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THE APPLICATION OF MODERN TECHNIQUES AND MEASUREMENT DEVICES FOR IDENTIFICATION OF COPPER ORE TYPES AND THEIR PROPERTIES

WYKORZYSTANIE NOWOCZESNYCH TECHNIK I URZĄDZEŃ POMIAROWYCH DO IDENTYFIKACJI TYPÓW RUD MIEDZI I ICH WŁAŚCIWOŚCI.

The paper concerns the application of modern methods and research techniques for investigations of copper ore properties. It presents the procedure and tools which, when put together, can constitute a source of information on properties of different products of processing and, simultaneously, can be used in the process control and optimization.

The copper ore of one of the branches of the KHGM Polska Miedz plc was investigated. The ore samples represented each of the three lithological types occurring in the Polish deposits, i.e. carbonate, shale and sandstone ores.

The paper presents the results of microscopic analyses, image analysis of scanning photographs and application procedures of the obtained information for the identification of ore types (application of neuron networks to the recognition of lithological compositions).

The present publication will present sample results of modelling of classification identifying two types of ores, i.e. carbonate-shale and sandstone.

Summing up the predictions of ore type fractions in respective mixtures for the considered problem of classification it can be stated that the prediction results are good and confirm the lithological predominance of certain ore types in the investigated mixtures.

The experimental part comprised the determination of mineralogical and lithological composition of ores (optical microscope) and also elemental composition in the microareas of analysed samples (scanning microscope). Next, the image analysis was performed and subsequently the models classifying the ore types were made.

Keywords: identification of ores, image analysis, scanning microscope, neuron networks

W rudzie miedzi przerabianej w zakładach wzbogacania O/ZWR KGHM Polska Miedź S.A. można wyróżnić trzy typy litologiczne: rudę węglanową, łupkową i piaskowcową. Typy te różnią się właściwościami między innymi takimi jak: rodzaj i zawartość minerałów miedzi, rodzaj minerałów nieużytecznych, zawartość miedzi, twardość i podatność na rozdrabnianie, ale także wielkością i kształtem ziaren minerałów miedzionośnych oraz rodzajem ich skupień i wprysnięć.

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Niezwykle istotne jest właściwe rozpoznanie rudy pod względem petrograficzno-mineralogicznym. Znajomość właściwości przerabianej rudy pozwala na pełniejsze jej wykorzystanie poprzez właściwe prowadzenie i sterowanie procesami, dobór ich parametrów takich m.in. jak: czas mielenia, parametry klasyfikacji, rodzaj odczynników flotacyjnych, czas flotacji.

W artykule przedstawiono wyniki przeprowadzonych analiz mikroskopowych, analizy obrazów zdjęć skaningowych oraz procedury wykorzystania otrzymanych informacji do identyfikacji typów rud (zastosowanie sieci neuronowych do rozpoznawania składów litologicznych).

W badaniach wykorzystano rudę miedzi, pochodzącą z jednego z zakładów górniczych KGHM Polska Miedź S.A. Pobrane próbki rudy reprezentowały każdy z trzech typów litologicznych występujących w krajowych złożach: węglanową, łupkową oraz piaskowcową.

Przeprowadzono ilościową analizę mineralogiczno-petrograficzną przy pomocy mikroskopu optycznego w świetle odbitym, a wyniki przedstawiono w tabelach 1 i 2. Wyniki te określają ilościowo stopień uwolnienia i zrosty dla jednego rodzaju minerału.

Pokazano także przykładowe zdjęcia mikroskopowe zgładów poszczególnych typów litologicznych rud oraz próbek proszkowych tych typów (rys. 1 i 2).

W kolejnym etapie badań wykorzystano skaningowy mikroskop elektronowy. Zdjęcia morfologii próbek uzyskane z mikroskopu elektronowego (obrazy SEM) były przedmiotem komputerowej analizy obrazu, umożliwiającej mikrostrukturalną klasyfikację ilościową typów rud. Analizowano wszystkie próbki poszczególnych typów litologicznych rudy miedzi: węglanowej, łupkowej i piaskowcowej oraz mieszanki tych typów w trzech klasach ziarnowych: 0÷45 μm, 45÷71 μm i 71÷100 μm.

Celem przekształceń wykorzystanych w procedurze komputerowej analizy obrazu jest otrzymanie poprawnie posegmentowanego obrazu binarnego, który umożliwiałby wyróżnienie badanych obiektów – pojedynczych (poszczególnych) ziaren oraz tła, a następnie wykonanie pomiarów parametrów zbinaryzowanych obiektów.

Spośród dużej ilości parametrów dostępnych w używanym oprogramowaniu do identyfikacji typów rud wybrano najważniejsze z punktu widzenia opisu ziaren. Obok parametrów opisujących podstawowe właściwości geometryczne tj. pole powierzchni, wysokość, szerokość, średnice Feret'a, oraz opisujących kształt ziaren, np. współczynniki wypełnienia, kolistości, wybrano parametry szarości obiektów.

W tabeli 3 podano wartości statystyczne zmiennych wykorzystywanych w obliczeniach modelowych, dla jednego z materiałów. Do analizy uzyskanych danych wykorzystano sieci neuronowe.

W niniejszej publikacji przedstawiono przykładowe wyniki modelowania dla zagadnienia klasyfikacji identyfikującego dwa typy rud: węglanowo-łupkową i piaskowcową. Połączenie rud: węglanowej i łupkowej w jeden typ ma swoje technologiczne uzasadnienie.

Obliczenia modelujące wykonano przy użyciu komputerowego programu do modelowania *Statistica Neural Networks* firmy StatSoft.

W tabeli 4 i 5 przedstawiono charakterystyki ostatecznych najskuteczniejszych modeli sieci neuronowych klasyfikujących typy rud.

Ogólnie modele sieci neuronowych, realizujące zagadnienie klasyfikacji typów rud, charakteryzowały się wysoką jakością działania oraz małymi błędami sieci dla poszczególnych podzbiorów danych (uczącego, walidacyjnego i testowego). Świadczy to o ich wysokiej stabilności i pewności działania w przypadku uruchamiania sieci na nowych zbiorach danych.

Weryfikacja zdolności predykcyjnych najskuteczniejszych modeli sieci neuronowych polegała na uruchomieniu sieci na nowych danych charakterystycznych dla poszczególnych mieszanek, oraz na porównaniu i ocenie uzyskanych przewidywań z rzeczywistymi udziałami poszczególnych typów rud miedzi w analizowanych mieszankach.

Na rysunkach 6 i 7 przedstawiono wyniki przewidywań udziałów odmian litologicznych rud miedzi w mieszankach.

Podsumowując przewidywania udziałów typów rud w poszczególnych mieszankach dla rozważanego zagadnienia klasyfikacji można stwierdzić, że wyniki przewidywań są dobre i potwierdzają przewagę litologiczną określonych odmian rud w badanych mieszankach. Szczególnie istotny z technologicznego punktu widzenia jest wysoki stopień trafności przewidywań typów rud dla szerokiej klasy ziarnowej, która odpowiada zazwyczaj rzeczywistemu składowi ziarnowemu nadawy do procesu flotacji. Trafność tych przewidywań jest większa dla mieszanek z przewagą rudy piaskowcowej.

Słowa kluczowe: identyfikacja typów rud, analiza obrazu, mikroskopia skaningowa, sieci neuronowe

1. Introduction

Three lithological types can be differentiated in copper ore processed in the ZWR Branch of the KGHM Polska Miedź plc. These are: carbonate ore, shale ore and sandstone ore. These types differ in their properties, i.e. type and content of copper minerals, types of useless minerals, copper content, hardness and susceptibility to crushing but also in sizes and shapes of copper-bearing minerals as well as types of their aggregates and disseminations (Grotowski et al., 1996; Spalińska et al., 1996).

Therefore it is extremely important to recognize the ore from the point of view of petrography and mineralogy. The knowledge of properties of the processed ore contributes to its better use by means of proper course and control of processes, the choice of their parameters, such as grinding time, classification parameters, types of flotation reagents and flotation time.

The present practice of mineralogical and petrographic investigations of the ore has been mainly based on the use of optical microscope and, despite the significant progress in automation of microscopic techniques, applying specialist software and computer techniques, the human factor in the research is very important and is limited to quiet tedious manual and decision-making actions.

The development of scanning microscopy enables the investigations in a similar range to be carried out, additionally delivering information about contents and aggregates of respective elements in a sample by means of microanalysis in a chosen sample area but, first of all, enables the investigation of materials of very fine grains since such appear in the copper ore processing products, characterised by small quantities of copper-bearing minerals.

The paper presents the results of microscopic analyses, image analysis of scanning photographs and application procedures of the obtained information for the identification of ore types (application of neuron networks to the recognition of lithological compositions).

The experimental part comprised the determination of mineralogical and lithological composition of ores (optical microscope) and also elemental composition in the microareas of analysed samples (scanning microscope). Next, the image analysis was performed and subsequently the models classifying the ore types were made. The photographs obtained from the optical and scanning microscopes were used in the investigations.

Computer image analysis is now widely used in metallurgy, biology, medicine and petrology. Is a good tool for porosity parameters measurement in clastic rocks (Labus, 2004) and for automatic analysis of rock structures (Młynarczuk, 2004). Image classification using artificial neural networks are very common in many industries to develop expert system for object recognition, also in material industry. Image processing is a technique to dig out constructive information by just visualizing its texture. Laine use the approach on-line determination of ore type using cluster analysis and neural networks (Laine et al., 1995).

Singh and Rao proposed a novel approach to classify the ores for ferromanganese metallurgical plant feed based on the visual texture of the ore particles and radial basis neural network. The visual texture of ore particles vary with the mineral contents. Results obtained show encouraging accuracy to apply the approach to develop an expert system for on line ore quality monitoring to control the ore blending in the feed ore circuits as well as separating gangue minerals present in the feed ores (Singh & Rao, 2005).

Sadr-Kazemi and Cilliers present an image processing algorithm that has been developed for froth surface bubble size distribution measurement, and that is largely insensitive to factors such as froth type, lighting conditions and bubble size (Sadr-Kazemi & Cilliers, 1997).

2. Preparation and characteristics of materials

The copper ore of one of the branches of the KHGM Polska Miedź plc was investigated. The ore samples represented each of the three lithological types occurring in the Polish deposits, i.e. carbonate, shale and sandstone ores. Samples in the form of a rock fragment were taken in order to prepare microsections to be analysed by scanning and optical microscopes. The remaining ore was crushed and sieved into appropriate grain classes: 0÷45, 45÷71, 71÷100 µm. The choice of classes resulted from the ore mineralogical properties and technology of enrichment.

The powder samples and microsections were subjected to microscopic tests with the optical and scanning microscopes.

3. Mineralogical and lithological quantitative analysis.

The mineralogical and lithological quantitative analysis was performed with the optical microscope in the reflected light for 9 powder preparations (3 ore types x 3 grain classes and 3 microsections). The authors used the 286 node planimetric network. For each preparation countings were performed in at least 30 areas, distributed evenly on the entire sample. Tables 1 and 2 present the results of the analysis. The results determine quantitatively the liberation degree and intergrowths for one mineral type. The table symbols denote:

S — sandstone ore,
SH — shale ore,
C — carbonate ore,
F — liberated sulfide,
s, sh, c — sulfide intergrowths with sandstone, shale and carbonate ores respectively.

The column "others" determines the total content of ore minerals, such as galena, sphalerite, pyrite, markasite and tennantite.

TABLE 1

Results of quantitative mineralogical analyses for powder samples

			Carbonate ore			Shale ore			Sandstone ore		
			0-45 µm	45-71 µm	71-100 µm	0-45 µm	45-71 µm	71-100 µm	0-45 µm	45-71 µm	71-100 µm
1			2	3	4	5	6	7	8	9	10
S			6,33	5,32	3,39			0,25	71,26	86,94	89,94
Sh						80,54	79,30	84,03			
C			91,30	89,09	92,83				15,19	0,14	0,38
chalcocite	F		2,18	5,24	0,62	19,46	16,15	2,26	6,23	5,58	4,92
	Inter-growths	s								0,07	0,14
		sh					4,46	13,34			
		c			3,16						
bornite	F			0,18				0,12	2,95	3,88	3,4
	inter-growths	s							0,11	0,56	0,28
		sh									
		c									0,05

1			2	3	4	5	6	7	8	9	10
chalcopy-rite	F		0,19	0,17			0,09		0,98	0,85	0,14
	inter-growths	s									
		sh									
		c									
covellite	F								0,77	0,78	0,42
	inter-growths	s									
		sh									
		c									
others	F								2,51	1,2	0,14
	inter-growths	s									0,14
		sh									
		c									0,05

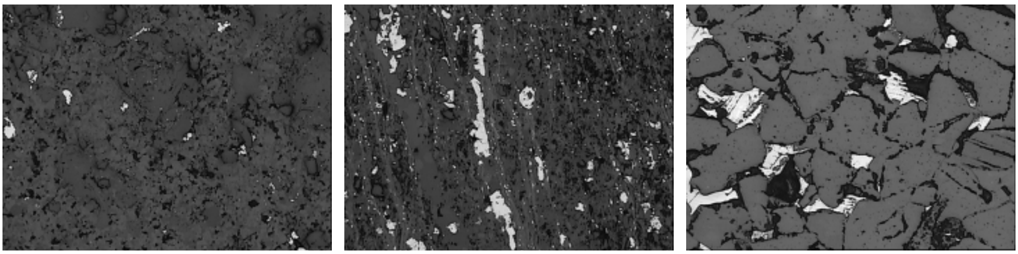
TABLE 2

Results of quantitative mineralogical-lithological analyses for microsections

	Waste rock	**Chalcocite**	**Bornite**	**Chalcopyrite**	**Covellite**	**Others**
Sandstone ore	97,98	1,95	0,03	—	0,03	0,02
Carbonate ore	99,45	0,55	—	—	—	—
Shale ore	93,92	6,08	—	—	—	—

Figures 1 and 2 present the examples of microscopic photographs of microsections of respective lithological types of ores and powder samples of these types for the grain class 45÷71 μm.

The obtained results allow the detailed description of the character and properties of respective ore types to be performed.

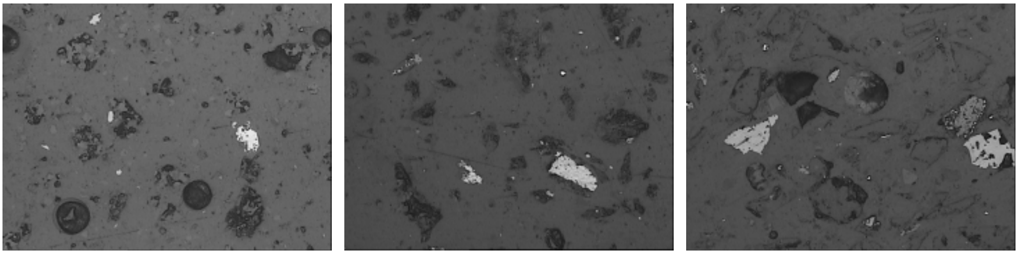


a) b) c)

Fig. 1. Microscopic photographs of microsections representing the ores: a) carbonate, b) shale, c) sandstone

Microsections

The investigated microsections constitute fragments of rock chips of the characteristic types of copper ore. The character of occurrence of metal minerals can be clearly observed from the surface analysis of microsections. In the shale ore of a clearly directional structure larger amounts of chalcocite with veined metallization were observed; in the poorer carbonate ore there were



a) b) c)

Fig. 2. Microscopic photographs of powder samples of the ores: a) carbonate, b) shale, c) sandstone in the grain class 45÷71 μm

tiny and dispersed sprinklings of copper sulfides whereas in the sandstone ore copper sulfides occur mainly in the binder between the quartz grains.

Chalcocite is the dominating copper-bearing mineral observed in the microsections of all ore types. Only the sandstone ore contains small amounts of bornite and covellite (0,03% each) and the group of minerals known as "others" (0,02%). The shale ore is the richest in copper and contains 6,08% of chalcocite (the basic metal mineral). The carbonate ore is the poorest which contains only 0,55% of chalcocite. Copper-bearing minerals constitute about 2,01% in the sandstone ore.

Powder samples

The composition of metal minerals in all the tested samples is quite stable and does not change significantly. Copper sulfides are represented mainly by chalcocite and only in the case of the sandstone ore also by bornite and, in smaller amounts, by chalcopyrite and covellite.

The performed planimetric analysis proved the fact that copper-bearing minerals occur in very tiny disseminations and the increase of their liberation degree proceeds together with the increase of sample crushing. In the class 71÷100 μm the liberation degree is very low, both in the carbonate ore and the shale one; only in the sandstone ore the majority of minerals occur in the free state. In the finest class, 0÷45 μm, the practically complete liberation of metal minerals was observed for all ore types. Therefore, from the technological point of view, the ores should be prepared to enrichment separately, according to the ore lithological type.

4. Analyses with scanning microscopy

The scanning electron microscope, JEOL Scanning Microscope JSM-5400, was used at the next stage of research.

12 images of each sample were applied for image analysis, enabling the microstructural quantitative classification of ore types. The recording procedure of sample images consisted in a random selection of 12 areas, distributed representatively on the entire surface of the preparation. Additionally, photographs of sample microareas were taken and elemental composition in these areas was analysed.

The photographs of samples morphology were used for the computer image analysis in further investigations. For each ore type, in Figs 3 and 4, the example photographs of microareas and the elemental composition in these areas in the grain class 0÷45 μm were shown. The observation results are described below.

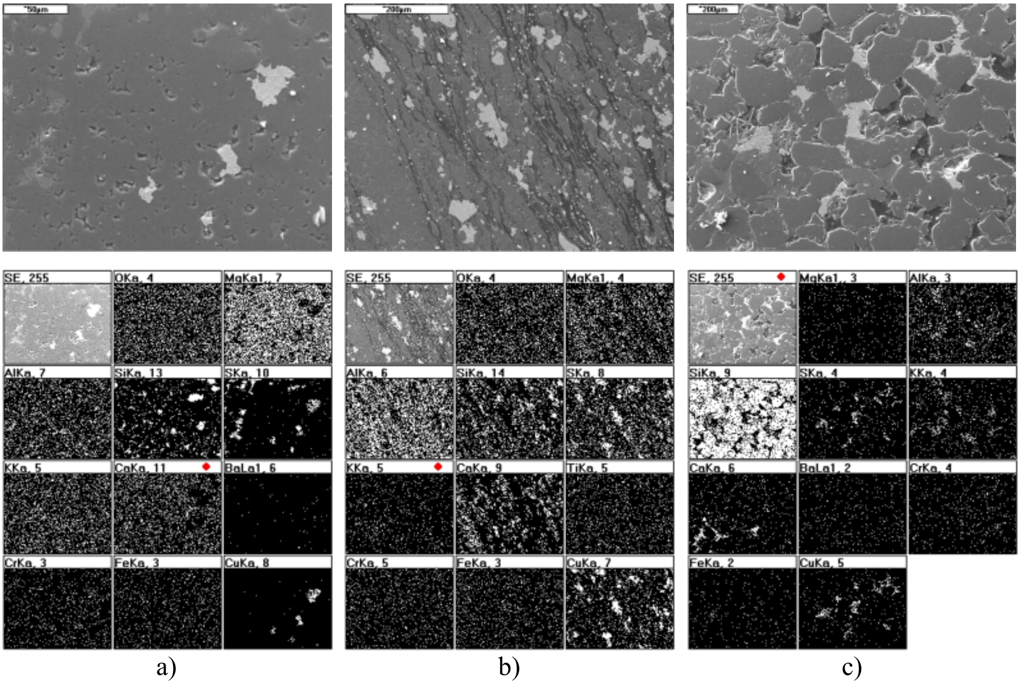


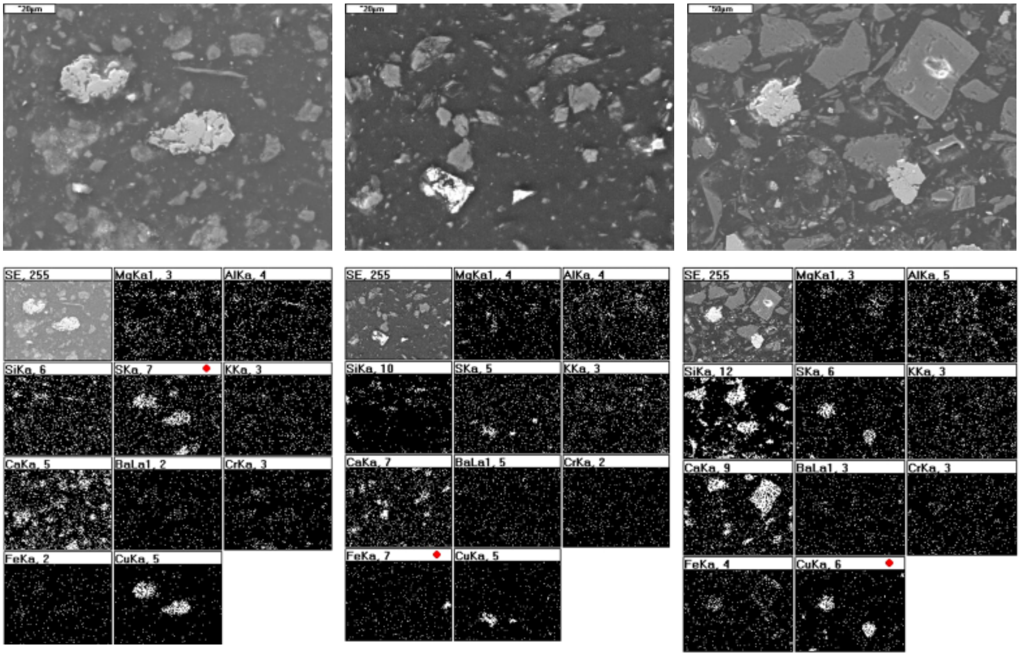
Fig. 3. Microscopic structures of selected sample areas together with the elemental distribution maps in these microareas for ore microsections: a) carbonate; b) shale; c) sandstone

The "maps" shown in the figures present the distribution of elements in the analysed sample areas. The presence of characteristic elements is confirmed by clear points. When the concentration of a given element is increased in the certain place of the sample, also the density of points in it increases.

Microsections

Carbonate ore

The microscopic photographs of the microsection of the carbonate ore sample are characterized by high lithological homogeneity and fairly compact structure. The Ca-Mg set dominates in the photographs which is characteristic for components of dolomite ($CaMg[CO_3]_2$) and, in smaller amounts, the Ca-S set, which may prove the presence of gypsum ($CaSO_4 \cdot 2H_2O$) or anhydrite ($CaSO_4$). Besides, there are Al, Si and K which are components of clay minerals, i.e. illite and kaolinite as well as Cu and S which confirm the occurrence of chalcocite which dominates in the copper-bearing mineral. These observations confirm the real composition of the carbonate ore,



a) b) c)

Fig. 4. Microscopic structures of selected sample areas together with the elemental distribution maps in these microareas for the powder ore samples: a) carbonate; b) shale; c) sandstone in the grain class 0÷45 µm

characteristic for the Polish copper ores. Chalcocite, present in the carbonate ore sample, forms mainly dispersed and nest structures.

Shale ore

The shale ore comprises mainly clay minerals, i.e. illite and kaolinite (in the form of the Al-Si-K sets and Al-Si sets) as well as carbonates, mainly dolomite (Ca-Mg). In smaller amounts there are quartz, feldspars (Ca-Al-Si, for example of the Na-Ca feldspars – anorthite $Ca[Al_2Si_2O_8]$ and mica (Mg-Al-Si).

The photograps show the characteristic directional texture of the shale ore which, among others, results from the parallel positioning of minerals with the folia habit of crystals (e.g. micas). Copper sulfides (Cu-S) in the shale ore occur most often in dispersed and veined structures. A large differentiation of aggregate sizes of these minerals is also observed.

Sandstone ore

Silicon as the component of quartz (SiO_2) is the dominating element depicted in all photographs of the sandstone ore microsection. Quartz grains are characterized by clearly marked boundaries, are bound by calcite and illite. Thus it results in the presence of Ca ($CaCO_3$ – calcite) and Al-Si-K ($(K,H_3O)Al_2[(OH)_2|AlSi_3O_{10}]$ – illite) which occur just between individual quartz grains. Metal minerals, observed in the microsection as a set of elements Cu-S, occur also most often between quartz grains, replacing the carbonate-clay binder of sandstone.

Powder samples

Microscopic photographs and “maps” of the elements in powder samples prove that the elemental composition of the analysed powder samples of different types of ores is similar to the composition of the above mentioned microsections. In the case of powder samples, however, the aggregations of particular elements can be observed which is shown by the boundaries of areas corresponding to respective grains.

Carbonate ore

The carbonate ore sample, both in the class 0÷45 μm and 45÷71 μm, contain large amounts of Ca and sets of Ca-Mg and Ca-S. Smaller amounts are represented by the sets of Al-Si-K, single grains of Cu-S as well as Si, Mg, S, Fe.

Such a configuration of elements confirms the occurrence of large amounts of calcite ($CaCO_3$), dolomite and anhydrite, which are the main mineral components of the carbonate ore.

In the grain class 71÷100 μm, on the other hand, the elemental sets Ca-Mg and Ca-S are dominating. Besides, Al-Si-K (clay minerals) occur in smaller quantities.

Shale ore

Large amounts of Ca are observed in the class 0÷45 μm. Also quartz Si is present as well as the elemental sets, observed clearly in the boundaries of single grains: Al-Si-K (clay minerals), Ca-Mg (dolomite) and Cu-S (chalcocite). In the class 45÷71 μm single grains of chalcopyrite (Cu-Fe-S) can be additionally observed. In the class 71÷100 μm the maps are dominated by the elemental sets of Ca-Al-Si and Mg-Al-Si. Large amounts of calcium occur, also the elemental groups of Al-Si-K and Ba-S as well as copper in the form of sulfides (Cu-S and Cu-Fe-S).

Sandstone ore

Large quantities of Si are observed in all the photographs of this ore in all three grain classes. The elemental sets are present in the areas of the same grains: Al-Si-K (clay minerals) and also Cu-S and Cu-Fe-S which confirm the presence of chalcocite (Cu_2S) and chalcopyrite ($CuFeS_2$), recognized by the optical microscope.

The elements Ba and S are component of barite (barium sulfate $BaSO_4$), the photographs show the characteristic plate-like shape of crystals of this mineral. Single grains of pyrite (Fe-S) were also observed.

5. Image analysis in the recognition of ore properties

The photographs of preparations obtained from the scanning electron microscope (SEM images) were subject to the computer image analysis. The authors analysed all the samples of respective lithological types of the copper ore, i.e. carbonate, shale and sandstone, and their mixtures made in the following proportions: mixture no 1 – 15% of carbonate ore, 15% of shale ore and 70% of sandstone ore, and mixture no 2 – 35% of carbonate ore, 35% of shale ore and 30% of sandstone ore, in three grain classes: 0÷45 μm, 45÷71 μm and 71÷100 μm. Aphelion 3.2 program was used for this stage of research.

Figure 5 shows a sample window of the performed procedure of image analysis for the sandstone ore sample. On the screen there are selected components of the applied algorithm; these are: a histogram of shades of grey, a binary image, an image after removing the smallest

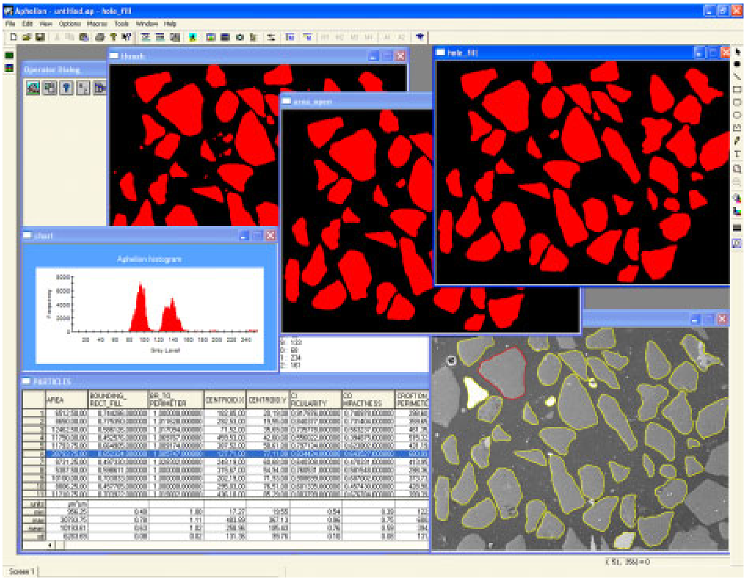


Fig. 5. Window of a sample project of image analysis in Aphelion program

grains, an image after spilling the holes, a spreadsheet with results in which a sample grain and describing parameters were differentiated.

The aim of transformations used in the computer image analysis is to obtain a properly segmented binary image which can distinguish the investigated objects, i.e. single (respective) grains and the background and, then, can execute the measurements of parameters of binarised objects (Tadeusiewicz & Korohoda, 1997; Wojnar et al., 2002).

In every algorithm of image processing of grain structures, regardless of their differentiation, similar stages of the analysis can be observed, i.e. the initial preparation of images, filtration, binarization, processing of binary images (for example, filling the "holes", removing too small objects, object "labeling", etc.) and measuring the characteristic features.

The first step of the algorithm consists in the initial preparation of an image which comprises scale calibration, appropriate for magnification of the photograph and the exchange of the RGB image into a grey image of 256 shades grey.

The next step consists in removing unnecessary noises. These noises could cause blurring the object contour lines, leading to their false identification, for example, to the detection redundant grains. Median filtering was applied for this purpose.

The initially filtered image is subject to the next filtration by means of the *AphImgNagaoFilter* operator which is an averaging filter, performing filtration towards the smallest variance of grey value. The task of this operator is to "smooth" the image while preserving the grain edges.

The detection of grain boundaries is the most important stage of the procedure (algorithm). The binarization procedure is the basis of detection in this processing algorithm whereas the filtered image undergoes the binarization process with the lower threshold.

At the next stage of image processing the authors performed the operation of "filling of holes". The holes, which originated as a result of previous processing procedures, where not real holes but only resulted from heterogeneous grain surfaces. The *AphImgHoleFill* operator was applied for filling the holes inside the objects. This operation is necessary for the proper determination of geometric parameters of grains.

The *AphImgAreaOpen* operator performs the operation of opening according to the area of structures present in the image. It is defined mathematically as a supremum of opening with all possible elements of the area larger or equal to the assumed one. The removal of grains smaller than the assumed threshold magnitude was the final result of the action of this operator. In this case it was the area of 150 pixels. The remaining objects of the areas of the assumed threshold value remained undisturbed.

The image of grains for a further analysis is stored as the image labelled ("PARTICLES"). By means of the *AphImgClustersObj* operator the values of successive natural numbers are attributed to the respective objects. All the pixels belonging to one grain have the same "label". The image background has a label 0 and is not taken into consideration in the measurements.

The *AphObjDraw* operator contours the set of objects marked in the previous task, which is the subject-matter of the final quantitative analysis. This operation has the following parameters: input images of the scanning microscope on which the grain contours are drawn ("init") and *objectSet* – the set of objects, formerly known as "PARTICLES".

The application of *AphObjComputeMeasurements* operator, which executes the measurements of the analysed objects, was the final stage of this part of processing. The operator generated the data describing, among others, geometry of grains, levels of grey and other parameters, accessible in the program, together with their principal statistics. The program is able to send these data to Excel spreadsheets.

Out of very many parameters available in the computer program the authors chose the ones which are the most important from the point of view of grain description for the identification of ore types. Apart from the parameters describing the basic geometrical properties, i.e. surface area, height, width, Feret's diameters and the ones describing the grain shape, e.g. the coefficients of filling and circularity, the authors selected the parameters of grey of objects, such as the minimum and maximum degree of grey, the average level of object grey, the standard deviation of grey on objects, etc.

Below, Table 3 presents the statistical values of variables used in further model calculations for one of the materials.

TABLE 3

Descriptive statistics of parameters obtained in the analysis of sandstone ore photographs in the class 45÷71 μm

Variables	Number of valid	Average	Minimum	Maximum	Standard deviation
K_1	335	0,590	0,140	0,834	0,118
K_2	335	0,666	0,396	0,839	0,080
K_3	335	1,035	1,000	1,290	0,039
K_{C1}	335	0,674	0,150	1,000	0,143
K_Z	335	0,524	0,134	0,799	0,117
K_{Cr}	335	28,717	8,583	111,856	18,061
K_E	335	0,539	0,015	0,992	0,229
$I_{Kurt.}$	335	2,772	-1,135	45,259	5,173

I_{Max}	335	197,096	141,000	255,000	34,953
I_{mean}	335	154,941	120,878	249,331	23,182
I_{Min}	335	112,839	87,000	161,000	12,012
I_{sr}	335	12,246	3,449	40,945	6,506
I_{Skew}	335	-0,012	-5,612	4,392	1,050
K_S	335	0,048	-0,574	0,680	0,206
K_β	335	2,603	1,594	9,470	0,875
K_α	335	1,904	1,000	7,930	0,843
K_W	335	1,597	1,263	3,077	0,231
K_F	335	0,999	0,209	3,750	0,490

where:

K_1 — fill rate (1);
K_2 — fill rate (2);
K_3 — convexity factor,
K_{C1} — sphericity factor,
K_z — compaction factor,
K_{Cr} — circularity factor,
K_E — elongation (in relation to elypsis),
I_{kurt} — kurtosis of grey level,
I_{max} — maximum value of object grey level,
I_{mean} — average value of object grey level,
I_{min} — minimum value of object grey level,
I_σ — standard deviation of grey level,
I_{skew} — skewness of grey level,
K_S — symmetric measure of grain elongation,
K_β — coefficient of corrugation of particle surfaces,
K_α — elongation rate (in relation to a circle),
K_W — Wadell's sphericity coefficient,
K_F — Feret's coefficient.

The method of determining and characteristics of shape coefficients K_1, K_2, K_3, K_{C1}, K_Z, K_E, K_S, K_β, K_α, K_W, K_F have been discussed in detail in the work (Krawczykowska, 2007), chapter 7, table 7.1.

The analysis of the above parameters (Table 3) by classical statistical methods cannot univocally show the differences in the sets of parameter values which correspond to the respective sample. The tendencies to changes are difficult to determine and therefore the differences between lithological types of the investigated ores cannot be directly observed. This is the reason why the authors applied neuron networks to analyse the obtained data (Tadeusiewicz, 2001; *Sieci* ..., 1999).

6. The results – models classifying the ore types

In the articles (Krawczykowska et al., 2008, 2009) the authors discussed in detail the procedure of forming and diagnosing the models, i.e. neuron networks. The most effective networks were subject to the qualitative and predictive evaluation.

The present publication will present sample results of modelling of classification identifying two types of ores, i.e. carbonate-shale and sandstone. Putting the carbonate ore and the shale one together resulted from technological reasons.

The modelling calculations were performed by means of the software for modelling of neuron networks Statistica Neural Networks by Statsoft.

Tables 4 and 5 show the characteristics of the final most effective models of neuron networks, classifying the ore types.

TABLE 4

Summing up the characteristics of the most effective models of neuron networks for the two-state problem of classification

Network no	**Class µm**	**Inputs**	**Hidden**	**Quality of training**	**Quality of validation**	**Quality of testing**	**Error of studying**	**Error of validation**	**Error of testing**
Two-state problem of classification									
8	0÷45	10	110	0,9475	0,8950	0,8895	0,2425	0,3286	0,3282
9	45÷71	10	44	0,8251	0,8462	0,8571	0,3494	0,3608	0,3628
10	71÷100	12	106	0,9665	0,9596	0,9552	0,2079	0,2365	0,2430
Group	0÷100	6	[5]	0,7911	0,7714	0,7627	0,3801	0,4084	0,4057

TABLE 5

Summing up of compatible classifications performed by the most effective models of neuron networks for the two-state problem of classification

Grain class [µm]	**Correct classification [%]**	
	Two-state problem of classification	
	Carbonate-shale ore	**Sandstone ore**
0÷45	92,94	91,21
45÷71	85,96	81,17
71÷100	98,17	93,08
0÷100	79,01	78,15

It results from summing up the above tables that good modelling results were obtained for all the tested cases.

In general, the models of neuron networks, performing the problem of ore type classification, are characterised by high performance quality and small errors for respective subsets of data (training, validation and testing ones). It proves their high stability and certainty of action in the case of starting the networks with the application of new sets of data.

Qualities and errors of network models are more favourable for narrow grain classes, especially in the class 71÷100 µm the qualities of network action are very high and the errors of startings are characterised by small values. These parameters are worse for the models corresponding to the wide grain class 0÷100 µm but they still indicate correctness of models.

Similar tendencies can be observed when comparing the percentage of correct classifications of grains by the models to respective ore types. The higher level of correct classifications is indicated by the models of neuron networks for narrow grain classes and, in particular, for the class 71÷100 µm.

7. Models verification and discussion

The verification of predictive abilities of the most effective models of neuron networks, characterised above, consisted in starting the networks on new data, characteristic for respective mixtures, and in comparing and evaluating the obtained predictions with real fractions of particular ore types in the analysed mixtures.

Figures 6 and 7 present the results of predictions of fractions of lithological types of copper ores in the mixtures.

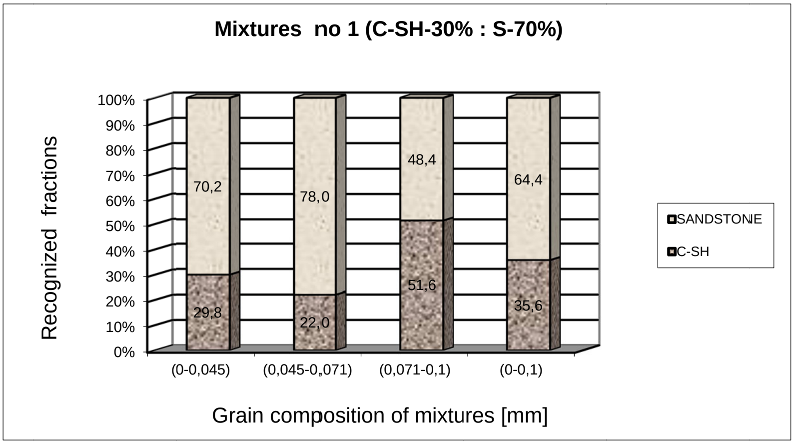


Fig. 6. Recognized fractions of two ore types in the mixtures with predominance of the sandstone ore in different grain classes

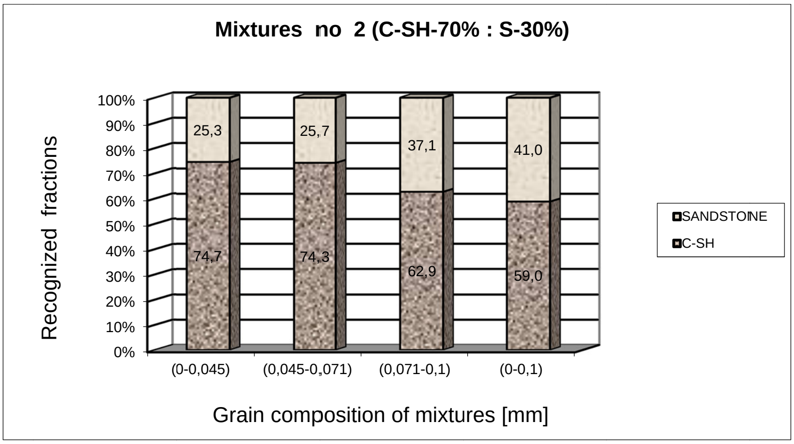


Fig. 7. Recognized fractions of two ore types in the mixtures with predominance of the carbonate-sandstone ore in different grain classes

As it results from the analysis of the above graphs, in the mixtures no 1 (predominance of the sandstone ore) the closest to real results were obtained by the network in the grain class 0÷45 μm while the results more different than the assumed ones were obtained for the most efficient model; in the class 71÷100 μm the model predicted 48,4% of sandstone ore and 51,6% of carbonate-shale ore.

In the considered problem for the mixture no 2 (predominance of the carbonate-shale ore) there is a tendency to more effective prediction of ore fractions by more effective models of neuron networks (in narrow grain classes of mixtures), moreover, the results of predictions are more stable than for the mixture no 1.

Summing up the predictions of ore type fractions in respective mixtures for the considered problem of classification it can be stated that the prediction results are good and confirm the lithological predominance of certain ore types in the investigated mixtures. The high pertinence of predictions of ore types for the broad grain class which corresponds usually to the real grain composition of the feed for flotation is especially significant from the technological point of view. This pertinence is higher for the mixtures with predominance of the sandstone ore.

8. Conclusions

1. The scanning microscope as a basic source of images used in the presented investigations is a device very useful for such investigations. It enables obtaining images of almost unlimited magnifications which is especially important in the analysis of very small objects, such as grains in mineral processing. It also delivers additionally the useful information, such as mappings of elements, elemental analysis in the microarea or along the chosen line.
2. The application of associated investigating procedures, applying the methods of image analysis and neuron networks appeared to be effective in recognising the ore types contained in their mixtures. Supplemented with additional information, delivered by the scanning and optical microscopes, contributed to the universal determination of properties of investigated ores.
3. The applied procedures and analytical tools can constitute the basis (supplement) of determining the selected significant properties of ore processing products and simultaneously, can be used in controlling of processes and their optimization.

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