Classification of fine particles from construction and demolition waste through image analysis

Otávio da Fonseca Martins Gomes
Centre for Mineral Technology
Rio de Janeiro, Brazil
ogomes@gmail.com

Paulo Roberto Lopes Lima
Department of Technology
State University of Feira de Santana
Feira de Santana, Brazil
lima.prl.uefs@gmail.com

Sidnei Paciornik, Daisiana Frozi Brisola, Bruna Maria da Cunha
Department of Materials Engineering
Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
sidnei@puc-rio.br, daisiana@gmail.com, brunamaria.arq@gmail.com

Abstract—Construction and demolition waste (CDW) has become one of the most important environmental problems in large and medium-sized cities around the world. The classification and segregation of CDW particles constitute the main difficulties for their recycling. The present paper proposes a methodology for classification of fine particles from CDW. It uses size, shape and texture parameters to discriminate between CDW particles from mortar, ceramic and concrete in a typical supervised classification procedure. The total success rate reached was 73.96% and the success rates for mortar and ceramic were greater than 80%. The main limitation was the recognition of the concrete particles; the best result obtained for its success rate was 56.30%.

***Keywords*—construction and demolition waste, shape, texture, supervised classification, scanning electron microscopy**

I. INTRODUCTION

The increasing amount of construction and demolition waste (CDW) produced in large and medium-sized cities has become a source of concern all over the world due to environmental, economic and even social issues [1]. In Brazil, CDW represents approximately 50% of the solid residues, with about 90% coming from mineral origin. Thus, there is an increasing interest to research the re-use and recycling of these residues.

The substitution of natural aggregates by recycled CDW is one of the most promising alternatives. However, recycled aggregates are not yet largely used due to the heterogeneity of CDW composition. In fact, the classification and segregation of CDW particles constitute the main difficulties for their recycling. The development of methods for separation and classification of each waste phase is essential for its utilization.

The present paper proposes a methodology for the classification of fine particles from CDW based on scanning electron microscopy (SEM) and image analysis. This classification system consists in a typical supervised algorithm that must be capable of identifying CDW fine particles according to their origins in one of the three following classes: mortar, ceramic or concrete.

Image analysis has been used satisfactorily for the characterization of construction materials [2]. In fact, image analysis systems can easily segment CDW particles by their gray levels on suitable SEM images. The challenge is to choose a characteristic or feature set that will group particles of the same class, accepting their intrinsic variability and, at the same time, provide maximum discrimination between classes.

In practice, a single characteristic is seldom enough to distinguish between two or more classes and the feature space becomes multidimensional. Therefore, in the present case study, several size, shape and texture description parameters were used as features in the classification system.

II. SHAPE CHARACTERIZATION

There is no universal definition for the shape of an object. Intuitively, the shape of an object can be described by comparison with another one. Thus, in image analysis, shape is commonly characterized by quantifying the difference between a given object and a reference shape.

The most traditional shape description parameters are probably the shape factors. They are dimensionless parameters derived from the basic geometrical measurements (area, perimeter, calipers, etc.). They generally vary between 0 and 1, the maximum value corresponding to perfect geometric shapes and the minimum corresponding to irregular shapes. Both the standard shapes and their theoretical models can vary widely and there are several parameters described in the literature.

Table I lists the shape factors used in the present paper, showing their definitions and the characteristics to which they are more sensitive. It is worth mentioning that the names and definitions of these parameters vary in the literature [3].

TABLE I. DIMENSIONLESS SHAPE FACTORS

Name	Definition[a]	Sensitivity
Solidity	$S = \frac{A}{Ac}$	convex shape, thin and long ramifications
Convexity	$C = \frac{Pc}{P}$	convex shape and contour irregularities
Circular Shape Factor	$CSF = \frac{4 \cdot \pi \cdot A}{P^2}$	circular shape and contour irregularities
Roundness	$R = \frac{4 \cdot A}{\pi \cdot Fmax^2}$	circular shape and elongation
Aspect Ratio	$AR = \frac{Fmin}{Fmax}$	elongation

a. Notation: *A*: area, *Ac*: convex area, *P*: perimeter, *Pc*: convex perimeter, *Fmin*: minimum feret, *Fmax*: maximum feret.

The shape description parameters should be independent of size. However, size and shape are strongly correlated properties [4].

Moreover, the discrete pixelization of an object image hampers its contour representation. This effect is inversely proportional to object size. The larger an object is in an image, the more pixels it contains, leading to a more accurate representation. On the other hand, in smaller objects, formed by few pixels, the representation is worse, causing a significant deterioration in shape measurements. Thus, the addition of size-related parameters to the feature set introduces size discrimination in feature space that may be helpful to compensate the size-shape correlation [5].

In the present paper, two size-related parameters were tested: area and maximum feret.

III. TEXTURE CHARACTERIZATION

Although no formal definition of texture exists, intuitively it denotes intrinsic properties of regions such as smoothness, coarseness, and regularity [6]. The human vision is capable of recognizing and distinguishing texture easily. Nevertheless, it appears to be a much more difficult task to characterize texture with some precisely defined parameters that allow a computer to perform this task [7].

In image analysis, texture can be defined as an attribute representing the spatial arrangement of the gray levels of pixels in a local region. Thus, a texture description parameter quantifies some characteristic of the gray level variation within an object [8].

It is worth mentioning that in Materials Science the term texture has a quite different meaning. It was traditionally connected with properties of polycrystals. Then, texture points to the distribution of crystallographic orientations of crystallites within polycrystalline materials. This concept maintains some relationship to visual texture, but the two contexts are hardly comparable [9].

The methods for texture characterization in image analysis are very diverse, reflecting different application areas. One of the simplest approaches is to use statistical measurements of gray level variation such as average, variance, standard deviation and so on. These parameters can be computed as moments of the gray level histogram of an image or object.

Nevertheless, the most commonly used methods are based on the gray level co-occurrence matrix from which texture description parameters are computed. Differently from typical occurrence statistics, like the average or standard deviation, the co-occurrence matrices map the presence of pairs of pixel values in neighboring pixels at different orientations.

Normally the first neighbors in an 8-neighborhood are considered, but larger distances can also be used. It is also common to consider the orientation average for 0, 45, 90 and 135 degrees, if directional characteristics are not important [10].

Haralick [11] defined fourteen parameters that represent several statistics of the co-occurrence matrices of pixel gray levels. Some of the parameters are clearly related to intuitive properties like contrast and uniformity. Nevertheless, it is not always easy to derive a physical meaning for many of them. The so-called Haralick parameters were originally proposed for distinguishing different kinds of terrain in remote sensing applications.

In the present paper, the first eleven Haralick parameters, which are provided by the employed image analysis software, were used. Since the texture of CDW particles does not seem to present directional features, the average orientations were computed. Moreover, the average and standard deviation of gray levels were also used as texture description parameters.

IV. EXPERIMENTS

A. *Sample preparation*

Synthetic samples of CDW from mortar, ceramic and concrete were segregated by a sieve series. The fractions between 500 and 250 µm, and between 250 and 125 µm of each original sample were employed. The obtained six samples were cold mounted with epoxy resin and subsequently ground and polished in a conventional metallographic approach. Then, the cross-sections were covered with an evaporated carbon layer to make them conductive and suitable for SEM analysis.

B. *Image acquisition*

For each sample, 70 fields regularly spaced on the cross-sections were imaged by SEM through specimen scanning with a motorized stage. The employed detector was a back-scattered electrons detector, which produces images with atomic number contrast [12]. The magnification was set at 100x for the -500+250 µm samples and 200x for the -250+125 µm ones, leading to resolutions of 3.07 and 1.54 µm/pixel, respectively. Thus, in total, 420 images (1024x768 pixels) and 17756 particles were obtained. Figure 1 shows typical images of CDW from mortar, ceramic and concrete, respectively, obtained as described above.

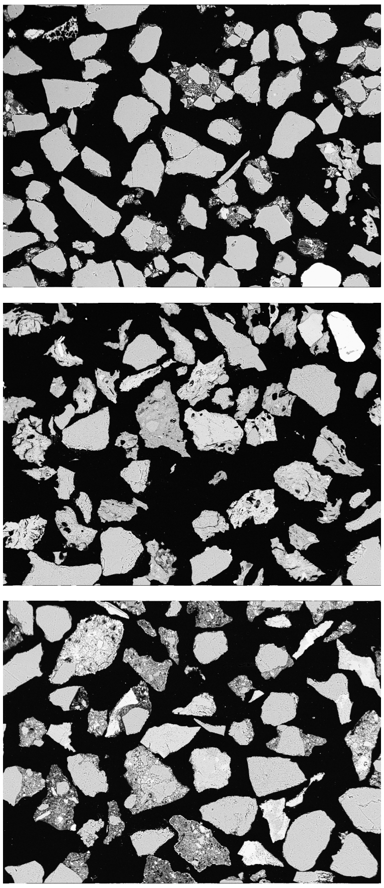

Figure 1. Images of CDW from: (a) mortar; (b) ceramic; and (c) concrete.

C. *Image analysis*

The image analysis procedure followed a simple and classical routine. It comprised the following sequence of image analysis steps:

- Segmentation of particles through thresholding of the gray level histogram, using a fixed threshold.
- Separation of touching particles through the watersheds method [13].
- Logical and morphological post-processing procedures to eliminate small spurious objects and objects that occur in the image borders.
- Feature extraction.
- Classification.

The careful image acquisition guaranteed that the brightness and contrast were reproducible and that the corresponding digital pixel values were stable. Thus, it was possible to use a fixed gray level threshold, effectively automating the segmentation step.

The feature extraction step involved the measurement of features for each particle. The tested features were: the five shape factors listed in Table I; two size-related parameters (area and maximum feret); and thirteen texture description parameters (the average and standard deviation of gray levels, and the first eleven Haralick parameters, as described above).

The classification procedure was supervised and the decision method was a Bayes [14] classifier. In its training stage, all particles, which were known previously, were used to compose the training set. The validation was carried out by resubstitution estimate [15]. This technique evaluates the classification performance through the classification of the training set objects and the evaluation of the success rates. Thus, four validation tests were performed with four different feature sets: (a) the shape factors; (b) the shape factors and the size-related parameters; (c) the texture parameters; (d) all tested features.

V. Results and Discussion

Table II shows the validation results. It presents the success rates that were achieved in the classification of mortar, ceramic and concrete particles employing the different feature sets. The second, third and fourth columns exhibit the success rates obtained with the feature sets composed by the shape factors, the shape factors and the size-related parameters, and the texture description parameters, respectively. In the last column, the success rates reached using all tested features as feature set are shown.

TABLE II. Validation Results

Class	**Success Rate (%)**			
	Shape features	***Shape and size features***	***Texture features***	***All features***
Mortar	55.00	55.60	80.94	80.91
Ceramic	37.65	43.82	83.67	82.85
Concrete	40.26	40.15	52.02	56.30
Total	44.47	46.77	72.95	73.96

Using only shape factors in the feature set, the total success rate was very low (44.47%). Even the addition of size-related parameters to the feature set didn't provide a considerable improvement as the total success rate remained very low (46.77%). These results indicate that there are no relevant shape differences in these particle classes.

On the other hand, the total success rate obtained employing the texture description parameters as feature set was much higher (72.95%). Moreover, the success rates for mortar and ceramic classes were greater than 80%. In fact, as one can see in Figure 1, the particle classes differ clearly by their texture.

When the feature set composed of all features was used, there was a small improvement for the concrete class (56.30 against 52.02) but a slight degradation for mortar and ceramic. The reasons for this behavior are not totally clear. Apparently, for classes which are already well discriminated through texture, the inclusion of size and shape parameters degrades the performance. However, for concrete, which has low classification rates for either size/shape or texture, their combination leads to slightly better results.

VI. CONCLUSIONS

An automatic method for the classification of CDW fine particles was developed. It uses size, shape and texture parameters to discriminate between CDW particles from mortar, ceramic and concrete.

Shape factors were insufficient to differentiate particles from these classes. The use of texture description parameters was fundamental for the classification system.

The main limitation was the recognition of the concrete particles. The best result obtained for its success rate was 56.30%.

The same methodology can be applied to other materials where some kind of particle classification is required. If a training set can be obtained and a feature set can be defined, the automatic method can be faster and more accurate than a visual classification.

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