Simulated Dataset to Verify the Overlapping and Segregation Problem on Computer Vision Granullometry of Fertilizers

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Abstract: Fertilizers are an important tool for agriculture to correct the nutrients of the soil. Several analyses are made to guarantee the quality of this product. The particle size analysis indicates how well the fertilizer will penetrate in the soil by the size. The idea is to estimate the size of the grain during the production process. The production of fertilizers is a very complex production involving meters of pipes and conveyor belts where the grains are composed and transformed into the final product. The classic method to estimate the size is the mechanical sieving, an invasive and time-consuming method. A non-invasive and cost-effective method is the digital image processing (DIP) technique applied online in the production flow. In this case, a camera can be localized in the top of a conveyor belt capturing grain images directly during their composition. However, due to the number of grains (tons of grains) present on the image, this method depends on particle separation to avoid the particle segregation and grain overlapping on sampled images. In this work, we investigate how a digital image processing algorithm for particle size analysis of fertilizers is affected by the segregation and overlapping issues. We propose a grain surface simulator to create different scenarios of particle dispersion, a useful tool to speed up the process of creation of data-sets about fertilizers. The results show how the overlapping and segregation of grains influences in the particle size analysis by DIP, and how these interferences in extreme situations could generate biased results.

Keywords: overlapping, segregation, fertilizers, image analysis, particle size analysis

1. INTRODUCTION

In the past years, food production became a worldwide concern. The world population keeps growing, while the number of farmable lands has been decreasing. The use of fertilizers per hectare of cropland has increased around the world to change this fact (FAO Statistical (2018)).

Analysis has to be performed to avoid the segregation of the grains to assure the quality of fertilizers to soil application. The size of the product must be uniform, otherwise, the results of the application in the soil will be erratic (Worsfold et al. (2019)). The particle size analysis by mechanical sieving is performed to assure the uniformity. However, this method is intrusive and time-consuming, especially when several analyses are needed (Kwan et al. (1999)).

The agriculture industries have demanded accurate and fast analyses of fields that handle with granular materials. To do this, it is possible to use computer vision to perform these analyses (Igathinathane et al. (2009)). An image containing several grains is captured using a calibrated camera, then an algorithm processes the image to segment the grains and analyses each particle to infer its size and mass. The methodology of digital image processing (DIP) has advantages when compared with mechanical sieving, allowing automated product analysis and non-destructive approach.

A method to determine the particle size distribution of fertilizers by digital image processing are proposed in Mendonça et al. (2019), using a watershed transform to digitally separate the edges of the particles. However, to simplify the method, the image of grains are dispersed and non-overlapping, which is not a realistic scenario. In the fertilizer industry, after the granulation process, the product is put in a conveyor belt where is possible to see tons of overlapping grains. The overlapping problem is inherent to the application of image analysis which uses a top-vision camera on conveyor belts as shown in Yen et al. (1998). The challenge is to estimate the granulometry of the set of grains given one superior image of the scene.

It is possible to model different dispersion patterns as an overlapping effect in layers of grains in a planar image of

the sample. In this context, the main contributions of this work are a grain surface simulator to help create a data-set of virtual images of different situations of dispersion scenarios. Also, digital image processing techniques are applied to investigate how well the algorithm handles the overlapping and segregation problem.

2. LITERATURE REVIEW

The quality of the product has been a priority necessity in the industry, making necessary the research of new methods that are more efficient, and economically valuable. In the industry of grains, this is not different. To evaluate the quality of the product, the particle size analysis is required to estimate the distribution of the size of the grains. For this matter, it is used mechanical sieving, which is invasive and time-consuming. On the other way, a computer vision method turns this process non-invasive and cost-effective. Furthermore, this process can be used even in hostile environments (Hundal et al. (1997)).

When particles are not overlapped, computer vision methods can be used to determine the size of each particle and classify them, resulting in the particle size of a sample (Mendonça et al. (2019)). In this work, digital image process techniques are used to enhance the captured images of fertilizers, and to extract geometrical features for data analysis. However, the situation becomes significantly more complex when particles are overlapped because of the segregation phenomenon.

2.1 Overlapping and the consequences in DIP

Particle overlap and segregation problems are inherent in particle size measurements using image-based methods in real-world cases. Particle size distributions measured from the exposed layer of a packed particle bed can be seriously biased by these problems, because the top layer may not represent the whole population properly (Yen et al. (1998)).

The overlapping grain is a problem that is present in the major particle size analyzes that use the digital image processing methodology, but it's often bypassed. In Zhang (2016) is proposed an interval statistical method to estimate the probability of overlapping particles on image analysis approaches. The results show that the absolute error is reduced when their proposed models are used.

Correction functions were developed by Yen et al. (1998), Cheung and Ord (1990) and Chavez et al. (1996) to transfer measured size data of the top layer of particles to the size data of total sample, but this kind of adjustment requires knowledge of specific features, like the average particle size and a measure of the variation of the size distribution. Besides being limited to a single particle's distribution model and only one segregation model. Therefore, they do not apply to real-world sensing problems where method adaptation to different samples is required.

The work of Hamzeloo et al. (2014) brings techniques of machine vision combined with neural networks to estimate the particle size distribution of coarse rocks. A consistent number of on-site images are captured and processed to the extraction of several geometrical features of the rocks.

But, to avoid the error caused by overlapping grains, the authors have to use particle separation at the conveyor belts, which makes the methodology invasive.

In real problems of particle size analysis, attention has to be given to the fact that a system containing particles of different properties tends to show segregation, particles with the same property grouping together in some part of the particle mass. Differences in size, density, shape, and resilience between particles are the factors that lead to segregation in a mixture of particles. But the difference in particle size is the most important in particle size analysis. (Williams (1976)).

2.2 Segregation models

There are four segregation models according to (Williams (1976)). The first one, and the most important is the percolation of fine particles. This model is based on the fact of small particles can easily penetrate the gaps formed by larger ones and reach lower equilibrium positions (Jha and Puri (2010)) and Tang and Puri (2005)).

Besides, the second model, the particle migration, is the rise of larger particles. This effect occurs because a larger particle causes an increase in pressure in the region below it which compacts the material and stops the particle from moving downwards. Any upward movement allows fines to run in under the coarse particle, and these, in turn, are locked in the position (Krishnan et al. (1996) and Dolgunin et al. (1998)).

Regarding of trajectory segregation, the third model of segregation, it is usually significant when particles are moving in a uid media, when segregation will occurs due to the fact that the large particles tend to travel further (Alexander et al. (2003) and Baumann et al. (1994)).

In the last model, free surface segregation occurs during bed formation in a moving conveyor. Large particles on the surface have greater momentum and roll to the sides of the particle bed (Drahun and Bridgwater (1983) and Gray and Thornton (2005)).

3. METHODOLOGY

In order to analyze the levels and models of segregation and overlapping grains in the particle size analysis by digital image processing, a grain surface simulator is developed. With this simulator, it is possible to create images that represent different scenarios. Such images are processed by the DIP algorithm shown below, and their performance is analyzed.

3.1 Grain Surface Simulator

The idea is to have a simulated data-set that represents a planar superior of a set of grains in a conveyor belt.

Each image is an overlapping composition of a big number of small samples of individual grain particle images. The first step to build the Grain Surface Simulator was the acquisition of images and data about a group of fertilizer grains. All grains in this is study is a mix of the fertilizer NPK 05-32-04, with 5 parts of N, 32 parts of P_2O_5, and 4

parts K_2O_5. The sample was obtained from the conveyor belt after the granulation process, which means they are not colored by oil coating.

For 40 grains, we measure the mass of each one using a high-precision scale. We also measure the dimensions of each particle with an electronic caliper. Using a Nikon P500 high-resolution camera, we took pictures for each isolated grain.

With all the collected data, the algorithm begins with a pre-processing step. The background of each image was removed, and the foreground object is centralized with the center of the image. So the grain is adjusted to be compatible with the real measure of the diameters obtained by the caliper The image of some pre-processed grains is shown in Fig 1.

Fig. 1. Image of pre-processed grains.

Using the image processing software ImageJ (Ferreira and Rasband (2012)), we obtained the measure of the maximum and minimum Feret's, measured in pixels. Feret's diameter is defined as the longest dimension of the particle, independent of its rotation at the moment the image was captured. This measure is also known as the caliper diameter.

After this, the images were resized until the ratio between the Feret's diameters matches the ratio of the real measure with the caliper.

The data of each grain is classified based on the real minor diameter measure, which corresponds to the sieve opening size where the grain passes in the sieving method. To categorize the grains between eight sieve-based categories, we use the U.S Mesh sieve size. This convention is used based on industrial applications. The mesh sieve size corresponds to:

- #4: Sieve with screen opening of 4.76 mm
- #5: Sieve with screen opening of 4.00 mm
- #6: Sieve with screen opening of 3.36 mm
- #7: Sieve with screen opening of 2.80 mm
- #8: Sieve with screen opening of 2.36 mm
- #10: Sieve with screen opening of 2.00 mm
- #12: Sieve with screen opening of 1.70 mm
- #18: Sieve with screen opening of 1.00 mm

With this classification, the grains are selected following a pre-determined logic based on segregation scenarios, and their center is put in a random position in the virtual image. Before the grains are placed in the image, they are rotated at a random angle and put in the ratio pixel/cm as previously determined. The virtual image has the dimensions of 3000x3000 pixels^2, corresponding to a 10x10 cm^2 of real area. After this, all the grains present in the image are readjusted to the ratio of 300 pixels/cm.

3.2 Overlapping Analysis

Taking in count that the place in the image where each grain is placed is defined by a random function, the overlapping is a consequence of the number of grains placed in the virtual image. For this study, images with 50, 100, 200, 300, 400, 500, 800, 1000, 1500, 2500, 5000, 7500 and 10000 grains are made. For all images, each class of particle size analysis has a probability to appear in the virtual image.

3.3 Segregation Analysis

There are four types of pre-determined order to the grain selection, based in the segregation models:

(1) Without any segregation model, representing an ideal mix of grains. The eight classes have the same probability to have a grain of his class placed in the image.
(2) Free Surface Segregation, with equal probability of each class, but the larger size grains are placed on the corners of the image and the smaller size grains stay placed in the middle.
(3) Middle Particle Migration and Percolation, where the surface has larger size grains, with a probability of 65% of larger size grains and 35% of smaller size grains.
(4) Larger Particle Migration and Percolation, where the surface has much larger size grains, with a probability of 80% of larger size grains and 20% of smaller size grains.

3.4 Digital Image Processing Algorithm

The second stage is to process the simulated images. The image processing was done with the software called ImageJ (Ferreira and Rasband (2012)), which is a tool with several functions for editing, processing, and analyzing images. This software allows the register and the visualization of each step of the image transformations, to create a macro to automatize the process.

With the images stored in the computer, the software runs the *digital image processing* algorithm as shown in Fig. 2.
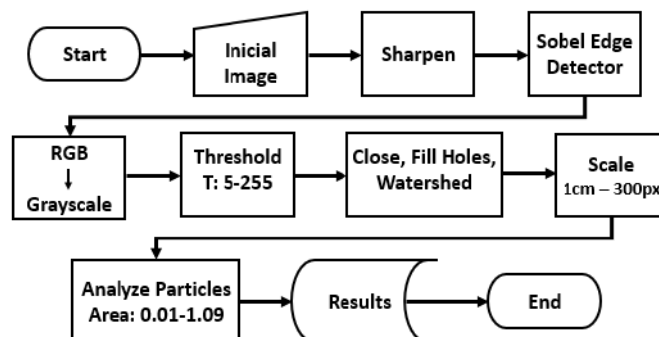
Fig. 2. Diagram of the DIP algorithm.

The *Sharpen* operation is a convolution filter that increases the contrast of the image and also accentuates the details, like the edges. After this, we applied an operation of *edge* detection that is made using the combination of the

two versions (vertical and horizontal) of the *Sobel Edge* detector.

Conversion to one *grayscale* channel from the three RGB channels image is made to continue further with the image processing

To segmentation, the grains, the *threshold* Isodata method is utilized to transform a gray-scale image to a binary image. With this, the morphological operators are applied to correct the artifacts in the image. Finally, the *watershed* transform is used to separate the touching grains.

To configure the feature extraction, a *scale* is created with the ratio pixel/mm. To do the *particle analyzes*, a limit of the area is chosen to separate the particles of the artifacts. The data analysis is made using a Python algorithm that classifies the extract features relative to the size of the particle, and classifies according to the mechanical sieving method Mendonça et al. (2019).

4. RESULTS AND DISCUSSIONS

4.1 Overlapping Analysis

The result of some virtual images made in the grain surface simulator is shown in Fig. 3. The shown images are from the left to right, in the number of grains shown in the image: 100, 500, 1000, 1500, 2500, 5000, and 10000.
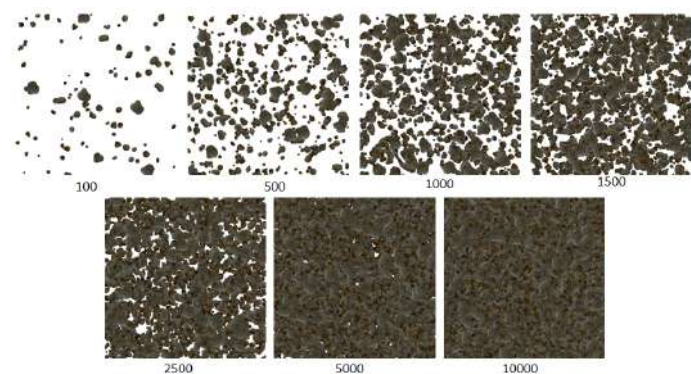

Fig. 3. Some of the scenarios of overlapping grains.

The graph in Fig. 4 shows the consequent error of the overlapping in the counting of grains. Given that the DIP algorithm can analyze just the surface layer when the cases of overlapping occur, the interference can see it in the quantity of the grains that the algorithm can count.
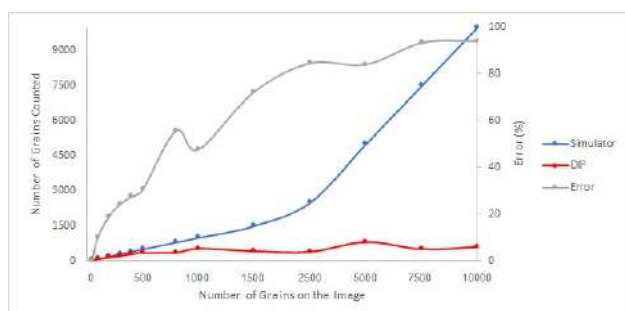

Fig. 4. Influence of Overlapping on grain count using line interpolation.

In the situations where there are a few grains, and so on less overlapping, the DIP can count almost all grains. As shown in the images with less than 500 grains, the presented algorithm can identify more than 70% of the placed grains in the image.

From the 500 counted grains, the overlapping intensifies and affects more the counting of the DIP algorithm, identify only 6% of the grains in the most extreme case, the simulate images with 10000 grains.

In order of exemplifying the results of each step, we will give highlights to the case with fewer segregation. As shown in Fig. 4, in the image of 200 grains the DIP algorithm counted 162 grains, more than 80% of all. Their classification and groundtruths are shown in Tab. 1.

Table 1. Grains classified by Mesh sieve size in 200 grains image.

Sieve	DIP	Simulator
#4	20	27
#5	18	25
#6	17	22
#7	20	24
#8	22	26
#10	25	28
#12	21	25
#18	19	23
Total	162	200

The following equation calculates the percentage of retained grains in each sieve with values of Tab. 1.

$$\%Retained_{Sieve} = \frac{\text{N}^{\text{o}} \text{ grains retained}_{Sieve}}{\text{Total N}^{\text{o}} \text{ of grains}} * 100 \quad (1)$$

The retained percentage of each sieve calculated by the DIP algorithm and by the simulator, which is the ground truth, is shown in Fig. 5. For the simulator, the results of the retained percentage of each sieve are approximately 12.5% because of the ideal mix scenario choose in the simulator, where the grains for all the sieves have the same probability to appear.
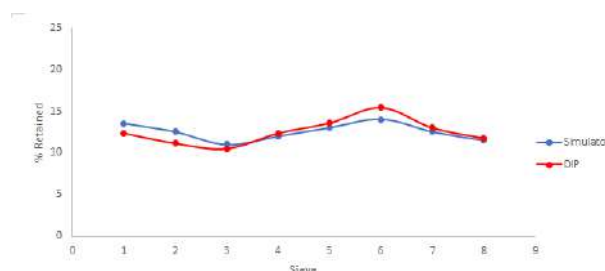

Fig. 5. % Retained of the 200 grains image.

With a difference between the $\%Retained_{Sieve}$ of DIP and simulator as an error in percentage points, the mean error and standard deviation were calculated. To the image of 200 grains, the mean error was infimal with 0,65 ± 0,78.

Figure 6 shows the results of each particle size analysis. The evolution of the mean error between the $\%Retained$ and their respective standard deviation as vertical bars
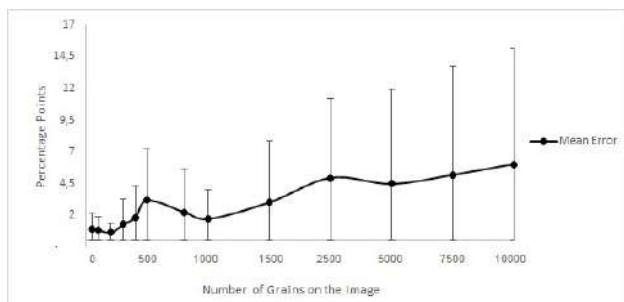
Fig. 6. Mean Error and standard deviation for the particle size analysis with DIP algorithm.

are shown as the number of grains and overlapping was occurring.

The comparison of Fig.4 and Fig.6 shows the relationship that the more grains in the images and consequently more overlapping, greater is the error in the grain count which leads to a higher mean error and standard deviation in the granulometric analysis by DIP.

4.2 Segregation Analysis

The result of the grain surface simulator to the four scenarios of dispersion, *ideal mix and free surface, middle percolation* and *larger percolation* is shown in Fig. 7.
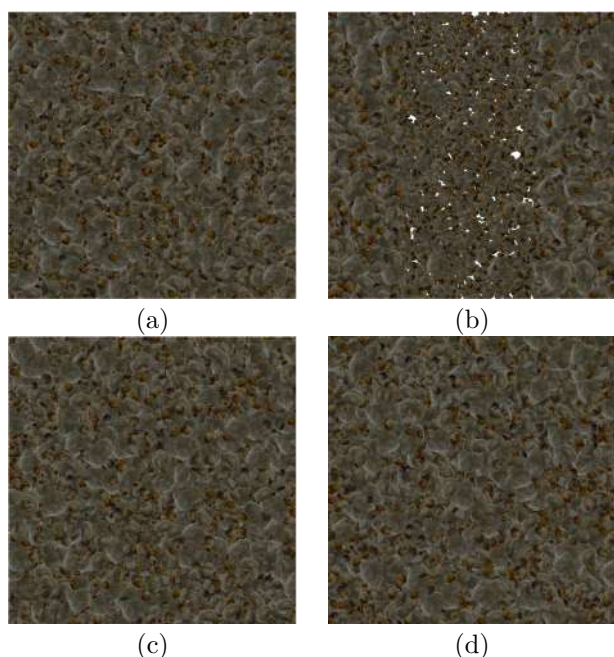

Fig. 7. The results for the scenarios of dispersion are shown as follows: (a) the first scenario of an ideal mix of grains, (b) free surface segregation, (c) the middle particle migration and percolation grain surface and (d) the larger particle migration and percolation grain surface.

With these images, the algorithm proposed in the methodology has applied the result are shown in Fig. 8 for the four scenarios following the description above.

The results for the particle size analysis for the four cases of the analysis of segregation are presented in the Tab. 2
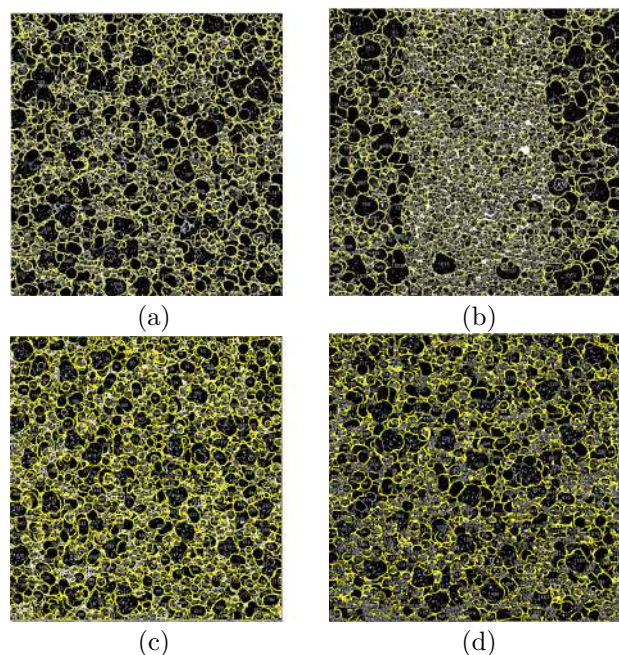

Fig. 8. The four scenarios of dispersion after the DIP algorithm.

Table 2. Results of particle size analysis in segregation scenarios.

	Counted Grains	Mean Error	Std. Dev.
Ideal mix	591	6.00%	9.14
Free Surface	1016	7.77%	11.05
Middle Particle Migration and Percolation	422	6.70%	9.34
Larger Particle Migration and Percolation	323	10.18%	12.73

The first point to be considered is the comparison of the cases ideal mix and free surface segregation. In both images are 10000 grains, and 1250 in each sieve class. The only difference between them is the grain arrangement. In the case of the free surface segregation the larger grains are accumulated in the extremities of the image, and the smaller ones in the middle. However, this scenario, because not mix large and small grains, shows two kinds of situations: First, this scenario does not show larger size grains covering the smaller ones, which enables a better view of the small grains in the surface layer. The output of this interference in small grains causes the grain count to increase relative to the Ideal mix.

The second situation refers to the tendency of clustered larger size grains overlap more easily than small grains. This causes the availability of large grains on the surface to fall, decreasing the large grains contained in the image.

These two factors made that images of the free surface segregation scenario be well represented in a relation of the smaller size grains, but less representative with the larger size class. Thus, the corresponding particle size analysis responds to a high proportion of small grains in a mixture that is equally divided. This justifies the increase in the mean error and standard deviation on the granulometry, even though more grains were accounted for.

With the explanation of the concentration of larger size grains is a factor that influences directly in the exponential increase of grain overlap, a decrease of counted grains,

increase of error and standard deviation, it is justified the particle migration and percolation segregation scenario because they are mixtures with higher concentrations of larger size class.

5. CONCLUSION AND FUTURE WORKS

In this work a methodology to investigate how far the digital image processing algorithm handles the overlapping problem in grain dispersion patterns is proposed. A grain surface simulator is produced to create different scenarios of overlapping and segregation interferences in the fertilizer industry.

The results have shown that for the most critical overlapping and segregation scenarios, the DIP algorithm shows a mean error of 10.8%± 12.73% concerning the ground truth, the simulator retained percentage. And the error was less than 2% for images of less than 500 grains.

The results of the overlapping analysis show that when the virtual image has a fewer number of grains, the DIP algorithm can identify the majority of grains, consequently with less error in the particle size analysis. And for the segregation analysis, it is seen that the larger grains are shown to flaw the results of particle size analysis because it easily overlaps the smaller grains.

However, as the analyzes in this study match the reality showing the consequences, tendencies, and errors of the overlapping and segregation of grains. Showing that the power and capacity of the simulator to create data-sets of images of surface grains surface.

The next step in the project will be to perform a more intense and careful analysis of the grains mixtures present in the different points on the industry. To further validation of the approach proposed in this paper, noises will be added to the simulator to approximate the images with the reality in the industry. With the recently presented grain surface simulator, this kind of scenario seen in the industry will be simulated to create a massive dataset.

As the images of the created data-set will follow the proportions found in the industries, it is expected that it can assist in training a convolutional neural network, with relatively high prediction accuracy. Different models of classification of machine learning techniques will be trained looking for the one with the industrially acceptable and highest accuracy to be used.

After obtained the results of the neural network, this methodology will be adapted to be applied in the industry, trying to reach the same results that have tested in a controlled environment, in the hostile environment of the industry.

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