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Energy-efficient systems for the sensing and separation of mixed polymers

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Abstract

Polymers are ubiquitous in modern manufactured products. The potential detrimental impacts of their end-of-life disposal have stimulated significant increases in recycling rates. Recyclate purity is paramount; however this must be achieved with a positive net energy balance. Existing technologies for identification and separation of polymers are often both expensive and energy intensive. This paper investigates Infrared (IR) imaging to extract information on thermal properties of various product polymers within a recycling line. An intelligent decision making support system is enabled using neural network based pattern recognition for automatic polymer identification and classification. Potential energy savings versus current technologies are discussed.

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1. Introduction

The use of plastics for the packaging of consumer goods has grown rapidly from their initial introduction, driven by the many functional and commercial benefits that these materials offer [1]. As a result, plastics packaging has now become ubiquitous in our modern society, particularly in the distribution and retail of food, beverage and other fast moving consumer products. One consequence of this is that plastics packaging now makes up a significant proportion of the Municipal Solid Waste in the UK; 22% by weight, which until recently was mainly disposed of in landfill [2]. However recent EU and UK government initiatives have targeted packaging waste in an attempt to reduce the amount going to landfill [3]. This has been approached from two directions – reducing the amount of waste being generated (material minimisation) and diverting material away from landfill through alternative waste management mechanisms (re-use, recovery and recycling [4]). Recycling is a major focus of the European Union's (EU) environmental policy, specifically in its 'Waste Framework Directive' and principles of 'Extended Producer Responsibility', where each material group (plastics, glass etc.) has its own recycling and recovery targets, which are likely to increase from 22.5% to 60% by 2025[5].

Meanwhile, driven by similar environmental and sustainability concerns the use of 'renewable' materials, such as bio-derived polymers, has also been promoted [6]. Conventional polymers are largely derived from fossil fuels, such as crude oil, which in addition to being a finite resource, is also widely considered to have reached maximum extraction levels, 'Peak Oil' [6]. Recent developments in bio-polymers, developed in response to these needs, have seen a number of new materials commercially adopted within mainstream packaging applications, such as bottles, trays and bags [7]. Whilst some of these bio-polymers are equivalent to their conventional counterparts such as bio-PE and Bio-PET, others such as PLA and PHA have no conventional polymer equivalent [8]. These unconventional bio-polymers have created problems for recyclers in the separation process even in very small quantities. This is significant both from an environmental and a commercial standpoint as the purity of the recyclate has a direct impact on its reuse application (closed loop) and its market value (a high purity recyclate can has a higher market value than its 'virgin' equivalent).

1.1. Plastic recycling

Recycling of municipal solid waste (MSW) generally involves two key stages: sorting and separation [9]. Sorting processes the waste into its different component parts and major material types without destroying the integrity of the original pack. The degree of sorting achieved depends on the sophistication of the technology used; however it is common for key packs/material groups to be generated, such as plastic bottles. Separation takes place after fragmentation and usually involves processing just one sorted group at a time i.e. plastic bottles. This will separate the fragmented plastics into individual polymer types, the purity of which will again depend on the sophistication of the technologies used [10].

Technologies used for plastics recycling (sorting and separation) fall largely into two key groups, physical and sensor based. Physical methods use a particular characteristic of the polymer or pack, such as its density, to separate or sort it from the other materials. Sensor based methods on the other hand firstly identify the polymer or pack and then use a computer controlled air jet to separate or sort them into individual waste streams [10]. Improvements in sorting will often lead directly to improvements in separation efficiency and with higher quality expectations [11].

However, sorting of waste often takes place further upstream in smaller, less specialized waste treatment plants. Plastic bottles are crushed into bales where they can be transported to centralized plastics processing plants. The quality of the bales significantly impacts the efficiencies of the plant with a high polymer mix requiring additional/repeated sorting/separation stages [9]. Also in less developed countries, improving the sorting of plastics, in mainly manual operations, could have additional safety and social benefits as well as improved environmental and commercial ones.

PLA and PET are two polymers used in bottles for drinking water which have proved difficult to separate using current technologies, such as wet density separation [6]. Sensor based systems like Near Infra-Red (NIR) can be used with a greater success but are expensive and require significant investment and resources to manufacture and to run, putting it out of the reach of smaller recyclers and reducing the environmental and economic efficiency of larger plants [11].

1.2. Theoretical principles

This research undertaken and presented in this paper investigates the application of thermal imaging as a low cost and low energy method for a polymer sensing system for use in the sorting of post-consumer plastics packaging waste; specifically PET and PLA bottles. These were chosen as they have similar densities making them harder to separate using current physical separation technology, as used by industry for separating PET from PE. Secondly, the bottles are very similar in appearance, as illustrated in Fig 1, making manual or automated visual sorting also problematic. This is increased when the bottles are crushed, contaminated and/or have labels removed. Thirdly, contamination of PET by even very small quantities of PLA can significantly effect is usability and resale value.

Fig 1: Tested Specimens (Left to Right: PLA (26.2g), PET (25.3g), PET (14.6g) and PET (12.1g)

PET and PLA however have very different thermal properties with significant differences in specific heat capacity and thermal conductivity as shown in Table 1.

The aim of this research was to develop a low energy, low cost sensor based technology that exploited these differences in thermal properties.

The experiments described in chapter 2 are based on the use of thermal imaging to detect differences in the cooling rates of 500ml plastic bottles made from a range of PET and PLA polymers.

Using Newton's Law of Cooling, it was initially calculated that PLA would cool at a slower rate than PET assuming equal starting temperatures and environmental conditions and it is asserted that this variation would be detectable in real time using a thermal imaging camera.

Newton's law of cooling is provided below:

$$\frac{dQ}{dt} = h.A.\Delta T(t)$$

Where:

Q is the thermal energy (J)

h is the convective heat transfer coefficient (W/m^{2}K)

A is the surface area associated with the heat transfer (m^2)

$\Delta T(t)$ refers to the transient thermal gradient between the object and 'air' temperature at a given time.

This can be re-arranged to provide an equation in terms of heat flux ($\dot{q}$) (W/m^2)

$$\dot{q} = -h(T_\infty - T_w)$$

Where T_∞ refers to the fluid temperature, and object wall temperature is denoted by T_w.

This initial Lump System analysis used a solid cube of each material.

Table 1: Comparison of polymer thermal properties

Polymer	Density (g/cm^3)	Specific Heat Capacity (J/Kg·K)	Thermal conductivity (W/(m·K) @23°C)
Polyethylene terephthalate (PET)	1.38-1.56	1000-1350	0.15-0.4
Polylactic acid (PLA)	1.25	1800	0.13
High-density polyethylene (HDPE)	0.95-1.27	1300-2400	0.45-0.52

However the physical geometry of a plastic bottle is not aligned to that of a compact system and furthermore, in a practical situation the heat transfer coefficient itself will practically change with temperature, therefore employing a constant value in analysis limits the accuracy of any formulations derived. It was therefore decided to continue with the practical experimentation and subsequent results analysis before undertaking more in depth theoretical modelling.

2. Materials and methods

2.1. Experimental procedure

An experimental campaign was carried out according to the methodology illustrated in Fig. 2. The first step consists in heating the bottle using a Carbolite fan assisted oven (see Fig. 3) up to 50°C. The specimens were then removed and placed in an open sided box in order to isolate other sources of light and heat, and allowed to cool down. During this cooling phase, a series of infrared (IR) digital thermal images were acquired in order to measure the temperature during the cooling. The temperature data recorded were then processed using two different techniques illustrated in the next sections.

An intelligent pattern recognition based decision making support system was set up with the aim of assessing the bottle types on the basis of their thermal properties.

2.2. Samples tested

Tests were carried out on a number of 500ml bottle variants that included different bottle weights and material options as shown in Table 2. In addition, for the lightest weight bottle, 3 degrees of bottle compaction were evaluated to simulate the 'real life' condition of packs entering a sorting plant. (It was hypothesized that vertical crushing of the bottle could potentially reduce the exposed surface and thus slow its rate of cooling). Table 3 provides the different condition codes for crushed bottle evaluation.

2.3. Experimental setup and programme

By combining the parameters related to bottle materials and bottle condition, and by repeating each experiment 5 times, a total of 35 experimental tests were performed and summarised in Table 4.
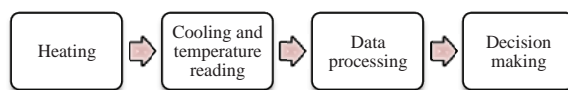

Fig. 2. Methodology flow chart

Table 2. Test specimens

Material Type	Bottle Volume (ml)	Uncapped Bottle Mass (g)	Bottle Test Code
PLA	500	26.2	A
PET	500	25.3	B
PET	500	14.6	C
PET	500	12.1	B

Table 3. Degrees of bottle compaction tested

Condition Code	Details
W	Whole Bottle
25%	Bottle Crushed to 25% of Original Shoulder Height
50%	Bottle Crushed to 50% of Original Shoulder Height
F	Flattened Bottle

Fig. 3. Experimental setup scheme

Table 4. Experimental programme

Test ID	Material	Bottle type	Condition	Rep.
T1	PLA	A	W	1
T2	PLA	A	W	2
T3	PLA	A	W	3
T4	PLA	A	W	4
T5	PLA	A	W	5
T6	PET_{THICK}	B	W	1
T7	PET_{THICK}	B	W	2
T8	PET_{THICK}	B	W	3
T9	PET_{THICK}	B	W	4
T10	PET_{THICK}	B	W	5
T11	PET_{THIN}	C	W	1
T12	PET_{THIN}	C	W	2
T13	PET_{THIN}	C	W	3
T14	PET_{THIN}	C	W	4
T15	PET_{THIN}	C	W	5
T16	PET_{THIN}	C	25%	1
T17	PET_{THIN}	C	25%	2
T18	PET_{THIN}	C	25%	3
T19	PET_{THIN}	C	25%	4
T20	PET_{THIN}	C	25%	5
T21	PET_{THIN}	C	50%	1
T22	PET_{THIN}	C	50%	2
T23	PET_{THIN}	C	50%	3
T24	PET_{THIN}	C	50%	4
T25	PET_{THIN}	C	50%	5
T26	PET_{THIN}	C	F	1
T27	PET_{THIN}	C	F	2
T28	PET_{THIN}	C	F	3
T29	PET_{THIN}	C	F	4
T30	PET_{THIN}	C	F	5
T31	PET_{MEDIUM}	D	W	1
T32	PET_{MEDIUM}	D	W	2
T33	PET_{MEDIUM}	D	W	3
T34	PET_{MEDIUM}	D	W	4
T35	PET_{MEDIUM}	D	W	5

3. Image acquisition and processing

Infrared temperature data acquisition was carried out using a Gobi-640-GigE thermal vision camera.

IR images were recorded with a frame rate equal to 0.2 fps which corresponds to 1 image every 5 seconds. The

experimental tests duration was set to 1 minute, thus, a total of 12 images were acquired during each experimental test.

Using Xeneth 2.5 software, temperature data was generated by defining a rectangular 60 x 40 pixels Region Of Interest (ROI) within the IR image (see Fig. 4). The ROI shape and size were selected in order to ensure a homogeneous portion of the bottle surface avoiding possible presence of paper or plastic labels.

The temperature data recorded was a spatial average over the ROI, in order to minimise the data variability increasing the reliability of the data reading [12,13]. An example of temperature data for Test T01 is reported in Fig. 5.

A fundamental parameter in infrared temperature data acquisition is the emissivity. It depends on a several factors such as environment temperature, materials and surface finish of the sample [14]. The thermography settings are reported in Table 5.

The extraction of data characteristic features from sensing systems is of primary importance in many information processing fields such as pattern recognition, predictive modelling, industrial process fault diagnosis and control [15].

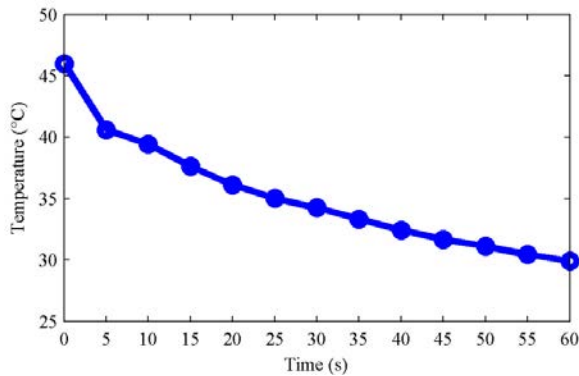Fig. 4. IR image acquired for Test T21 (PET Thick)

Fig. 5. Temperature data recorded for Test T01

Table 5. IR thermography settings

Tool camera distance	0.5 m
Atmospheric temperature	17°C
Reflected temperature	17°C
Total emissivity coefficient	**0.9**

In this paper two methodologies were adopted to extract features: Statistical features and Polynomial features. Both methodologies are described in the next sections.

3.1. Statistical features

Four statistical indicators were calculated from the temperature data of each experimental test:
- Mean
- Variance
- Skewness
- Kurtosis

The four statistical features mentioned above were grouped (Table 6) into 4-element feature vectors [15] to be used as input to a neural network based decision making support system.

3.2. Polynomial features

This kind of features consists in computing the coefficients of the polynomial $f(x)$ of degree 2 that fits the IR temperature data in a least squares sense.

The result is 3-element feature vector [15] containing the polynomial coefficients in descending powers:

$$f(x) = \alpha x^2 + \beta x + \gamma$$

Therefore a set of 3 features, i.e. the polynomial coefficients $[\alpha\ \beta\ \gamma]$, was extracted from the segmented signal of each experimental test, as shown in Fig. 6 and partially reported in Table 7.

Table 6. Statistical features vector

ID Test	Mean	Variance	Skewness	Kurtosis
T1	34.3345	12.4254	0.4728	2.0167
T2	36.2723	28.3071	0.4907	1.9474
…	…	…	…	…
T35	24.4814	14.8275	0.5757	2.3187
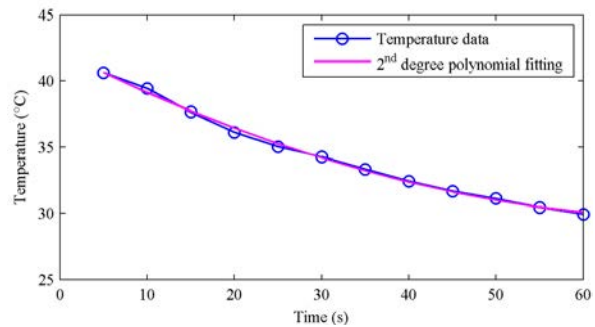
Fig. 6. 2nd degree polynomial fitting of temperature data

Table 7. Polynomial features vector

ID Test	α	β	γ
T1	0.0022	-0.3362	42.2648
T2	0.0038	-0.5377	48.5545
…	…	…	…
T35	0.0027	-0.3835	33.3073

4. Pattern recognition decision making

Neural network (NN) pattern recognition based on temperature data features extracted through the methodologies described above was utilised for decision making on polymer categorisation under two classifying perspectives: single bottle type classification and PLA/PET bottle identification. The features vectors obtained with the two methodologies were used to construct feature vectors [15] to input to a neural network (NN) based pattern recognition procedure [15–18] for decision making on polymer categorisation.

The two sets of feature vectors made up two different training sets for NN learning using diverse architectures for pattern recognition [19]. Data for classification problems are set up for a NN by organising the data into two matrices, the input matrix and the target matrix. The input matrix consists of a 3- or 4-element feature vectors (columns) and either 20 test cases (rows) for the whole bottles dataset (W) or 35 rows for the full dataset which includes both whole and crushed bottles (W+ C). The feed-forward (FF) back-propagation (BP) NN is the most commonly used family of NN for pattern classification purposes [20]. Its structure is made of three layers (input, hidden and output layer respectively.

In this application the following NN architecture configurations were adopted:

The number of input nodes was equal to the number of input features vector elements:

- 4 nodes for statistical features as the feature vector is made of 4 elements: Mean, Variance, Skewness and Kurtosis.
- 3 nodes for polynomial features as the features vector elements are the polynomial coefficients α, β, and γ.

The number of hidden layer nodes was set to 24.

The output layer contained either 4 nodes, yielding a coded value associated with the bottle type, or only 1 node, in case of PLA / PET bottle identification. In this work, the algorithm for FF BP NN learning is the Levenberg-Marquardt algorithm which is considered one of the fastest methods for learning moderate-sized FF BP NN [21,22]. Data division for NN learning was carried out randomly with the following percentages: 70% for training; 15% for validation; 15% for testing.

4.1. Single bottle type classification

In the case of single bottle type classification, the bottles were clustered into four classes: A, B, C and D as reported in Table 2. Each row of the target matrix has four elements, consisting of three zeros and a one in the location of the associated bottle type.

4.2. PLA / PET identification

In the case of PLA/PET identification, the bottles were grouped into two clusters, according to the material type:
- PLA Cluster, Class A
- PET Cluster, Classes B, C and D

The NN target vector, in this case, contains zeros for the PLA and ones for the PET.

5. Results and discussions

Tables 8 and 9 report the NN pattern recognition success rate (SR), i.e. the ratio of correct classifications over total training cases, for single bottle type classification and PLA / PET bottle type identification using statistical and polynomial feature vectors.

The NN SR values are always higher than 90%, confirming the capability of both methodologies in extracting valuable data features for bottle material separation monitoring.

The single bottle type classification results (Table 8 and Fig. 7) show a constant SR when using the W dataset (95%) regardless the feature extraction methodology. When considering the W+C dataset, instead, the statistical features lead to a higher SR (98.3%) compared to the polynomial features (91.4%).

Table 8. Single bottle type classification SRs

Single bottle type		Dataset	
		W	W + C
Features	Statistical	95%	94.30%
	Polynomial	95%	91.40%

Table 9. PLA / PET identification SRs

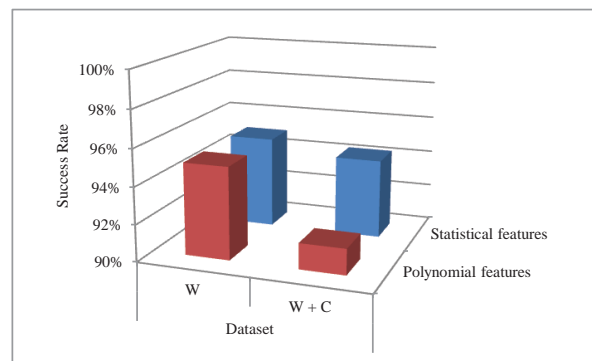| PLA / PET		Dataset	
		W	W + C
Features	Statistical	95%	97.10%
	Polynomial	95%	94.30%

Fig. 7. Single bottle type classification success rates
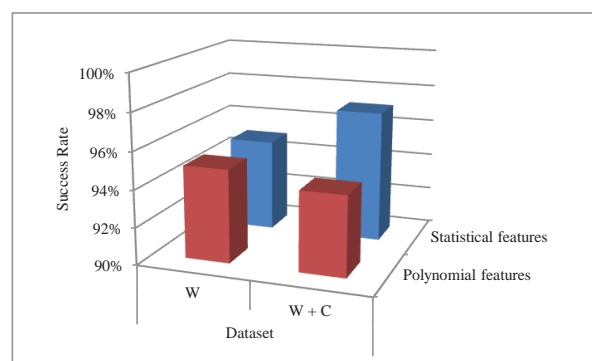

Fig. 8. PLA / PET identification success rates

The PLA/PET identification results (Table 9 and Fig. 8) show again a constant SR for the W dataset (95%) and for both the feature extraction methodologies. The W+C dataset results show a better performance of statistical features (97.1%) and a lower SR for polynomial features (94.3%).

The different success rates for the two assessment purposes can be explained by the fact that a four-class recognition task (the four bottle types) is inherently more complex than a two-class discrimination task (PLA/PET). In general, using a larger dataset, statistical features yielded higher SRs than polynomial features.

6. Conclusions

The sustainable recycling of plastics from MSW requires efficient and effective sorting and separation processes. Improved sorting can have a direct benefit on the efficiency and effectiveness of the subsequent separation process and the final quality and commercial viability of the recyclate.

Current sorting and separation technologies are effective for some waste polymer combinations where sufficient density variation provides an effective means of segregation, however for others, such as PLA with PET, alternatives to density separation are required.

Thermal imaging can provide an effective mechanism for polymers classification in controlled conditions where variations in thermal properties are sufficient to allow detectable cooling or warming differences. For use in the sorting of plastic bottles from MSW, the thermal imaging data requires additional processing due to the effect of variable bottle weights, crushing and contamination.

The sensitivity of this detection and variation can be further improved through the subsequent analysis of a larger data sets and shorter time lapse for image acquisition. Further testing is required across a wider range of material and bottle types and with larger sample sizes before the potential of this method can be confirmed.

Acknowledgements

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