CHARACTERIZATION OF FINE METAL PARTICLES USING HYPERSPECTRAL IMAGING IN AUTOMATIC WEEE RECYCLING SYSTEMS

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ABSTRACT

Waste from electric and electronic equipment (WEEE) represents the fastest growing waste stream in EU. The large amount and the high variability of electric and electronic products introduced every year in the market make the WEEE recycling process a complex task, especially considering that mechanical processes currently used by recycling companies are not flexible enough. In this context, hyperspectral imaging systems (HSI) can represent an enabling technology able to improve the recycling rates and the quality of the output products. This study shows the preliminary results achieved using a HSI technology in a WEEE recycling pilot plant, for the characterization of fine metal particles derived from WEEE shredding.

Index Terms— *WEEE Recycling, Hyperspectral Imaging, Fine Particles Characterization*

1. INTRODUCTION

Waste from electric and electronic equipment (WEEE) represents both a disposal issue and a market opportunity. WEEE is the fastest growing waste stream in EU, with an increasing rate of 3%–5% per year. The large amount of electrical and electronic equipment introduced every year in the market and the wide variety of materials used to manufacture these products lead to the problem of managing and treating the electrical and electronic waste, making the process required to recycle WEEE a very complex task. According to the Eurostat review, only one third of WEEE is recycled and reused. The remaining WEEE is either collected by unregistered enterprises or disposed to landfills or incinerators as part of residual waste. On the other hand, electrical and electronic waste can represent a very important source of key-metals for advanced technological products. For example, printed circuit boards (PCBs) are called "urban mineral resources", since they are composed by 25%–40% (in weight) of valuable metals such as copper, iron, brass, tin, nickel, gold and silver.

Due to the problem of WEEE recovering, the growth of primary material costs, as well as the supply shortage risk for key metals used in high-tech applications, many countries have introduced laws designed to improve material recycling rates, such as the recent EC WEEE Recycling Directive [1], which states that all EU countries have to recover about 70%–80% of the weight of the produced WEEE and to reuse 50%–75% of the recovered materials or components. For these reasons, the interest of companies in WEEE recycling has substantially increased in recent years. In the European recycling industry 85% of these companies are small and medium enterprises (SMEs) which, despite the high variability and the continuous evolution of EEE products, use extremely rigid mechanical processes. The rigidity of the system coupled with the high variability in the input material composition ultimately causes i) poor recycling rates, especially for key-metals, ii) the abuse of landfilling also for those materials which are potentially recyclable and iii) the lack of competitiveness of SMEs due to low purity of recycled materials.

In this context, hyperspectral imaging systems (HSI) can represent an enabling technology to support both the characterization of particles derived from the shredding of WEEE and the control parameters of sorting systems, finalized to ensure a high quality of the output product. Although preliminary studies regarding the application of HSI in WEEE recycling processes have been carried out, the developed solution are mainly related to WEEE fractions with sizes ranging from 10 *mm* to 50 *mm* [2]. The main constraint is that usually these dimensions do not guarantee the generation of pure particles of high value materials (key metals and rare earth). Currently, a HSI system able to characterize metallic particles with a size lower than 10 *mm*, has only been tested in [3] for the characterization of a mixture derived from the shredding of electric cables.

This paper shows the preliminary results obtained in the characterization of fine metal particles (lower than 2 *mm*) derived from WEEE post-shredding, using a HSI system integrated in the de-manufacturing pilot plant developed at the Institute of Industrial Technologies and Automation – National Research Council of Italy (ITIA-CNR).

2. MATERIALS AND METHODS

2.1. System overview

The ITIA-CNR de-manufacturing pilot plant consists of three cells for the end-of-life products treatment: Cell-1, *Disassembly*; Cell-2, *Reworking*; Cell-3, *Recycling*.

In particular, Cell-3 includes two shredding systems (coarse and fine), a Corona Electrostatic Separator (CES), the vision system and a pneumatic transport system that ensure the process re-configurability.

The vision system includes i) the hyperspectral camera, ii) the illumination system and iii) the transport system. The hyperspectral camera used in this study is the PFD model from Specim, Finland. It consists of an ImSpector V10E covering the wavelength range 400–1000 *nm*, and a high speed CMOS detector. The CMOS sensor can register 1312 spatial pixels in 768 spectral bands at a frame rate of 65 *fps*. This rate can be increased up to 100 *fps* using a spectral binning up to 8x (98 spectral bands). The camera mounts an OLE 23 fore objective lens with a focal length of 23 *mm* and a FOV of 25.7°. The camera has been placed at approximately 30 *cm* from the transport system: at this distance, the FOV guarantees a spatial coverage of 13 *cm* with a spatial resolution of 0.1 *mm*. The camera is controlled by a PC unit equipped with the SpectralDAQ software [4], which allows data acquisition, camera parameters setting and image visualization in real time. The illumination system is based on a dark-field configuration which provides high-contrast images and highlights specific components or defects. Dark-field illumination directs most reflected light away from a camera so surface variations or features appear bright on a dark background field. The transport system consists of a moving conveyor belt (width = 20 *cm* and length = 100 *cm*) with an adjustable speed ranging from 0 to 4 *m/min*. Spectra acquisition could be carried out continuously or at specific time intervals.

2.2. Data acquisition

For this study, several fine metal particles have been manually selected from the shredded material. These particles have been sorted according to their colors (yellowish, greyish or reddish) and attached to a 5x5 *cm* plate in a grid of 9x7 particles (Fig. 1).

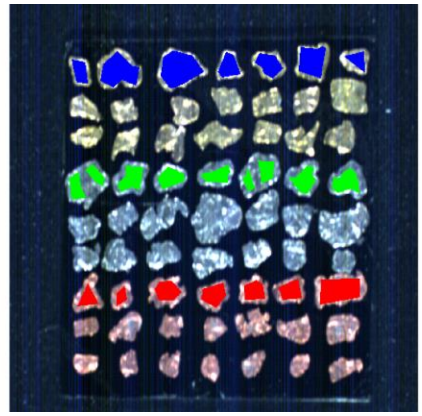

Fig. 1 – Input image showing the fine metal particles derived by WEEE shredding, sorted by color in a 9x7 grid. The overlaid polygons in blue (brass), green (iron) and red (copper) are the samples used to train the classification algorithms.

A raw image (DN) of the plate with the particles has been acquired using the PFD camera, with an 8x spectral binning, resulting in 98 spectral bands. Images of dark current (B) and white reference (W) have been measured as well with the PFD in the same configuration. The white reference image has been acquired using a standard white calibration tile (300x25x10 *mm*).

Each particle on the plate has been also analyzed by a Scanning Electronic Microscope (SEM). The SEM analysis has allowed the recognition of the yellowish particles as brass, the greyish particles as iron and the reddish particles as copper. This information has been used as a reference for the classification, in both training and validation steps.

2.3. Data processing

The processing chain adopted in this study includes the following steps.

The first step is represented by the calibration of the input image for the illumination source. This has been performed using the dark current and the white reference images according to the following equation:

$$L(\lambda)=\frac{DN(\lambda)-B(\lambda)}{W(\lambda)-B(\lambda)}. \qquad \textbf{Eq. 1}$$

In order to avoid bands with poor signal to noise ratio, bands at both edges of the sensor spectral range have been removed, resizing the original spectral range to 500–900 *nm*.

Anyway, the high number of bands included in the data cube leads to a high level of redundant information. In order to reduce the amount of data and their level of redundancy, the original bands have been merged together using a method based on spectral fuzzy sets proposed in [5]. In this method the membership value for each band of the spectrum is defined by a triangular function. This method is not only useful for the data compression but also to reduce band noise, since the triangular membership helps to smooth the resulting spectral values. In this study, we have analyzed the effect of different numbers of fuzzy sets, ranging from 4 to 24, on the classification results.

As observed in [6], the acquisition process of the hyperspectral image is highly affected by shadows, specular reflections (highlights), and inhomogeneous particles illumination. To compensate for these effects, we have tested two normalization methods, originally proposed in [7] and [8], as well as the Standard Normal Variate (SNV) method:

$$L_{normSG}(\lambda)=\frac{L(\lambda)}{\sum_{i=1}^{N}L(\lambda_i)}-\min_{j\in[1,N]}\frac{L(\lambda_j)}{\sum_{i=1}^{N}L(\lambda_i)} \quad \textbf{Eq. 2}$$

$$L_{normM}(\lambda)=\frac{L(\lambda)-\min_{j\in[1,N]}L(\lambda)}{\sum_{i=1}^{N}\left(L(\lambda_i)-\min_{j\in[1,N]}L(\lambda)\right)} \quad \textbf{Eq. 3}$$

$$L_{normSNV}(\lambda)=\frac{L(\lambda)-\mu_L}{\sigma_L} \quad \textbf{Eq. 4}$$

where μ_L and σ_L represent the spectrum average and the spectrum standard deviation, respectively.

The classification step has been performed testing four different classification algorithms, for each normalization method used in the previous step. The four algorithms chosen for this study are the Spectral Angle Mapper (SAM, [9]), the Minimum Distance (MD, [10]), the Mahalanobis Distance (MahalDist, [10]) and the Maximum Likelihood (ML, [10]). The samples used to train these algorithms have been selected from Regions Of Interest (ROI) drawn on each particle in the first row of the three different metals (Fig. 1).

The testing samples for the validation step have been generated using a stratified random sampling strategy. For each of the three classes, 100 pixels have been randomly selected, visually checked and corrected when necessary. The resulting testing samples have been used to assess the performances of each classification performed in this study.

3. RESULTS AND DISCUSSIONS

The classification results for each combination of illumination normalizations and classification algorithms are presented in Fig. 2. The results derived by the validation analysis are summarized in Tab. 1, in terms of overall accuracy (OA) and kappa coefficient (K).

Tab. 1 – Results of the validation expressed in terms of overall accuracy (OA) and Kappa coefficient (K)

OA	SAM	MD	MahalDist	ML
NONorm	83.7%	57.3%	96.3%	92.0%
NormSG	59.0%	89.0%	98.0%	98.3%
NormM	66.3%	67.0%	81.3%	95.7%
NormSNV	56.0%	71.3%	87.3%	90.0%

K	SAM	MD	MahalDist	ML
NONorm	0.75	0.36	0.95	0.88
NormSG	0.38	0.83	0.97	0.98
NormM	0.49	0.50	0.72	0.94
NormSNV	0.34	0.57	0.81	0.85

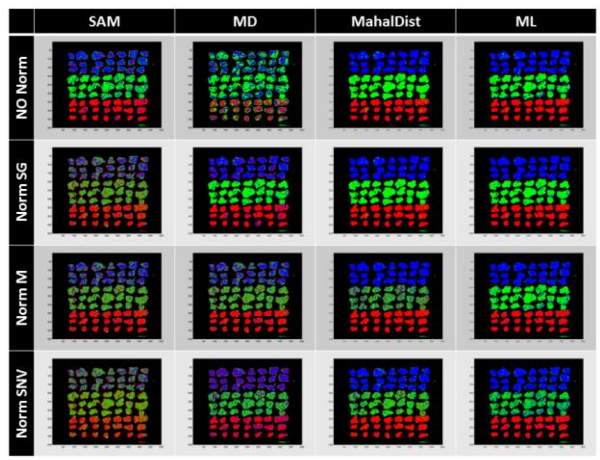

Fig. 2 – Classification results for each combination of compensation method and classification algorithm (metals are represented in blue (Brass), green (Iron) and red (Copper)).

The best classification results have been achieved using the ML and the MahalDist algorithms, with the NormSG normalization. Regarding the NormM normalization, only the ML algorithms reached values of OA and K greater than 90% and 0.9, respectively. Surprisingly enough, both the MahalDist and the ML algorithms present very good results – with OA values greater than 90% – even for data without the illumination compensation.

In order to understand the influence of the number of fuzzy sets on the classification performances, a sensitivity analysis has been conducted using the MahalDist algorithm with both the NONorm and the NormSG normalizations. In this test, the number of fuzzy sets has been changed from 4 to 24. The results, illustrated in Fig. 3, show for both cases that very good level of performances can be achieved starting from 10-12 fuzzy sets. Considering that the classification process should be performed on-line, this result is very important, showing that good classification performances can be achieved with a high data compression, thus helping to speed up the process.

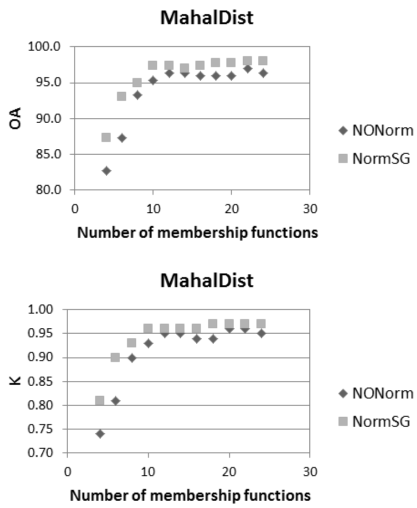

Fig. 3 – Sensitivity analysis of the classification using the MahalDist algorithm changing the number of fuzzy sets from 4 to 24. The results are shown in terms of OA and K values.

4. CONCLUSIONS

This study presents the preliminary results relative to the classification of fine metal particles (lower than 2 *mm*) derived from the shredding of waste from electric and electronic equipment. After a feature reduction through a fuzzy set approach, several combination of normalization methods and classification algorithms have been tested. The best results have been obtained with the Mahalanobis distance and the maximum likelihood algorithms, normalizing the dataset during the pre-processing step, to take into account different illumination conditions. However, the Mahalanobis distance algorithm has guaranteed very good performances even without using any data normalization. The sensitivity analysis performed changing the number of fuzzy sets has shown that very good performances can be achieved starting from 10-12 membership functions.

These preliminary results seem promising (OA greater than 95% and K greater than 0.95) and support the use of hyperspectral imaging analysis within a WEEE recycling system. The role of HSI can be manifold: it can be useful i) to characterize the WEEE mixture before the sorting process, ii) to provide the proper parameters to the separator, and iii) as a quality control system on the sorted output. Future work will aim to both increase the number of different metals to characterize and describe shapes and dimensions of the WEEE particles.

5. ACKNOWLEDGMENTS

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