure 1: Handheld Discrete Spectrometer

Further mentions of the term 'measurement window' will refer to the circular cutout in the black case of the device.

B. Discrete Spectrometer Electronics

The discrete spectrometer consists of different light emitting diodes (LED) (white, 850 nm, 960 nm, 1200 nm, 1300 nm, 1450 nm, 1550 nm, 1650 nm) and a InGaAs photodetector. The photocurrent of the detector is measured using a

24 bit analog digital converter (ADC) and the LEDs are controlled using a dedicated controller. A microprocessor controls the measurement and establishes a USB connection to the host computer. When a new measurement is requested by USB the LEDs are turned on one by one. During the on-time, the photocurrent is filtered analog and measured by the ADC. This procedure is carried out for all eight LEDs in a row and afterwards transmitted back using USB.

C. Calibration and Noise Reduction

When items are measured using the system neither transmittance of light through the item nor direct entry of light to the photodiode can be ruled out. As radiation in near infrared range is commonly present (e.g. halogen light bulbs) and no optical filters are present in the system, solutions for the reduction of its influence had to be developed. In addition to this, the influence of the LEDs to the Photodiode further reduce the signal noise ratio of the measurement. That's why calibration and reference measurements are required to enable good system performance.
First the calibration of the system specific LED-Photodiode influence is conducted. The LEDs are turned on in a non-reflective chamber and in the meantime the photodiode current is measured. This way only the direct light shining onto the photodiode and reflected from the systems case are measured. The measured value can then be subtracted from each individual measured value.
To further improve the quality of the measurement, the influence of additional light sources is deducted from the measured values. This is achieved by measuring a sample without the NIR LEDS being turned on before and after each actual measurement. Using this method only ambient light is measured which can later be averaged and subtracted from the actual measurement sample.

D. Data Transfer and Storage

To communicate with the custom discrete spectrometer, a python script is used. It runs on a host computer and automatically handles received data. The external light, as well as the LED-photodiode influence, (section II.C) get subtracted automatically from the measured sample itself.
Training samples for the machine learning are stored in a comma separated values (CSV) file. This way they can be easily modified and managed.
When the system is used for identification, detection samples get uploaded to a real time database.

III. EVALUATION

For the system samples evaluation process, plastic items are collected and used to train the machine learning model. Afterwards the system can be used to make predictions for unknown plastic items.

A. Plastic Items and Collected Samples

The plastic items used in the present study are collected from municipal waste. For each plastic type (PET, HDPE, PP, PS) several different colored items were selected based on their ability to cover the systems measurement window. Table 1 shows the composition of the scanned items.

Table 1: Measurement Sample Overview

Type	Colors	Color in Figure 2	Number of Items
PET	white, transparent-blue, transparent-green	blue	3
HDPE	blue, light-blue,white	cyan	8
PP	white, transparent-white	green	3
PS	white	magenta	2

Samples of all individual plastic items were collected. Ten measurements per individual item are collected as explained in section II.D and stored to a CSV file.

B. Collected Data Analysis

Another publication has shown that accurate identification of plastic types can be obtained

through calculating the relative reflectance at two wavelengths in the NIR region [4]. Applying this concept of relative reflectance to a discrete spectrometer, the ratios of individual sample wavelengths will add crucial information to the machine learning model. The different ratios visible in Table 2 represent characteristic absorption spikes within the full resolution NIR reflectance spectra of the different types of plastic.
The ratio $R_{(1200\,nm)}/R_{(1300\,nm)}$ therefore represents the relation of the reflection values obtained at 1200 nm and 1300 nm.

Table 2: Reflectance Ratios used for Plastic identification

Ratio1	$R_{(1200\,nm)}/R_{(1300\,nm)}$
Ratio2	$R_{(1450nm)}/R_{(1550nm)}$
Ratio3	$R_{(1550nm)}/R_{(1650nm)}$

Plotting those values in a three dimensional scatter plot allows easy visual identification of the different plastic types. Figure 2 visualizes the samples collected according to Table 1 and clearly shows a separation of the individual sample groups.

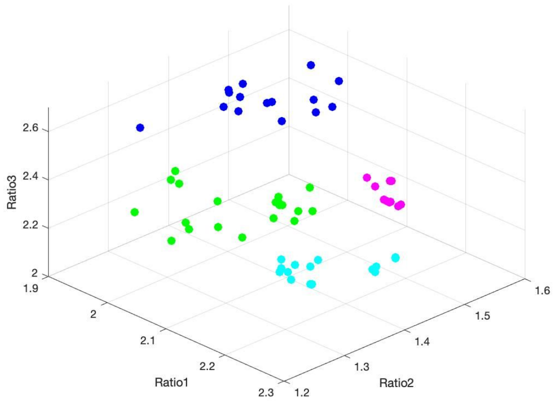

Figure 2: 3D scatter plot of identification features

C. Plastic Identification using Machine Learning

For data analysis a deep neural net (DNN) is used. This dramatically decreased the development time as no specific algorithms had to be developed. The model was trained to tell apart the individual types of plastic using roughly 200 measurement samples. The trained model is stored in a file and can be loaded by a python script. This happens within a python script which listens for new data to be uploaded to the real time database. New data is then downloaded, fed to the machine learning model and the prediction is uploaded back to the database. Predictions can then be visualized in a web application. The accuracy of the trained model reached a high of 95%. Using the machine learning model for predictions of the previously trained plastic samples was therefore possible. During testing of more than 100 individual scans no wrong positives occured.

V. CONCLUSION

It has been demonstrated that the identification of municipal plastic waste using discrete NIR spectroscopy is theoretically possible. Only measurements at few measured wavelengths are required to make highly accurate predictions among a limited range of samples.
To be able to apply this approach to generic identification of plastic samples, the signal processing needs to be improved and additional wavelength LEDs should be added. This way a low-cost and small form solution can be provided for use in recycling education and small scale recycling facilities.

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