



PET and PVC separation with hyperspectral imaging

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Plastic market data 2012

- Global production: 288 milioni di t
- Annual production in Europe: ۲ 57 milioni di tons
- 62.2% of the total derives from • household waste (mainly container and packaging)
- Mechanical recycling involved ۲ about 26 % of total postconsumer plastics
- 35.6% was recovered for • energy in municipal waste incineration plants or as refuse derived fuel material
- The residual 38.1 % of plastic • waste was landfilled









- Plastic is one of the most used materials in practical applications.
- Mechanical recycling of plastics can be used to obtain homogeneous materials.

<u>BUT</u>

 The separation of plastics in various polymers is difficult to achieve with traditional methods of separation because of the variability of the properties of different polymers in a reduced interval.

IN FACT

 The separation of different polymers by gravimetric techniques is quite difficult in case of slight differences in density

eg. PVC (density: 1.32–1.37 g/cm³) vs PET (density ranging from 1.33-1.37 g/cm³)

Moreover, cross-contamination problems may arise among the different polymers.

Thus, it is necessary to develop effective technologies to separate chlorinated plastic from other heavy plastics!!



The hyperspectral method represents a methodology alternative to more traditional tools to separate both different types of plastic polymers and contaminants from plastic wastes.

Advantages:

- low cost

allows overcoming problems such as: the influence of moisture, surface status and low feeding speed of particles in electrostatic separation;
no additive addition in separation by flotation and density

- no more separation steps to classify a heterogeneous mixture of plastic wastes containing different useful fractions

This technology combines:

- spectral reflectance measurements
- image processing technologies





Hyperspectral platform

The characterization of materials is based on the use of two spectrometers. The first spectrometer (VIS) is centered in the visible range of the electromagnetic spectrum (400 nm to 1000 nm), and the second spectrometer (NIR) is centered in the near infrared region (900 nm to 1800 nm).

Linear spectrometer configuration:

VIS Specim Imspector spectrometer (S1) mounted in front of a Dalsa Falcon 1.4M100 CMOS camera (1400× 1024 pixels @ 25 fps, spectral resolution up to 3 nm);
NIR Specim Imspector spectrometer (S2) mounted in front of an InGaAs Sensor Unlimited camera (320× 256 pixels @ 50 fps, spectral resolution up to 3 nm);

- high-speed DVR CORE with two Camera Link inputs used to acquire and manage the data, containing 1terabyte solid state disk array;
- processing computer for controlling the entire system and acquiring images;
- conveyor belt to allow the target constant displacement.







- Plastic samples of PET and PVC have been collected at different stages of their life cycle:
- virgin plastic: regular shape granules of different color, density and composition, representing the raw materials used for the manufacture of products
- In plastic wastes: collected from many sources (urban and industrial waste plants)
- regenerated second raw materials: used for the production of new products



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Experimental section: Plastic materials tested



Virgin, waste and regenerated PET samples

NAME	DESCRIPTION	SAMPLE ORIGIN	COLOR	MEASURED DENSITY (g/cm ³)	MEAN PARTICLE SIZE (cm)
PET 1-V	Virgin particles in granules	Virgin material	White/tra nsparent	1.30	0.20
PET 3-F	Coca-Cola bottle flakes	Wastes in flakes	Transpar ent	1.35	0.43 0.52
PET 4-F	Water bottle flakes	Wastes in flakes	Green/tra nsparent	1.35	0.36 0.72
PET 5-R	Bottle flakes	Secondary raw plastics (regenerated) in flakes	Multicolo r/ transpare nt	1.33	0.64 1.02

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Experimental section: Plastic materials tested



Virgin, waste and regenerated PVC samples

NAME	DESCRIPTION	SAMPLE ORIGIN	COLOR	MEASURED DENSITY (g/cm ³)	MEAN PARTICLE SIZE (cm)
PVC 1-V	Virgin particles in granules	Virgin material	Transpare nt	1.30	0.40
PVC 2-V	Virgin particles in granules	Virgin material	Green	1.37	0.18
PVC 3-F	Tube flakes	Wastes in flakes	Orange	1.61	0.17 0.28
PVC 4-F	Processing waste flakes	Wastes in flakes	White	0.61	0.40 0.61
PVC 5-R	Recovered from waste flakes	Secondary raw plastics (regenerated) in flakes	White	1.44	0.36 0.622



Experimental section: Plastic materials tested



PET and PVC samples in pieces

NAME	DESCRIPTION	SAMPLE ORIGIN	COLOR	MEASURED DENSITY (g/cm ³)	MEAN PARTICLE SIZE (cm)
PET 3-P	Coca-Cola bottle piece	Wastes in pieces	Transpare nt	1.35	4.07 3.31
PET 4-P	Water bottle piece	Wastes in pieces	Green/tran sparent	1.35	4.81 3.71
PVC 3-P	Tube piece	Wastes in pieces	Orange	1.61	2.47 4.97
PVC 4-P	Processing waste piece	Wastes in pieces	White	0.61	3.16 4.88



•Geometric spectral calibration: for assigning wavelength to image columns or rows.

•Imagery acquisition: linear spectrometer captures a line image of target and disperses the light from each line image pixel into a spectrum. Each high-resolution spectral image contains then line pixels in a spatial axis and spectral pixels in a spectral axis.

•Acquired imagery processing: creation of an image for each wavelength of interest. A spectral image sequence can be formed by sequentially acquiring image of a moving target.

•Imagery correction to enhance the image quality.

•Creation of hyperspectral cube: it is a three-dimensional array containing spatial information on the x and y axes (image) and spectral information on the z axis.

•Creation of spectral signatures: the dark current contributes to the signal recorded by the sensors, and this should be subtracted from the data. The reflectance is therefore computed as: $\rho = (R-D)/(W-D)$ where R is the measured sample data, D is the dark current image and W is the white image captured from reference material (Halon tile).





NIR signatures of PET and PVC samples. Near-infrared reflectance spectra extracted from hyperspectral images of PET-PVC samples were used to determine characteristic peaks at wavelengths that can be used to distinguish the two plastic materials.

-PET :1120-1130, 1160-1180, 1410-1420 and 1660-1670; -PVC: 1190-1200 nm and 1410-1430 nm.





Statistical analysis

From the hyperspectral cubes of the plastics under investigation, the spectral signatures of pixels belonging to regions of interest comprising the area occupied by the Virgin plastics have been considered.

The correlation matrix, C, was computed as follows:

$$C(\lambda_i, \lambda_j) = \sum_{N_{-sam}} \frac{(\rho(\lambda_i) - \overline{\rho(\lambda_i)})(\rho(\lambda_j) - \overline{\rho(\lambda_j)})}{\sigma_{\rho(\lambda_i)}\sigma_{\rho(\lambda_j)}}$$

Where $\rho(\lambda_k)$ is the reflectance at the generic wavelength λ_k , $\overline{\rho(\lambda_k)}$ is the average reflectance at λ_k , $\sigma_{\rho(\lambda_k)}$ is the standard deviation of the reflectance at λ_k and N_sam is the number of spectral signatures employed to compute the correlation matrix.





Statistical analysis

As expected, the correlation matrix is included between 0 and 1, where the lower values identify couples of wavelengths associated to a low correlation of the reflectance values. In other words, since the spectral signatures employed to compute the correlation matrix belong to both PVC and PET samples, the statistical analysis provides the couple of wavelengths allowing the two typologies of plastics to be separated.



The lowest value of the correlation is approximately 0.05 and is located at wavelengths 1200 nm-1660 nm.



The difference between the reflectance values at wavelengths 1200 nm and 1660 nm was then computed for the entire dataset of spectral signatures detected. The tables below present the number of spectral signatures measured for each plastic typology, the mean value of the difference (ρ_{1200} - ρ_{1660}) for each plastic typology and the standard deviation.

	Plas typol	tic ogy	egy PET 1-V		PET 3-F		PET 4-F		PET 3-P		PET 4-P		PET 5-R		
	Numb samp	iber of 19		60	2156		1000		1269		1159		1525		
	Mean		0.2	266	0.172		0.1	0.244		244	0.257		0.121		
	Stanc devia	lard tion	l 0.029		0.043 0.1		48	0.058		0.099		0.090			
Pla type	astic ology	PVC	1-V	PVC	2-V	PVC	23-F	PVC	24-F	PVC	23-P	PVC	C 4-P	PVC	5-R
Num sam	ber of oples	27	54	28	80	23	14	29	04	13	45	12	254	22	10
Μ	ean	-0.0)72	-0.0)37	-0.0)10	-0.0)30	-0.0)24	-0.	257	-0.0)09
Star devi	ndard ation	0.0	40	0.0	19	0.0	36	0.0	40	0.0	57	0.0)89	0.0	52

The tables suggest the difference $(\rho_{1200}-\rho_{1660})$ is positive for PET samples and negative for PVC samples.



The hyperspectral analysis conducted in the near infrared region (900-1700 nm) has highlighted as materials belonging to the same type of polymer present spectral curves similar, differing only in the reflectance values.

This behavior characterizes samples belonging to a given plastic typologies no matter the dimension, the phases in the product life cycle (virgin, recovered or post-consumer), or, finally, the form (flakes or pieces). This confirms the validity of hyperspectral imaging for plastic separation, which can be used in any stage of the life cycle of a product.

The results obtained show that the hyperspectral analysis is suitable to be used to identify, and then separate, PET and PVC.

The wide range of density assumed by the same typology of plastics demonstrates how hyperspectral systems represent a viable alternative to traditional systems of separation by type of polymer based on density.





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End of presentation

Thank you for your attention



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