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Virtual Environment for Granulometry Analysis

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Abstract – *The analysis of granulometry of substances is relevant in a great variety of the research and industrial applications. Unfortunately, image-based algorithms for granulometry analysis are difficult to tune and validate. In a typical setup, one or more cameras acquire images of a scene with a great number of objects or particles that must be measured. The distribution of the sizes/shape characteristics of the elements are the common output of such systems. The creation of supervised image database where the coordinates of all elements are known is very important and it allows for testing in a suitable manner the final size/shape distribution of particles produced by the image processing system with respect to the real distribution. Due to the great amount of objects or particles in the images, it is not often convenient, or even impossible, to individually measure each single objects in order to test the capability of the image processing system to locate and measure the elements (creation of a supervised dataset). One possible solution encompasses the creation of a synthetic image dataset where the position of each elements is known a priori. In this paper we propose a virtual environment to create and test an image-based granulometric system based on the 3D engine Blender. Results are encouraging and show the effectiveness of the proposed method.*

Keywords – *Granulometry analysis, virtual environment, synthetic image creation.*

I. INTRODUCTION

Granulometry analyzes a population of particles in order to estimate the distribution of the sizes of the particles. This task has a relevant importance in a great variety of industrial applications and in many research fields. Applications of granulometry analysis can range from the medical and pharmaceutical sector to the food sector, papermaking and coating, basic materials production and in many innovative applications [1] [2] [3] [4]. Often, the properties and the characteristics of the final products are strongly correlated to the distribution of the shapes and sizes of the particles composing the mixtures and ingredients used in the production [5] [6].

Up to now, the most common method to estimate the granulometry is performed by a mechanical division of the particles using vibrating sifters, followed by a weighting operation of the obtained partitions. As the analysis is made by human experts on a single sample of the production, this kind of estima-

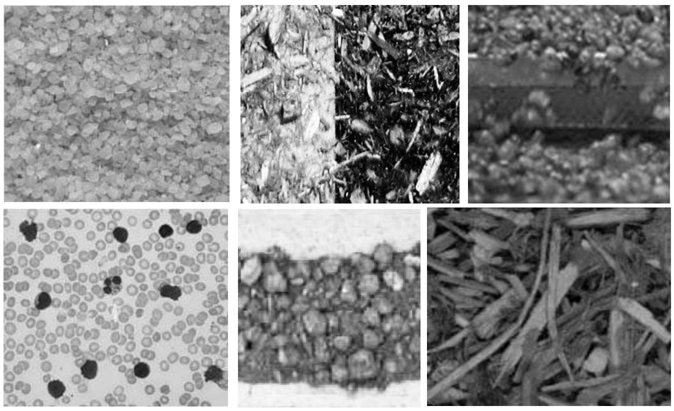


Fig. 1. Examples of input images for vision-based granulometry analysis. Clockwise: desert sand, falling pine tree chips, falling coffee seeds, red and white blood cells from microscope imaging system, oil sands on conveyor belt, heterogeneous wood chips for wood panel production.

tion suffers of many drawbacks: (i) it is slow and (ii) it presents a not standardized accuracy due to the operator's capabilities or the correct application of the measurement procedures.

Vision-based systems face the problem of the granulometry analysis by estimating the distributions of the objects present in a region of interest of the acquired image. In this case, the procedures can operate without contact and the analysis can be fully automated. Commonly, the systems can work on single amount of the product extracted from the production line (spin-off approaches) or directly on the production line (in-line approaches). One typical setup of this systems encompasses a camera placed directly above the surface where the elements to be acquired are deposed (e.g., a top view of a conveyor belt). Different setups can acquire the particles during a short free-fall from a surface to another. Fig. 1 shows examples of images taken during granulometry analysis in different applications using the top-view and free-fall setups, and an example of the distribution of cells in a classical microscope blood image. It should be noted that the classical granulometry images present some elements of complexity: for instance, the objects can be superimposed and their shapes have an high degree of variability.

Most of the times, it is practically unfeasible to locate and measure all the objects present in the scene. Hence there is no proper reference to estimate the accuracy achieved by an image processing algorithm applied to the granulometry analysis. Therefore, a proper comparison of different algorithms is hard to be performed.

In order to test image-based granulometric systems, we proposed to generate a dataset of synthetic images containing realistic particle distributions. In particular, the paper describes how it is possible to set up a virtual 3D experiment which allow for creating a complex and realistic particle disposition on a surface, where the positions and the size of every particle at the end of the synthetic simulation are known. Then, it is possible to shoot a picture of the virtual scene addressing the production of a image where the coordinates and the properties of each objects are known. Hence, the produced image dataset is a proper tool that allow to tune and test any algorithm for an image-based granulometric analyzer.

The structure of the paper is the following: in the next section the previous works available in literature are discussed, then the proposed method is presented, and in the last section the experimental results are analyzed.

II. PREVIOUS WORKS

In most vision-based granulometric systems the process of the acquired image is structured in two steps: in the first step, the image is segmented, producing a description of the objects that compose the scene depicted in the acquired image, while in the second step the objects' properties are evaluated, obtaining an estimation of their distribution. The more objects have been measured, the more confident will be the estimation of the size distribution of the particles [3][6]. In biological applications similar approaches are used, and they are based on successive structural morphological openings of the segmented image [1][2][4].

The image-based granulometry systems must face with two main problems:

- The particles distribution is measured as the number of objects which belongs to a specific size range expressed in pixels (*size granulometry*), but, more commonly, the distribution is expressed as the weight fraction of the objects which belongs to the specific range of sizes (*weight granulometry*).
- The accuracy of such systems is difficult to be estimated under realistic conditions or assumptions.

Concerning size granulometry, the solution requires a proper calibration algorithm capable to correctly map the pixels of the acquired image into the real size of the particles, taking into account perspective deformations and the optic aberrations. Then, if weight granulometry is requested, it is needed a proper model capable to map the selected objects in the image in the corresponding weight, taking into account the shape of the particles and the density of their material. This additional step can be a valuable source of errors in the final estimated distributions. In the following of the paper we assume the size-to-weight model as given and we focus our attention on the size granulometry.

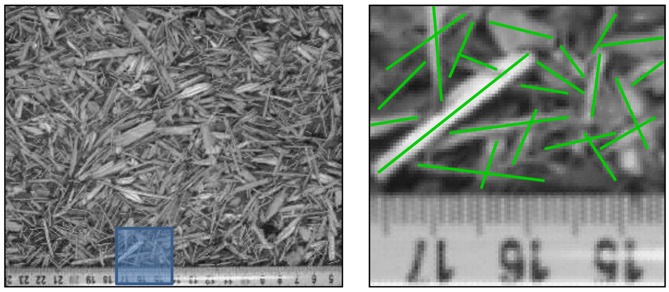


Fig. 2. Examples of manual classification of input images by using a graphical user interface. The zoom subplot on the right enlightens the difficulty of correctly identify the terminal points of elements the scene is composed by, which introduces measurement error.

The difficulty to obtain proper supervised data concerning the coordinates and the measurements of all the objects present in the scene, often produce the absence of a a proper reference to estimate the accuracy of the proposed systems. That is true also for the segmentation phases (identification of the single elements with respect to the background), as like as for the measurement phase of the properties of the elements (such as sizes or area).

In some cases the reference dataset can be create by manually locating the elements in the image by using a Graphical User Interface, but this approach is very unfeasible for a large image dataset. Besides important errors can be introduced. Fig. 2 shows the application of the manual approach in the case of wood chips. It is notable that the identification of elements is not a trivial task and identification errors can happens (missing elements, false positive and negative identifications, errors in the objects' edge identifications).

The usage of synthetic images for the validation of image-based granulometry algorithms has been introduced in [7] where a very simple approach has been used for obtains images of a group of superimposed elements. In this case, only the spherical shape has been introduced, and only the final distribution of element's radii has been considered in the validation phase.

In the following we present a complete methodology to obtain a dataset of realistic synthetic images where all the parameters of objects are available for the validation phase and capable to dispose the elements in a natural fashion as it can be commonly found in granulometric applications.

III. THE PROPOSED METHOD

In this section a method to create a photorealistic image dataset for granulometric analysis is presented. In our method we use a system that simulates an experiment where numerous particles fall on a flat surface (Fig. 3) and generates a picture

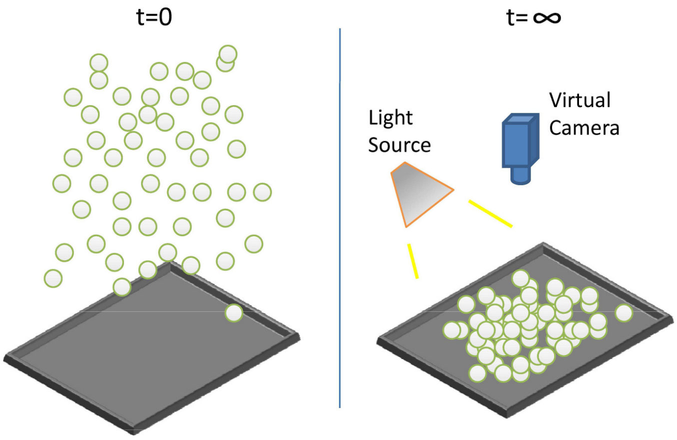


Fig. 3. Virtual experiment for the creation of one synthetic image.

of the resulting scene when the particles reach a stable state. The produced images represent a set of numerous particle, different in size and shape superimposed on a flat surface. Each synthetic image aims to reproduce a real image acquired in a typical granulometric analysis setup.

A. The procedure and the simulated environment

The proposed method produces the granulometric image dataset by following four main steps:

1. the definition of the statistical distribution for each feature defining the elements composing the scene (sizes, shapes, surfaces and materials);
2. the generation of the set of elements and their initial positioning in the scene;
3. the dynamic simulation of the set of elements created in the previous step;
4. the photorealistic rendering of the resulting scene obtained when the particles reach a stable state.

In the first step, the user defines the properties of the material which is interested to analyze. All the features that will be used in the creation of the elements can be directly enumerated. When this approach is unfeasible due to the large number of elements required, the statistical distribution of the elements features can be described by the user by using a model of the probability density. For example, the user may require 10000 elements with the major axis length, $L \sim |N(\mu, \sigma)|$, for suitable values μ and σ. Similarly, the user may specify the statistical laws that rule the other axes length, or other elements' features. The second step consists in the generation of the geometrical models of the elements and their positioning in a scene in a format suitable for the following simulating step (Fig. 3). That can be considered as the initial condition of the particles set for the next step: a dynamic simulation modifies the input scene by applying to the elements a gravitational force and taking into consideration the collision interactions. When the scene simulation reaches a stable state, it is possible to render the scene (the last step of our method). There are many rendering options valuable for the granulometry analysis; they mimic the acquisition techniques and setups used in real image processing application. Among them it worth to mention the following.

- Stereoscopic views: the images are captured from two or more different point of views, allowing to reconstructing the z-axis of an object of the scene by using the disparity in the position of the object in the captured images.
- Stroboscopic views: the images are captured from a single point of view using different light conditions; this technique allows to disambiguate the shadows and reflexes from the darker and the lighter parts of the objects.
- Range images: this type of image are produced by 3D scanners; each pixel of a range image represents the distance of the captured object from the acquisition device.

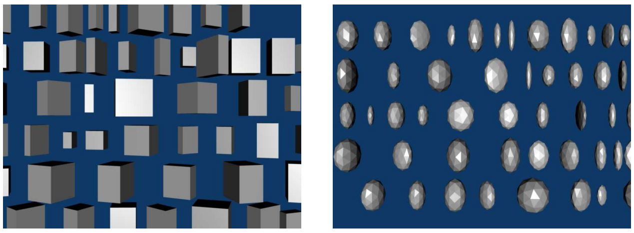
The presented method is general and it allows for a wide range of simulation conditions. As a consequence, it is capable to test a large variety of image-based algorithm for granulometry analysis reproducing the specific physical situation exploited by the different methods.

B. The implementation of the method

The first two steps of the method described in Section A can be implemented by using different description paradigms and tools. Among them, an *ad-hoc* graphical tool would probably be the best solution, as it would provide usability and interactivity, but it has the drawback of being rigid. Several environment and programming language oriented to mathematical and statistical computation (such as Matlab, Mathematica, R) can be also used to describe the statistical distribution and the geometrical properties of the elements of the scene. At the end, the scene may be generated by a program written in any scripting or programming language: this solution allows the maximum flexibility for describing the statistical law that rules the elements' aspect and properties, but has the drawback of necessitating programming skills and may require more time for subsidiary activities (e.g., for debugging).

The third step can be performed by any decent physical simulator. Factors that should drive the choice of the simulator are: (i) the efficiency and (ii) the accuracy of the computation, and (iii) the ability of interacting with the tools that implement the other steps of the method. This last point includes the possibility of importing and exporting the scene description in formats suitable to be processed by the other tools.

The fourth step can be implemented by using a render engine for creating photorealistic images. Valuable features of the renderer are the variety of the available rendering techniques (e.g., photorealistic, shadowless, or depth-map), and the possibility of using it as a tools of an 3D modeling environment, as it simplify the setting up of the virtual lights and cameras.



(a) (b)

Fig. 4. Objects' size distributions. In panel (a), a cubic shaped population that has the axes' size uniformly distributed. In panel (b), a spherical shaped population that has the axes' size proportional.

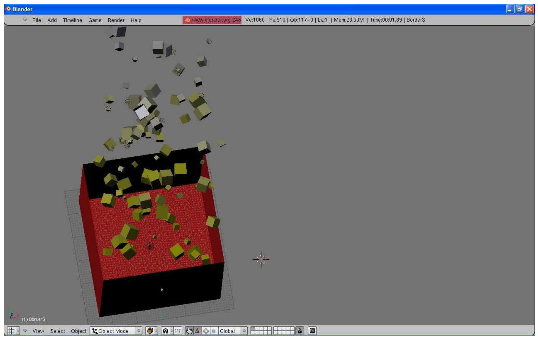


Fig. 5. After the generation of the scene.

We chose to implement the system using Blender [8], an open source suite for creating 3D contents. Blender's interesting features comprises the Blender Python [9] API, a collection of Python modules that allows to access to part of the Blender's internal data and functions, and an integrated physics simulations engine, Bullet [10]. Exploiting the capabilities of Blender, is possible to implement all the four steps that composes the proposed method.

The first two steps of the proposed method (proper generation of the objects and the scene) has been realized by a Python script that can be called from the Blender environment. The script can be easily customized and extended. A GUI allows to set the main parameters of the procedure and the following objects' properties: the objects' shape, the cardinality of the objects, the objects' size distribution, the container's size, and the physical properties of the objects. It should be noted that, although in principle there are no limits to the complexity of the shape of the objects, it impacts on the computational cost and the accuracy of the simulation. For this reasons, we used only cubic or spherical shaped objects. However, this is not a limit for the effectiveness of the methodology. Another factor that can increase the computational cost of the simulation (which is usually the more time demanding phase of the methodology) is the number of objects.

The statistical law that rules the distribution of the objects' size allows to control both the similarity of the objects of the scene and the volume of the objects (Fig. 4). In particular, we chose to control the similarity of the population by regulating the variability of the proportions of the three axes of the objects, while the volume of the objects is regulated by the distribution of the main axis' length. These laws are highly customizable for covering a large spectrum of working conditions and materials. We experiment two distributions of objects' size: uniform and inversely proportional to the volume.

The populating script generates a scene with the objects positioned at different heights over a proper container. The purpose of the container is to bound the objects when they fall during the simulation. When the scene has been generated, it is automatically loaded in the Blender environment; this allows to visually inspect the initial scene (Fig. 5).

The evolution of the scene during the simulation is governed by the physical properties of the objects. In particular, the two main properties are the object's mass (which impacts on the effect of the forces during the simulation) and its bounding shape (usually simpler than the object's shape) used by physical engine to detect the object collisions (which impacts on the accuracy of the simulation). Although Blender supports the simulation of elastic bodies, we choose to set all the objects as rigid bodies.

Once the scene in Blender is populated by the objects, the third step of the method (simulation) can be performed. The user can start the simulation and record the trajectory of the objects using the proper Game functions. The 3D graphical interface allows to observe the evolution of the scene from different points of view. It should be noted that Blender simplifies the use of the Bullet simulator. However, if a fine tuning of the simulation parameters would be necessary, Bullet can be used as stand-alone simulator which can be fed by the scene exported from Blender in the COLLADA format [11].

When the objects in the scene reach a stable equilibrium, the user can stop the simulation and generate the synthetic images according to desired type of output (fourth step, rendering). Several elements affects the rendering results: lights, virtual cameras, virtual material, and rendering algorithm. Several acquisition techniques can be easily simulated. Stereoscopic images can be acquired rendering the final scene from to different positions (e.g., using two virtual cameras). Similarly, stroboscopic images can be taken by switching on several light sources, one for each image (Fig. 6). Range images can be obtained from the Z-depth channel of the rendered image.

Properly mixing virtual material, light sources and rendering algorithm allow to obtain images of the same scene at different degrees of photorealism (Figs. 7 and 8). For instance, non-realistic rendering can be useful for generating shadow-free images which can be used for investigating the robustness of a granulometric system to the environmental conditions. Besides, shadeless material may used for obtaining images where the size of the object is encoded in the color of the object itself (which can be useful when occlusions occur).

Finally, as the 3D coordinates of each object are known, it is possible to exactly locate all the particles from the top view, and, for instance, evaluate the performance of the manual

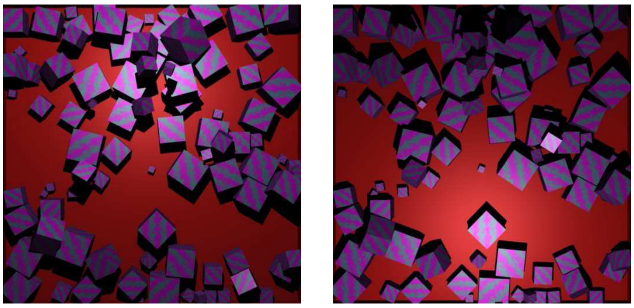
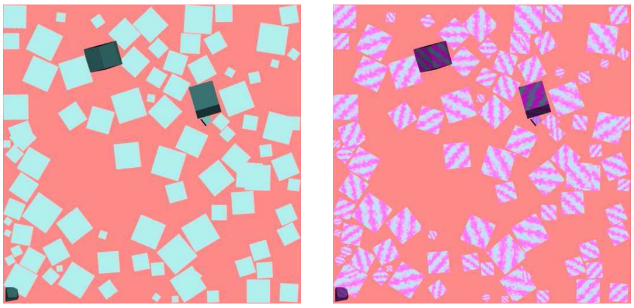


Fig. 6. The same scene illuminated with two different light sources simulates the acquisition of a pair of stroboscopic images.



(a) (b)

Fig. 7. Two different synthetic images generated from the same scene. (a) Non photo-realistic rendering. (b) Marble textured objects.

classification of the rendered images.

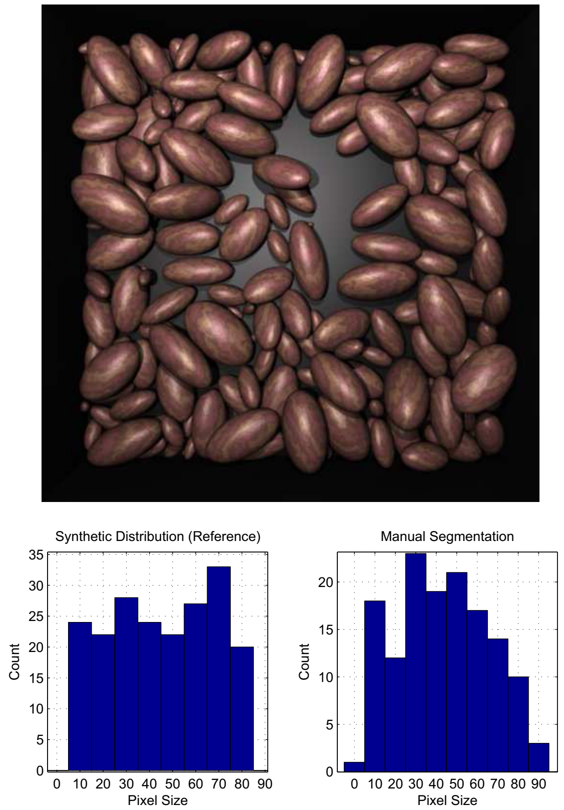


Fig. 8. A photo-realistic rendering of the final scene. In the bottom panel, the real particles size distribution (left) and the manual estimated one (right) are reported.

IV. CONCLUSIONS

The paper presented an innovative virtual environment for the creation of supervised datasets of synthetic images for tuning and verifying the accuracy of image-based granulometry systems. The implemented system produces images by simulating an experiments with numerous particles falling on a flat surface. Exploiting the capability of the 3D engine Blender to simulate the interaction of the moving elements of the scene, it is possible to simulate the final configuration of particles deposed by the simulation on the surface. Then we discussed how to setup a proper illumination and how to shoot virtual pictures of the final configuration of the particle. Since the 3D coordinates of all particle are known, it is possible to exactly locate those ones are visible from the top view. The obtained dataset of images is very realistic, and the relative supervised coordinate data can be effectively useful to test and tune image-based system for granulometry analysis. Besides, the methodology allows to obtain images of the same scene as they were captured using different acquisition techniques, allowing the proper comparison of the performances of granulometric systems based on different image processing techniques.

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