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GRAIN SIZE DETERMINATION AND CLASSIFICATION USING ADAPTIVE IMAGE SEGMENTATION WITH GRAIN SHAPE INFORMATION FOR MILLING QUALITY EVALUATION

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Abstract

In this paper, authors described methods of material granularity evaluation and a novel method for grain size determination with inline electromagnetic mill device diagnostics. The milling process quality evaluation can be carried out with vibration measurements, analysis of the milling material images or well-known screening machines. The method proposed in this paper is developed to the online examination of the milled product during the milling process using real-time digital images. In this paper, authors concentrated their work on copper ore milling process. Determination of the total number of the grain, the size of each grain, also the classification of the grains are the main goal of the developed method. In the proposed method the vision camera with lightning mounted at two assumed angles has been used. The detection of the grains has been based on an adaptive segmentation algorithm, improved with distance transform to enhance grains detection. The information about particles shape and context is used to optimize the grain classification process in the next step. The final classification is based on the rule-based method with defined particle shape and size parameters.

Keywords: grain classification, particle analysis, image segmentation, feature extraction

OKREŚLENIE ROZMIARU ZIARNA I KLASYFIKACJA Z UŻYCIEM ADAPTACYJNEJ SEGMENTACJI OBRAZU I INFORMACJI O KSZTAŁCIE DLA OCENY JAKOŚCI MIELENIA

Streszczenie

W pracy autorzy opisali metody oceny uziarnienia materiału i nową metodę określania wielkości ziaren z jednoczesną diagnostyką pracy młyna elektromagnetycznego. Ocena jakości mielenia może być realizowana na kilka sposobów, tj. poprzez pomiar drgań, analizę obrazów materiału zmielonego, lub wykorzystanie matryc przesiewowych. Proces mielenia jest procesem obciążonym znacznym zużyciem energii, dlatego proces diagnostyki powinien być wykonywany z dużą efektywnością. Metoda zaproponowana w niniejszym artykule opiera się na badaniu mielonego produktu podczas procesu mielenia przy użyciu analizy obrazów cyfrowych w czasie rzeczywistym. Głównym celem opracowanej metody jest określenie całkowitej liczby ziaren, wielkości ziaren, jak i klasyfikacja ziaren. W zaproponowanej metodzie wykorzystano akwizycję obrazów z kamery przy oświetlaniu badanych próbek pod kątem, co pozwala zwiększyć liczbę wykrywanych ziaren. Detekcja ziaren bazuje na metodzie segmentacji adaptacyjnej rozszerzonej o analizę map odległościowych w celu poprawienia jakości i liczby wykrytych ziaren. Informacje na temat kształtu ziaren są wykorzystywane w celu optymalizacji procesu klasyfikacji ziaren. Ostateczna klasyfikacja opiera się na metodzie bazującej na regułach, w których określono zależności dla różnych parametrów kształtu i rozmiaru ziaren.

Słowa kluczowe: klasyfikacja ziaren, analiza wielkości ziaren, segmentacja obrazów, ekstrakcja cech

1. INTRODUCTION

The milling process is one of the most substantial parts of a wide range of industrial processes based on the disintegration of the material such as cement production, cereal preparation, coal and metal ore milling [1], production of sand and gravel, building materials, chip-pings, minerals, pellets, sinter, petrol coke, chemical products and salts and sugar and many others. Based on the application different type of the mill is used such as a ball, electromagnetic, rod, SAG, Buhrstone and many others. They are characterized by different construction, energy consumption [2], mass, and dimensions, take into account cost and effectiveness of the milling process. Most of the designed industrial mill obtain final grains with a diameter less than 1mm, especially for copper ore material. To reach high-quality process – assumed grain size, energy consumption should be carried out continuous control system which should control all the necessary process parameters. One of the main parts of the control system should be diagnostics of the milling or grinding. This can be evaluated by an indirect method such as grain size recognition and classification into some assumed classes of size e.g. less than 100µm for copper ore. In consequence, the grain size of the final product can be used as a feedback to the mill control system and can be used as a source of information about possible faults in the process. In Figure 1, the scheme of the electromagnetic mill used in the experiments has been presented, including main elements such as: material stream (1), working chamber (2), working space (3), air stream and additional air stream (4), final product (5), reverse stream (6), stream of the not grinded material (7), winding inductor and cooling medium (8), source of the air (9). The proposed method of indirect quality evaluation is a part of the main classification module (dotted line). When the material will not pass the assumed particle size will be reversed through (6) directly to the working space (3).

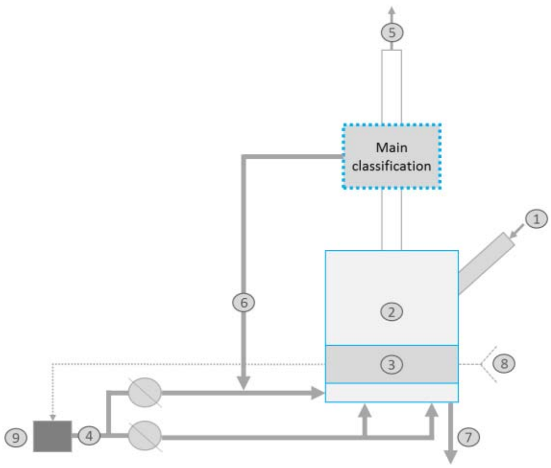


Fig. 1. Scheme of the electromagnetic mill

The description of working principle and methods of control can be found in [3]. The main idea is based on the grinding of the material in working chamber by the grinding medium, which is moved in the chamber by generated a rotating electromagnetic field and by a collision between grinding medium and material, the grains are grinded from their starting size – feed material has variable size in range 0-2 mm into 50-100 µm final product with constant size. In Figure 2 infrared image of the working chamber with grinding medium has been presented. In our investigation has been used grinding medium as steel rods with 1–3 mm in diameter and 9–20 mm in length.

This paper is organized as follows. In Section 2, the review of previous studies related to the grain size measurement has been presented. In Section 3 the proposed method of grain size evaluation has been described. The experimental results obtained on acquired real samples of copper ore and sand can be found in Section 4. Finally, the conclusions are presented in Section 5.

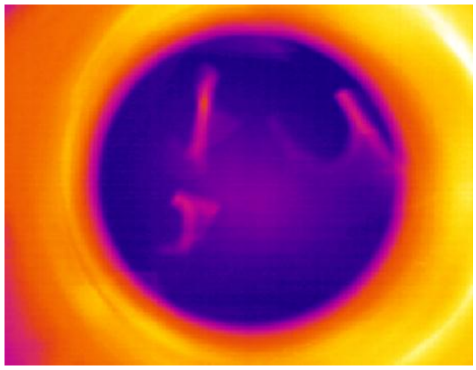


Fig. 2. Infrared image of the working chamber

2. RELATED WORKS

A well-known method of grain size evaluation is based on the usage of granulometer which produces most accurate results, but the process must be performed off-line in the laboratory. In the recent literature, numerous methods of grain parameters measurement can be found. They are described by a different time consumption, grain size range which can be recognized, method of sample preparation, also, of course, some of them are quite expensive. All the semi or full automatic grain parameters evaluation methods are divided into a few separated groups, such as vibration screening technology, vibration measurements, acoustics and flow measurements and machine vision.

One of the most popular methods used in the industry to classify grains are screening machines, called also sieves machines [4]. Generally, it is based on the screening material through screens with different hole size using vibrations which make material falling through next screening panels with different mesh size. Some disadvantages, such as especially clogging, are resolved using smart solution in which machines are self-clogging by some excitations. The screening result depends on the correct assessment of the original material, the choice of the screening plate mesh and the adjustment of the machine, thus some of the researchers concentrate their work on the vibrating screens with reconfigurable or adjustable screen surface structures [5] which already are in production and used by the industry.

An interesting solution for grains classification is indirect measurement based on vibration sensing [6]. Authors adopted vibration measurements – used in recent literature to mill diagnostics [7] or generally machine diagnostics [8]; to the falling material examination on the laboratory set-up with prepared six classes of granularity material. Generally, the measured vibrations of the loose material in the pipelines are used to evaluate granularity and flow rate. This method is based on the assumption that the processed material at different mass transported through the pipelines from the mill will produce different vibrations which can be measured with small, not expensive and non-invasive vibration sensors. Issues related to the calibration of the sensors must be taken into account [9]. Obtained results of measurement should include information about their quality in the form of uncertainty [10].

One of the most rapidly growing technique in the machine diagnostics is the machine vision. Depending on application there exists numerous possibilities to detect, recognize and classify objects, colours, shapes, boundaries, texture, as well as more detailed features such as physical, statistical as dynamic changes in some parameters values. Furthermore, a variety of the instruments, such as image analysis in different colour space and image processing in time or frequency domain, can be used. The grain recognition based on the 2D images have the wide range of application such as river-bed grain size determination based on neural fuzzy network [11], segmentation of petrographic thin section images [12], the monitoring of an industrial flotation cell in an iron flotation plant [13] to the particle size distribution of ball-and gyro-milled lignite and hard coal [14]. Most of the recent publications on grains recognition are based on the two ways: edge-based methods such as boundaries between grains detected and analysed [15], the second one is region-based such as region growing segmentation [16]. First group of methods are based on simple thresholding technique of the gradient images with some post-processing such as thickening and skeleton for reliable grain detection. The second one is based particularly on region growing segmentation with some manual merging and/or splitting detected regions. Obara proposed grain segmentation of the rocks with image colour space transformation from RGB to CIElab, in consequence, the efficiency of the segmentation has increased [17]. Another segmentation technique based on the constrained automated seeded region growing has been developed in [18].

3. PROPOSED METHOD

Many authors of the papers similar to the one presented in this work, ignore part of the sample preparation in real time, by using complex microscopes or other expensive off-line devices. The off-line method requires some time for taking the sample from a technological line, preparation of the sample and analysis by the application. Another well-known objective is a time consumption what is the result of complex image processing algorithms. Most of the already developed methods are based on one of two classic ways mentioned in the previous section and are focused only on the one type of the structure or one type of the feature, such as colour, size, or shape. The novelty of the proposed solution focuses on the higher granularity range recognition in real-time, which can be recognized by the algorithm thanks to the usage of the different angle lighting, procedure of the sample quality checking and combined classification of the detected grains.

Some of the issues identified during our experiments should be taken into consideration. First, the character of the process – the raw sample of the material directly after milling with constant frequency still on the rig can be taken.

a) b) c)

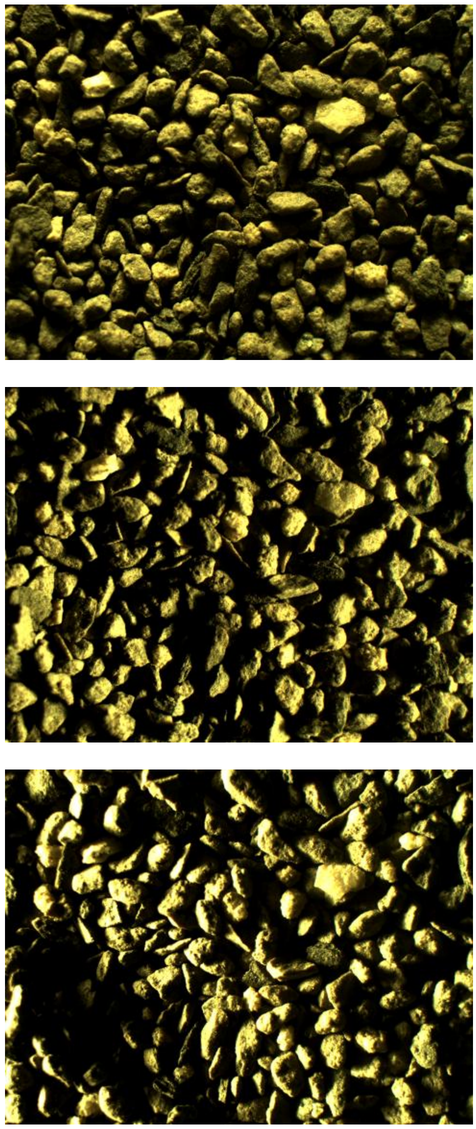


Fig. 3. Sample images of the copper ore acquired under different lightning direction – centre (a), right (b), left (c)

Next, the structure of the grains sample in most cases is not homogeneous and flat. In the Figure 3 images taken under the different direction of the lightning have been presented. In the Fig.3a taken under perpendicular to the observed material angle non-uniformity of the surface is not visible, but in Fig.3b and especially Fig.3c regions with black colour can be found. Images have been taken under 45° angle from the camera at the right and left side respectively. In consequence, we have important information about the quality of the samples, because all the faults, such as valleys and hills in the sample will affect results of particle size classification.

Furthermore, the method should be not limited to any fixed grain size, of course with some wide predefined grain range. The grain classification, grain distribution, shape of the grains and other extracted features can be used to indirect mill diagnostics to complement other methods of diagnostics such as history of mill operations, visual inspections and process measurements of the mill elements - separator, mill chamber, grinding media distribution in the rig.

Based on the above-identified issues authors developed a method which is based on the online examination of the product during the milling process. Determination of the total number of the grain, the size of each grain, also the classification of the grains are the main goal of proposed method. In the proposed method the camera with white lightning mounted at an assumed angle has been used, in order to increase significantly a number of the extracted features and detection of the fault samples.

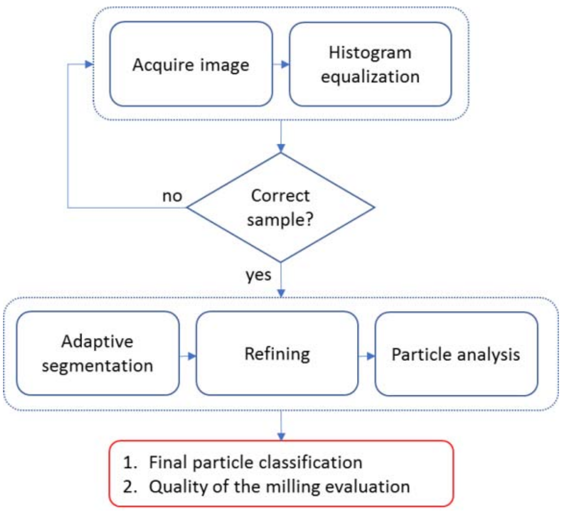


Fig. 4. Block diagram of the proposed method

Next, the quality of the image is increased using histogram equalization to extract some of the non-visible grains (Fig.5). Histogram equalization is a fully automatic and fast contrast improvement technique. In the recent literature can be found numerous methods of contrast enhancing such as based on the bi-histogram equalization median plateau limit [19], exposure based sub-image histogram equalization [20], edge preserving local histogram equalization [21] and many others. In this paper authors used classic histogram equalization with global information. For milled material images, the algorithm improves the contrast to the required one for proper analysis. In the next step, images are extracted in order to remove borders of the images.

After above pre-processing steps, the sample must be checked in quality sample step. Authors decided to divide each image into four segments with the same area. For each segment, we calculate average intensity and standard deviation. Next, these parameters are compared with nominal parameters calculated for a set of nominal samples. If they are less than 80% of nominal parameters the sample should be rejected and a new sample should be taken, in other case samples can be processed through the algorithm.

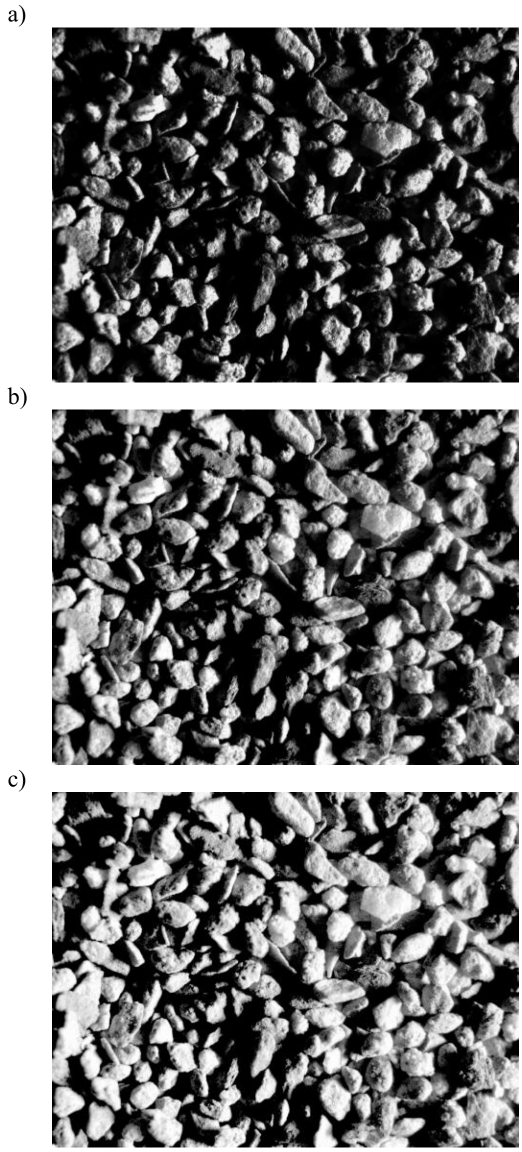
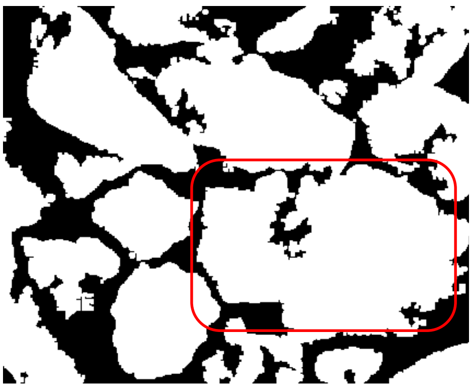


Fig. 5. Original image (a), after logarithmic operation (b), after histogram equalization (c)

The detection of the particles is performed by an adaptive segmentation based on the inter-class variance. This method utilizes discriminant analysis to find the maximum separability of classes, in order to the rules: find the threshold that minimizes the weighted with-in-class variance for each possible threshold value. In consequence, the means of two classes can be separated as far as possible and the variances in both classes will be as minimal as possible. Generally, the segmentation is based on the method called in the literature as Otsu method [22] with improvements for better segmentation of complex images. The method computes histogram and probabilities values for each intensity level of the image. Next, the class means and class probabilities must be calculated for each possible threshold. The morphological refining is the set of fast morphology operations which improve the quality of the segmented particles and are based on the hole filling and small particles removing, in order to the mean value of the particles area. Taking into account that the particles are classified basing mostly on the particle size, proposed Otsu segmentation and refining methods produce in most cases connected particles, which can be treated by the classification procedure as one large particle. Thus authors propose method of particles separation, which is based on the calculation of the Euclidean distance transform. Based on the centres of the distance map, grains are divided into separated ones exactly in a half way between centres. It is important that not for all particles the distance transform has been calculated, only those for which aspect ratio value is low. In Figure 6 has been presented results of segmentation and distance transform for all the detected particles. In the red rectangle connected particles has been checked and distance transform, which in this case indicates that the particle detected as one contains two separate grains. During our experiments distance transform changes the number of the particles 10-15% in relation to the nominal number of the particles calculated manually - depending on the granularity class.

a)



b)

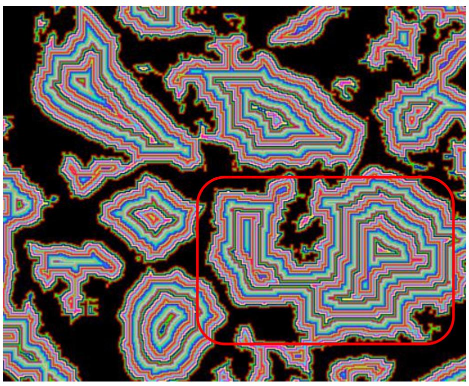


Fig. 6. Segmented image (a), distance transform (b)

At the final stage, all recognized grains are described by a set of parameters such as the centre of mass, perimeter, area, percent of area/image, compactness factor and Heywood factor. The perimeter and area values are used to classify grains, percent of area/image is used to obtain information about overall segmentation quality: value less than 70% means that 30% of the image area does not contain any of the grain.

4. EXPERIMENTS AND DISCUSSION

The proposed solution has been tested on the dedicated machine vision set-up equipped with a 1624x1234 resolution colour CCD camera, 16 mm lens with two spacer rings, the source of the white light with flexible mounting and PC computer with software in static laboratory stand. With the use of laboratory sieves, sand grains were partitioned into six sizes: of 0.2-0.25 mm, 0.25-0.3 mm, 0.3-0.385 mm, 0.385-0.43 mm, 0.43-0.49 mm and 0.49-0.75 mm diameter, also in our experiments we used copper ore partitioned into five sizes: of 0.045-0.071 mm, 0.071-0.1 mm, 0.1-0.2 mm, 0.2-05 mm and 0.5-1 mm. Each time images have been taken with the same camera position, but different light source direction: left with an 45^o angle, centre and right with an 45^o angle.

Proposed method uses an adaptive segmentation based on inter-class in-variance which is most suited to the shape of the grains. Of course, the algorithm has been adapted to the sand and copper ore grains. Images taken during experiments in most cases are non-uniformity, thus only adaptive segmentation can deal with this limitation. Local analysis of the particle regions produces too detailed results, where one particle is divided into a few ones. During our experiments, a few well-known methods of segmentations have been tested (see Fig.7). Segmentation based on the entropy function produces thinned grains and only larger ones can be detected, other will be removed from the resulting image. The clustering method produces many larger grains. The inter-class invariance thresholding method produces most suitable results.

In Figure 8 results of the proposed algorithms steps have been presented. Most of the grains have been correctly segmented, but some of them include some holes as an effect of grain texture segmentation, some other are too small and must be removed. The final result has been presented on the Fig.8e with labelled one in Fig.8f. Taking into account the main goal of the proposed method which is grain size detection and the overall classification of the sample, the most interesting are larger grains, because their greater participation in a total number of grains carries information about milling quality, also the distribution of the different classes of the particle should be uniform.

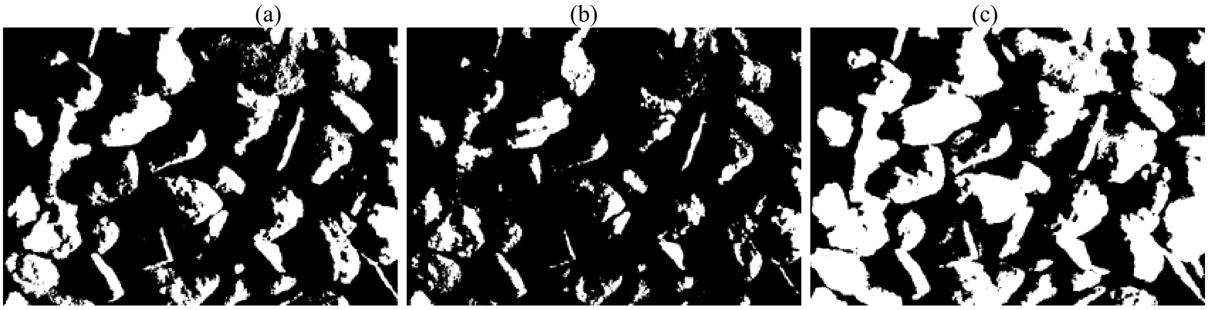


Fig. 7. Results of image segmentation using proposed method (a), entropy (b), clustering (c)

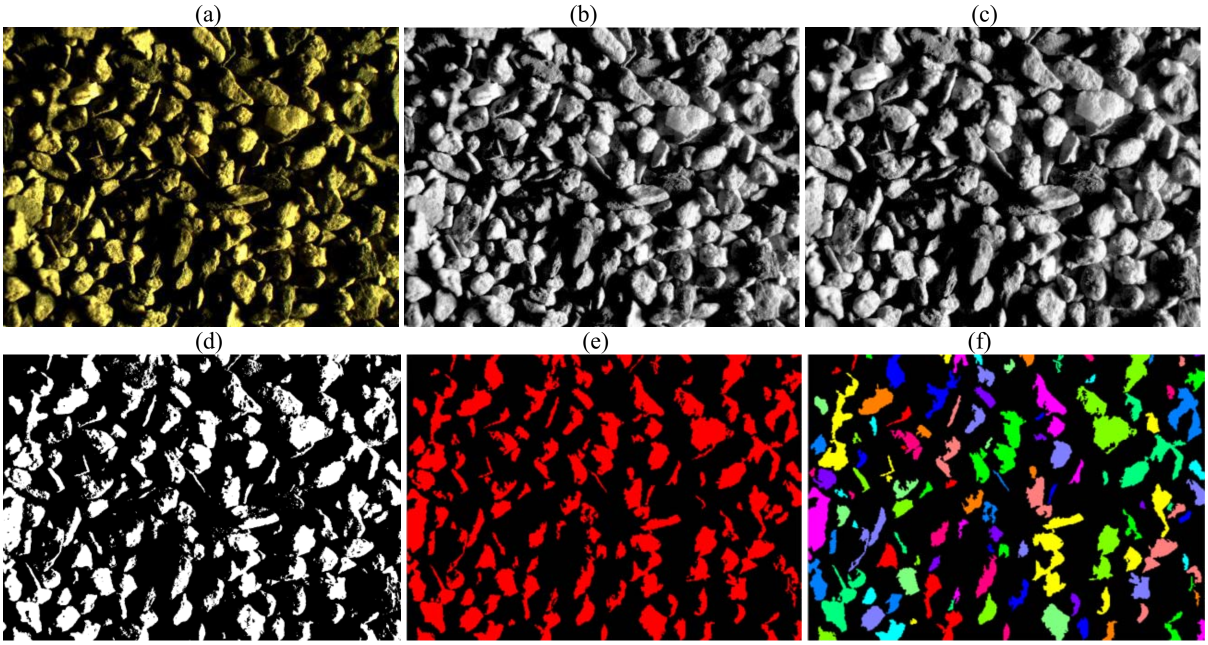


Fig. 8. Original image (a), after histogram equalization (b), after extraction (c), after segmentation (d), after refining (e), final result (f)

Table 1. Sample of diagnostic parameters values determined in course of experiments

Parameter/Particle no	1	2	3	4	5	6	7	8	9
Centre of Mass X	140,89	349,13	500,95	862,15	526,73	931,78	748,30	437,44	235,22
Centre of Mass Y	70,03	16,72	3,83	9,27	50,73	106,71	174,45	81,65	149,33
Perimeter	870,81	181,14	68,52	99,99	200,02	793,16	798,72	148,59	714,71
Max Feret Diameter	253,21	75,27	29,15	41,59	78,10	211,69	232,82	57,14	226,15
Waddel Disk Diameter	163,63	50,16	17,15	27,27	59,87	144,79	197,15	44,06	139,10
Area	21028,00	1976,00	231,00	584,00	2815,00	16466,00	30528,00	1525,00	15196,00
Orientation	29,18	162,83	175,10	20,38	42,79	128,64	111,55	163,95	32,51
Elongation Factor	2,52	2,87	3,68	2,96	2,17	1,94	1,58	2,14	2,53
Compactness Factor	0,57	0,68	0,72	0,73	0,70	0,48	0,65	0,64	0,44
Heywood Factor	1,69	1,15	1,27	1,17	1,06	1,74	1,29	1,07	1,64
Type factor	0,75	0,91	0,92	0,89	0,92	0,60	0,89	0,95	0,59

For each localized grain, the algorithm produces a set of parameters. A sample set of parameters for selected particles in the image has been presented in Table 1. All the parameters have been selected regarding to the assumption that they should describe geometric features in the particle, also they are sensitivity for changes in the shape of the particle. In consequence, some of them as Heywood factor, compactness factor, and particle area is used in classification procedure.

The proposed algorithm can be used in a few scenarios. First, as tracking algorithm of assumed one granularity – particle size. In this case, the algorithm should be able to acquire images with constant frequency and as result of processing each time, it produces percent of particles in the sample with assumed granularity. Second, as a typical distribution of the particle sizes classes for one taken sample. In this case, we are interested in changes in time between next distributions. Generally, the participation of the larger particles in a total number of particles should decrease through the time during milling. If not, there can be a probable problem with milling medium. Third, based on the assumption that quality of the final milling product specify quality of the milling in general, method will recognize e.g. problem with milling media – it's reduction; by observing the Heywood factor value and area, problem with extraction of the milled material unit by observing total Area value.

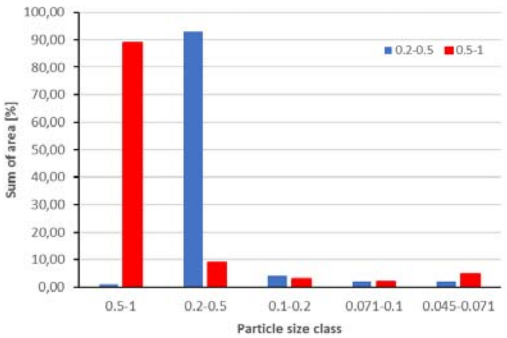


Fig. 9. Results of the different grain class distribution

In Figure 9 has been presented mentioned distribution as a result of proposed method for a correctly prepared sample with uniform well-known granularity. Detected other classes of the grain sizes are the result of some regions, where grain are placed in front of narrow surface, also as result of the segmentation process.

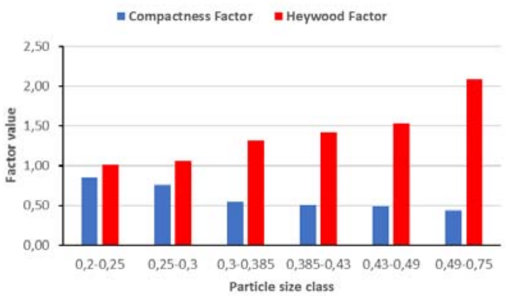


Fig. 10. Compactness and Heywood circularity factor for sand grains samples

In Figure 10 compactness and Heywood factor for different classes has been presented. Calculated values for nominal samples can be used during diagnostics because for smallest grains both parameters values should be closest to 1. Other hand, for larger granularity, both parameters should be characterized by the opposite trend in order to 1. Compactness factor is associated directly with a density of the grain, whereas information about the circularity of the grain is represented by the Heywood factor.

The classification procedure is based on the simple rule-based system in order to the procedure: define all required grain classes, calculate necessary parameters in each defined class for nominal samples, which must be created with e.g. sieves and proposed method, take the image from the rig, classify particles. In Figure 11 final results of detection and classification have been presented. Proposed method produce results most similar to the manual selection, but it must be taken into account that manual selection also includes some imperfections, especially for a large number of the smaller particles.

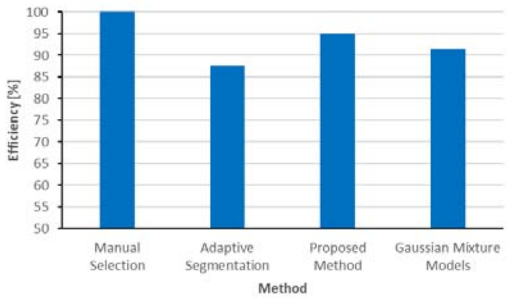


Fig. 11. Efficiency of the detection methods

5. CONCLUSIONS

In this paper, the method of grain detection and particle classification has been presented, based on improved adaptive segmentation. The research has been focused on the different type of the material with a predefined granularity classes. The obtained results show the relationship between measured parameters and overall quality of the milling process. Furthermore, authors had discussed different scenario of proposed method utilization. Using INTEL i5 2.60GHz PC computer our algorithm takes overall about 400ms. Our future work will be concentrated on the optimization of the segmentation method for real-time applications and developing a new contrast image enhancing method.

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