Pattern recognition in the differentiated image for the powder and granulated materials particle size classification

D V Yunovidov¹,², M N Nadezhin¹,² and V A Shabalov²

¹ JSC “NIUIF”, 162622, Severnoe shosse 75, Cherepovets, Russia
² Cherepovets State University, 162622, office 203, Lunacharsky str. 5, Cherepovets, Russia

Dm.Yunovidov@gmail.com

Abstract. The paper shows and investigates the technique of classifying the particle size of powder and granulated materials. The objects of the study are industrially produced mineral fertilizers. Samples with different composition (about five types of mineral fertilizers) and various degrees of particle size (less than 100 µm, less than 500 µm and granules of 2-5 mm) were examined. The samples particles have an irregular shape, close to spherical (in the case of granules) or cubic (in the case of powders). To improve the accuracy and eliminate the particle shape influence on analysis, the preliminary pressing of samples on a boric acid substrate was used. The keynote of the proposed technique is to obtain an optoelectronic image of an object with a resolution of at least 640x480 pixels (a three-dimensional matrix of pixel intensity in the Red-Green-Blue (RGB) system). Next, the area of analysis is separated from the obtained image and transformed into grayscale (a two-dimensional matrix of pixel intensities with a resolution of at least 200x200 pixels). The influence of external illumination (gradient, temperature and brightness) is eliminated by the grayscale image differentiation. The result is the "surface map" of the sample, which reflects defects in the pressed structure (patterns, which are responsible for the size of the particles). According to the found patterns, the samples are classified according to their particle size. Four classification algorithms were investigated (linear, linear with L1 and L2 regularization, and a nonlinear “random forest”). All proposed approaches are automated and implemented in the Python 3.6 programming language. There is provided the selection of the operating parameters of all the described algorithms.

1. Introduction

Many authors write about a new industrial revolution in recent years (Industry 4.0) [1,2]. This phenomenon is characterized by the use of flexible and decentralized industrial processes. It also applies to the quality control of products. The phenomenon of Industry 4.0 and flexible control are particularly relevant for large and actively modernizing facilities, where the control is based on visual indicators. Examples of such industries are metallurgy [3], cement industry [4,5] and mineral fertilizers production [6,7]. One of important quality parameters in these industries is the particle size distribution of granular and powder materials [4,8,9]. With this parameter the production of mineral fertilizers is reviewed (where the particle size is responsible for the quality of the technological process [6,7], the quality of pellets [10,11], the agronomic effect [12] and the quality of sample preparation for chemical and physical analyses [13]). Methods of sieve analyses [8,13], laser light scattering (LLS) [4,14] and optoelectronic control [4,9,15,16] are often used to determine the particle size. Unfortunately, they all have a number of disadvantages. The sieve analysis cannot provide continuous control of the particle...
size distribution and it highly depends on the shape of the particles [8]. The LLS is a fundamental and highly accurate method of analysis. However, it is limited by the size of the studied particles and cannot estimate the shape and the colour of materials [4,14]. The third group of methods (optoelectronic control) is the most universal. It is based on work with the image of particles and allow us to estimate a wide range of parameters. Optoelectronic control is widely used in industrial production [5,9]. There are several examples where this method provides control of the shape and colour of particles [15,16]. However, the optoelectronic method has a significant drawback - it strongly depends on external measurement conditions of illumination (gradient, brightness and temperature). The solution of this problem isn’t really covered in the studied literature.

The purpose of this work is to develop an automated method for the classification of granular and powder materials by its particle size using the optoelectronic image with elimination of dependence on the external illumination (brightness, temperature, and gradient).

2. Objects and Methods

2.1. Objects of the analysis and sample preparation

In this work there are 5 types of mineral fertilizers investigated (products of the JSC “Apatit”). Each sample was prepared as raw granules (2-5 mm) and grounded powder with two fractions (< 500 µm and < 100 µm) in 10 series. Further, samples were pressed into tablets in the form of a “sandwich structure” (in molds of 20 mm in diameter). At first, the plate of boric acid (about 3 g) was made by pressing with a figure punch and 100 bar force (3 t/cm²) for 30 seconds. Then the mineral fertilizer sample (about 1.5 g) was put into the boric acid plate and pressed with a usual punch at 260 - 280 bar (10-11 t/cm²) for 60 seconds. About 150 samples were prepared.

2.2. Obtaining the optoelectronic signal

Pressed samples were placed on a white sheet of paper and were photographed at a fixed distance to the sample surface (10.0 ± 0.5 cm) with natural light illumination (sufficient for visual determination of the surface structure of the sample). A digital USB video camera was used as an optoelectronic device for obtaining the image (frame resolution of at least 640x480 pixels, focal length 2.8 - 12 mm and a sensor of 1/2.7” CMOS). Furthermore, the image (figure 1) was transferred to a computer via USB protocol. For each image we can observe difference in brightness, temperature, and gradient of illumination.

![Figure 1](image1.png)

**Figure 1.** The example of the objects images. The three different fertilizers with <100 µm (a); with <500 µm (b) and with 2-5 mm granules (c) and the 200x200 pixels area of the analysis (d).

2.3. The image processing algorithm

In this paper, the authors solve the novel problem of optical analysis of powder size with varying external illumination (brightness, temperature, and gradient). The possibility of classifying samples using the set of standard algorithms is evaluated. The work uses the following approach.

- Record of the objects image with a resolution of at least 640 × 480 in RGB format.
- Select the surface area (at least 200 x 200 pixels) and calculate it average brightness (feature No.1).
- Transform image into a greyscale (two-dimensional matrix of pixel brightness intensities).
- Differentiate the image to eliminate the effect of illumination. The sample “surface map” is formed as the result (the two-dimensional array, which characterizing the pressed sample surface).
• Smooth the “surface map” by the median filter (it preserves the boundaries of the patterns [17]).
• Calculate the average number and average area of patterns on the "surface map" (relative to image area) by the "marching square" algorithm [18] (feature No.2 and 3).
• Classify the particle size according to the value of found normalized features.

All stages were selected experimentally for the studied objects, providing standardization of external conditions and work with sufficient accuracy. Adjustable parameters of image processing algorithms are the smoothing window for median filter and "contour constant" for the "marching squares" algorithm [19]. Further, with obtained features (the average number and area of the patterns and the average brightness of the image) the “objects-features” matrix for classification is compiled. Using a compiled matrix and the information about particle size of the pressed material, the different classification approaches were calculated (linear without regularization, linear with L1 and L2 regularization, and non-linear algorithm of “random forest”). The F-measure (harmonic mean of precision and recall) was chosen as the quality metric [20]. The classification algorithms were tested using a cross-validation strategy (with 30% of randomly selected objects from the total set with preserving the distribution of target classes). All proposed algorithms were implemented in the Python 3.6 programming language.

3. Results and discussion
According to the described method, about 150 samples of 5 types of fertilizers were analysed. For each image of the sample, a “surface map” was made (figure 2).

![Figure 2](image-url)

**Figure 2.** The original (a); differentiated (b) and smoothed (c) "surface map" of pressed powder.

Further, the patterns (pixels in “surface map” whose intensity is different from 0) were approximated as closed contours. Their average area and quantity were calculated using (1) and (2) formulas.

\[ N_T = \frac{N}{a \cdot b} \]  
\[ S_T = \frac{\sum_{i=1}^{N} S_i}{a \cdot b} \]

Where \( N_T \) is the average number of patterns; \( N \) is the number of found patterns; \( a \) and \( b \) are the length and width of the image in pixels.

As the addition feature we have calculated the average brightness of the image in grayscale (3).

\[ I_g = \frac{\sum_{i=1}^{N} I_i \times I_w}{N} \]

Where \( I_g \) is the average brightness of the image surface; \( I_i \) is the brightness of the \( i \) pixel (from 0 to 255 rel. units); \( N \) is the number of pixels; \( I_w \) is the average brightness of the white background. It was established experimentally that the multiplication with average white intensity (not the division or subtraction) made the finest contribution to the particle size classification.

Parameters of smoothing the image (the range from 1 to 31 with a pace of 5 pixels) and the approximation of patterns (the range from 0.1 to 2.0 with a pace of 0.1 relative units) were selected from the range to improve the further classification. We have used the method of the “grid search”. Spearman
correlation between the average amount (and average area) of the calculated patterns and the size of the sample particles was used as the quality metric (figure 3).

**Figure 3.** Map of changes in the Spearman correlation between the particles size and the average amount (a) or average area (b) of the patterns.

The optimal parameters were 13 pixels and 1.3 units. It is interesting to note that the Spearman correlation also works well in the range of parameters 5 – 15 pixels and 0.5 – 1 units. In this regard, a calculation of the number of patterns was made (figure 4).

**Figure 4.** Map of changes in the number of average quantity (a) and average area (b) of patterns.

With previously selected parameters of 15 pixels and 1.3 units, the values of the number and area of patterns tend to 0. This is caused by poor recognition of patterns on samples with small particles size (< 100 µm). At the same time, an increase in the correlation coefficient is caused by a reduction in the number of classes. Thus, the contour constant should not exceed 1 and the best values of the coefficients were 7 pixels and 0.8 relative units.

With obtained parameters and features the several classification algorithms were investigated. The target variable is the particle size in the pressed sample (categorical variable, with values < 100 µm, < 500 µm and 2-5 mm). We also select configurable parameters of each classifiers [21] using the grid search. To study the effect of selected features on the classification, their significance were also calculated (4) (table 1).

\[ im_j = \frac{w_j}{\sum_i w_i} \times 100 \]  

Where the \(im_j\) is the “importance” of the \(j\) feature in %; \(w_j\) is the weight of the \(j\) feature in the classification equation, \(w_i\) is the weight of the \(i\) feature in the classification equation.

The random forest algorithm shows the best results (93%). This behaviour is predictable. The number and area of patterns of the image are related to each other and do not necessarily linear depend on the particle size. However the linear algorithms show the good results too (86%). The most significant feature were the average number of defined patterns. Actually, for pressed samples the variability of the defects area will be small. Consequently, their weight for linear classification will also be small. On the contrary, for the non-linear algorithm the significance of features is slightly equalized. Separately, we note that the average brightness of pixels plays a smaller role for the classification. This suggests that the differential correction of the illuminate works well.
4. Conclusion

As the result of this work, the novel automated method for the classification of granular and powder materials by its particle size and correction method for the illumination in optoelectronic image (gradient, temperature and brightness) were proposed. The classification of the particle size according to the selected features of average number and area of image patterns was carried out based on various industrially produced mineral fertilizers. The work of 4 different classification algorithms (both linear and non-linear) was investigated. The quality of the classification was achieved in 93 % by F-measure after the parameters were chosen. The best result was shown by the “random forest” algorithm (the number of “trees” is 82, the maximum number of signs is unlimited, the maximum depth of each tree is unlimited, the bootstrap is false, weighed registers are true). The best linear algorithm is the linear classification with or without L1 regularization (86% by F-measure). The achieved quality of the classification indicates that the proposed technique can be used in industrial control. The proposed approaches are automated and quite simple to implement. Experimental data is provided [22].

5. References

[1] Meissner H, Ilsen R and Aurich J 2017 Procedia CIRP 62 165-9
[2] Qin J, Liu Y and Grosvenor R 2016 Procedia CIRP 52 173–8
[3] Murphy T and Schade C 2019 Additive Manufacturing for the Aerospace Industry 99 142
[4] Lifkov V, Dimitrova E and Gaidardzhiev S 1999 Cem. Concr. Res. 29(1) 3–8
[5] Pasquazzi A, Weissenbacher R and Oehlers M 2017 Int. J. Refract. Met. Hard. Mater. 62 118–25
[6] Swisher D, Borgelt S and Suduth K 2002 Trans. ASAE 45(4) 881–8
[7] Zhang R, Wang X, Guo J, Chen L, Zhou J and Ma W 2014 Sensors & Transducers 26 1–6
[8] Besler H. 2008 Dev Sedimentol. 59 73–98
[9] Bjork T, Mair K and Austrheim H 2009 J. Struct. Geol. 31(7) 637–53
[10] Wiajcik J, Molenda M and Stasiak M 2018 Particuology 39 88–95
[11] Yohannes B, Liu X, Yacobian G and Cuitiño A 2018 Adv. Powder Technol. 29(12) 2978–86
[12] Tarragó E, Puig S, Ruscalleda M, Balagué M and Colprim J 2016 Chem. Eng. J. 302 819–27
[13] Kimura M 2013 Testing Methods for Fertilizers (Tokio: Incorporated Administrative Agency Food and Agricultural Materials Inspection Center) p 370
[14] 2009 International Standard ISO 13320 First Edition 2009-11 (United Kingdom)
[15] Chávez GM, Sarocchi D, Santana E and Borselli L 2015 Comput. Geosci. 85 248–57
[16] 2006 International Standard ISO 13322-2 First Edition 2006-11 (United Kingdom)
[17] Strugailo V 2012 Sci. Educ. Bauman MSTU 12(5) 270–81
[18] Mantz H, Jacobs K and Mecke K 2008 J. Stat. Mech. Theory Exp. 12 2-28
[19] Scikit-image Module 2019 [Online] Available: http://scikit-image.org/docs/dev/api/skimage.measure.html#skimage.measure.find_contours
[20] Powers D 2011 J. Mach. Learn Technol. 2(1) 37–63
[21] Scikit-learn Module 2019 [Online] Available: https://scikit-learn.org/stable/supervised_learning.html
[22] Yunovidov D 2019 mineral fertilizer images (pressed samples) Mendeley Data, v1 [Online] Available: http://dx.doi.org/10.17632/2yw4bmbz5m.1
## Authors’ background

| Your Name         | Title                          | Research Field                                                                 | Personal website                      |
|-------------------|--------------------------------|--------------------------------------------------------------------------------|----------------------------------------|
| Dmitry Yunovidov | Ph.D, lecture                  | Big data analysis, Analytical chemistry, Automation, Optical recognition, Mineral fertilizer industry | https://www.dimyun.space/             |
| Maksim Nadejin   | master student                 | Big data analysis, Automation, Optical recognition                             | -                                      |
| Viktor Shabalov  | Ph.D, lecture, associate professor | Automation, Optical recognition                                                 | -                                      |