

An Image Analysis-Based Methodology for Chromite Exploration through Opto-Geometric Parameters; a Case Study of Faryab Area, SE of Iran

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ABSTRACT

Traditional methods of chromite exploration are mostly based on geophysical techniques and drilling operations which are expensive and time-consuming. Furthermore, they suffer from several shortcomings such as lack of sufficient geophysical density contrast. In order to overcome these drawbacks, the current research was carried out to introduce a novel, automatic and opto-geometric image analysis (OGIA) technique for extracting the structural properties of chromite minerals using polished thin sections prepared from outcrops. Several images were taken from polished sections through a reflected-light microscope equipped with a digital camera. The images were processed in filtering and segmentation steps to extract the worthwhile information of chromite minerals. The directional density of chromite minerals, as a textural property, was studied in different inclinations, and the main trend of chromite growth was identified. Microscopic inclination of chromite veins can be generalized for exploring the macroscopic layers of chromite buried under either the surface quaternary alluvium or the overburden rocks. The performance of the OGIA methodology was applied on a real case study, where several exploratory boreholes were drilled. The results show that the microscopic investigation outlines through image analysis are in good agreement with that of obtained from interpretation of boreholes. The OGIA method represents a reliable map for absence or existence of chromite ore deposits in different horizontal surfaces. Directing the exploration investigations toward more susceptible zones (potentials) and preventing from wasting time and budget are the major contributions of the OGIA methodology. It helps to make optimal managerial and economical decisions.

Keywords : *Opto-geometric parameters, Chromite ore deposits, Microscopic inclination, Directional density, Thin section image.*

1. Introduction

In the early 20th century, Murdoch [1] detailed the color and reflectance of ore minerals, and used micro-chemical techniques to identify minerals. His work was later expanded by other mineralogists to include photometric measurements and polarizing techniques. As microscopes and optical lenses improved over time, other properties of minerals were observed. In 1962, the commission on ore microscopy produced a table of quantitative data which contained the incorporation of reflectance standards to assist in mineral identification [2]. The works of mineralogists have presented this data along with detailed descriptions which can be utilized to identify the ore minerals [3-7]. Application of traditional methods for exploration of chromite ore deposits has several shortcomings and limitations. Such techniques include the process of grain-by-grain density measurement of chromite mineralization. This process is extremely time-consuming and needs high expertise. Furthermore, this process requires large samples to be carried to laboratory for preparation and analysis of polished sections. Recently, the Fry analysis method has been introduced to mitigate the limitations of the traditional methods [8]. Application of this method involves large databases of geological information of the regional and local scale. It may be computationally time-consuming and expensive. Fry analysis is a complement method for structural geology and geo-statistical methods, while it has limited applications for mineral exploration in microscopic scales of polished sections. Development of computers has

made it possible to study minerals more accurate, easier, and efficient. Image processing and image analysis have brought a step forward in global characterization of micro-properties of rocks including pore spaces, minerals, fractures, grain sizing, and layer thickness, and texture, phase analysis and detection of grain boundaries, image analysis, pattern recognition, and image processing have been applied in various branches of science due to their accurate results, rapid measurement, and cost-effectiveness. To date, several researchers have worked on the capabilities of both the polished and thin section images for rock characterization. Here, a brief overview is presented related to the topics of the current research.

The method of grain boundary detection may be called semi-automatic in the sense that the segmentation artefacts are manually corrected [9-17]. This sort of interactive method was tested by Heilbronner [12] and proved to be both accurate and fast compared with the fully manual procedure. Grove and Jerram [18] developed a fast and effective method to measure the total optical porosity of impregnated thin sections. They introduced a macro-file, named jPOR.txt, which can be used in digital photomicrographs of thin sections. Ghiasi-Freez et al. [19] employed the capabilities of image analysis and pattern recognition techniques to introduce a semi-automated classification model of pore spaces from thin section images. Ghiasi-Freez et al. [20] developed an automated intelligent model in order to classify the texture of carbonate rocks based on the Dunham classification through image processing and neural network. Arena et al. [21] proposed a crack quantification method based on a 2D image analysis. These researches are just a few of

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numerous studies that have particularly focused on image analysis of polished or thin sections. Studying remote sensing images is another branch of geoscience that has been developed by image processing and analysis techniques [8]. A quick look at the previous efforts shows the importance and capabilities of image processing and image analysis in the geosciences world. In this study, we investigated the capabilities of digital image processing technique for structural and mineralogical studying in recognition of chromite minerals in polished section images captured under a polarized microscope. In this work, we tried to solve two drawbacks of conventional observations in studying polished sections. Structural and mineralogical conventional observations under a polarizing microscope have become very subjective and qualitative due to the observers' experiences. On the other hand, such studies are qualitative, and it is not possible to present an accurate quantitative measurement. The advantage of image processing technique is not only to solve the previous drawbacks of conventional observations, but also to provide rapid, precise, and quantitative measurements. This study was designed on a laboratory scale to introduce a novel and accurate technique for exploring the general trend of chromite mineralization in a field scale. To achieve this goal, the single studied polished section images were interpreted on the geological map of the area. The results of the opto-geometric image analysis (OGIA) method were compared to the field data obtained from coring during drilling multiple exploration boreholes.

This paper is organized as follows. First, the traditional techniques of chromite exploration are discussed. This section explains the fundamentals of chromite exploration, and also, clarifies the advantages of the OGIA approach compared to traditional methods. Then, the fundamentals of image analysis are explained in the second section. Different steps of sample preparation and image capturing are discussed for better understanding of readers in the third section of the paper. The fourth section is the main part of this paper in which the details of the OGIA algorithm are discussed. Finally, the algorithm results are compiled on a map and compared with that of exploration boreholes. In fact, the performance of the algorithm is verified by the outlines of drilled boreholes in a real case study.

2. Traditional techniques of chromite exploration

The science of structure of ore fields and deposits was developed in the Soviet Union. It is based upon the background of large-scale, and in many geological studies, of vast territories in Central Asia, Ukraine, Caucasus, and Iran. The discovery of numerous deposits in known and new metallogenic provinces, belts, and regions including such large and unique deposits as Kempirsai (Cr), base-metal massive sulfide giants of the Rudny Altai, Dzhezkazgan (Cu, Pb, Zn), Kounrad (Cu, Mo, W), Murantau (Au), Almalyk (Cu, Mo, Au), Ingichke (W), Altyn-Topkan (Pb, Zn), Kanimansur (Ag, Pb, Zn), Dzhezihikrut (Sb), Khaidarkan (Hg), Kadzharan (Cu, Mo), and many others made it possible and necessary to develop investigations in all geological and structural settings and for all known types of mineral resources. Studies were carried out at virtually all significant deposits which resulted in creation of an extensive database on structural control of ore mineralization by faults and fractures, folds, growth structural units, magmatic bodies, and their prototectonic elements [22-23]. Studies of Russian geologists showed that the geological parameters such as faults, type of geological structures, and genesis of chromite ore play an important role in exploration of Alpien chromite ores. Great Kempirsai ore field, located in the south of Kazakhstan, was discovered by the traditional method of density measurement of chromite mineralization [24]. Polished sections, taken from ore samples were manually studied to find the trend of chromite extension through an induction approach. Induction is the process of making a generalization about particular instances or patterns in a set of observations or data [24]. On the other hand, deduction is the process of confirming particular instances based on a generalization about patterns in a set of observations or data [25]. Kravchenko [24] divided the studied area into several blocks and found the trend of chromite growth in each block through studying the polished sections. Then, he generalized the results to the whole area. This approach

showed acceptable results for exploration of hidden chromite ores by studying the polished sections. Trubetskoy et al. [26] and Pouyan et al. [27] have introduced a quantitative image analysis-based method using color, brightness, and morphometry parameters. They extended the Krachenko's method and implemented his style in an automated computer-based technique in a laboratory scale.

The current research aims to introduce a computer-based method using the image processing techniques applicable in real world platforms (mine scale). In the next section, the basics of image analysis are explained, and then the main steps of proposed algorithm are discussed.

3. Digital image analysis

The digital image processing technique has expeditiously opened its way more than before after considerable advances in hardware and software programming of computers. Digital image processing is the advanced form of signal processing in which the input is an image and the output can be either an image or a set of extracted parameters from the image. The main procedure of an image processing procedure involves five main steps, namely image acquisition (imaging), pre-processing, segmentation, feature extraction, and interpretation. Figure 1 shows the workflow of automated segmentation task.

In the first step, the necessary images are captured from polished sections. Selecting the optimum magnification is the most important parameter that should be taken into account; light source and light polarity should be fixed during the imaging step. The second step is pre-processing, which includes image filtering, enhancement, and restoration. In this step, the probable noises of the captured images are removed through some image processing techniques; edge enhancement is the result of this step. The third step is segmentation, which is the heart of an image analysis procedure. In this step the image pixels are partitioned into two classes to make the image more meaningful for analysis. The input of segmentation step is a color image, while the output is a binary (black and white) image in which the desired parts of the image are clearly separated from the gangue parts. The fourth step is feature extraction in which the important characteristics of the image or some special objects are measured. Assigning a label to the segmented objects is the final step also known as interpretation or recognition.

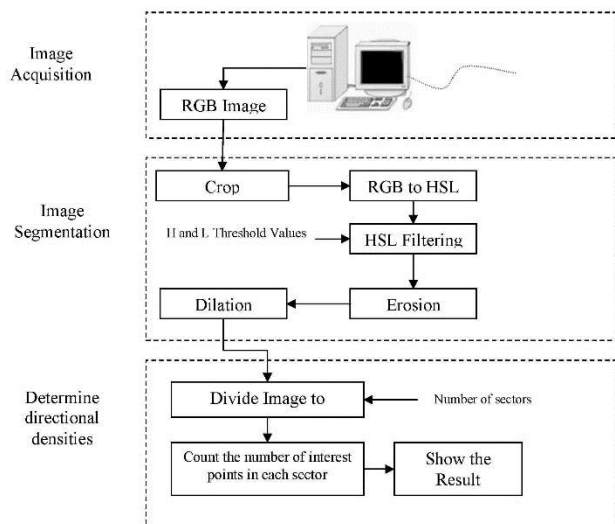


Fig. 1. A workflow of automated segmentation task.

4. Sample preparation

The outcrops of a chromite vein which has experienced no or slight alteration with limited number of fractures and joints are selected for coring through a portable coring drill. The drill bit is a cylindrical hole with a 25-mm diameter and a 15-cm length. Fig. 2 shows the drill used

for sample preparation and the way the sample should be taken from the outcrop. The geographical inclination (North) as well as dip of samples is recorded for each core plug. To record these two parameters, first a straight line is drawn on the outcrop. The North direction is identified for the sample and marked on it (Fig. 2). The drilling should be done perpendicular to this line. However, sometimes due to limitations, the core plugs are taken directionally. Mostly, two samples should be taken from each station. The distance of samples can be changed between 10 and 100 m, while shorter distances are more desirable since a better representation of the chromite distribution trend can be shown. After drilling, the dip of the sample is also recorded, as shown in Fig. 2. The recorded information are used in the polished section preparation step. Each core plug is divided into four slides, each with a 22-mm thickness. The North direction of the taken core plug is written on each slide. The slides are numbered from top to down as 1, 2, 3, and 4, respectively. These slides are polished and then can be used for mineralogical studies and image capturing, as discussed below.



Fig. 1. Sampling procedure in the study area.

5. Methodology

For centuries, micro-structural and mineralogical analyses have been done manually using a polarizing microscope by fixing some optical properties such as color, hardness, reflectance, pleochroism, anisotropism, geometrical form, and internal reflection. Geologists and mineralogists started using computer for mineral identification by the advent of new image processing techniques. The current paper introduces an algorithmic image processing technique to extract chromite minerals in polished sections.

Segmentation of polished section images is an important task for automating the measurement of grain properties as well as detecting and recognizing objects in structural and mineralogical analysis. In the proposed method, the task of polished section analysis is performed in 5 major stages:

- I. Image acquisition
- II. Pre-processing
- III. Segmentation and filtering
- IV. Extracting chromite minerals
- V. Determining directional density

5.1. Image acquisition

A Canon Powershot A640 digital camera attached to the trinocular head of a Zeiss Axioscope optical microscope is used to capture images of polished sections. A special tool, named glide stage, is used to control the movement of the polished section. Using this tool, it is possible to move the section in micron-scale. The field of view is chosen to be 20X. Only 2% of a polished section area can be seen under the lens of the microscope by this magnification. To cover the whole area of a polished section, each section is divided into 49 parts hypnotically, and a mosaic

system of image capturing is used. In other words, 49 images are orderly taken from each polished section to include the complete surface of the polished section. Each image shows a small portion of the polished section, and studying a single image does not reflect the worthwhile information about the general trend of chromite mineral; therefore, the images should be gathered together so that they show the inclination of chromite minerals. Fig. 3a illustrates a single image of chromite, while Fig. 3b shows a complete image of the whole area of a polished section composed of 49 images. Some mosaic images do not include all parts of the section but they cover more than 85% of the section, which can be an acceptable representation of the chromite inclination. It is worth mentioning that the North direction is fixed in all images because of its importance in the study. One hundred polished sections are imaged based on this algorithm.

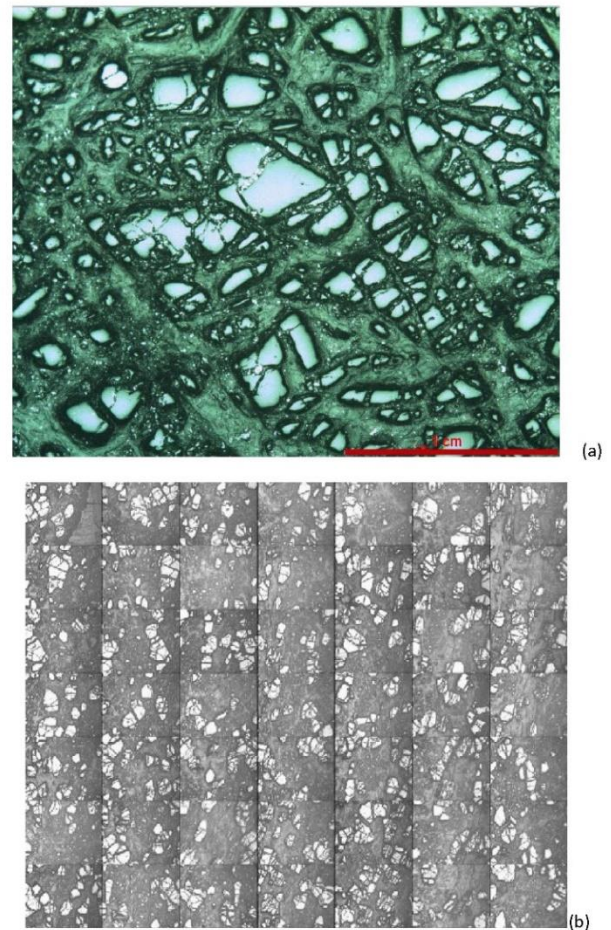


Fig. 3. Two polished thin section images: (a) covers only 2% of thin section captured by magnification of 20X, (b) is a complete image of whole area of thin section made by a mosaic algorithm. Sampling procedure in the study area.

5.2. Pre-processing

In this paper, an automatic method is proposed to recognize chromite elements in an image from non-chromite elements based on optical properties of chromite such as its color and luminance. In this step, the raw image is prepared to be analyzed in the next steps. The images are captured in the red, green, and blue (RGB) color space. In this color space, the color of each pixel is determined by the combination of three main color channels including red, green, and blue. Since there is a high correlation between the dimensions of RGB, the filtering process often leads to inaccurate results. In addition, this color space does not support luminance filtering which is an important factor for distinguishing the textural properties of chromite minerals such as inclination and trend.

To overcome these problems, the image has to map to another appropriate color space that satisfy the above-mentioned requirements. The hue, saturation, and luminance (HSL) color space is used in the proposed method. HSL is a relevant representation of RGB that attempts to describe perceptual color relationships more accurately than RGB, while remaining computationally simple.

In order to convert each pixel from RGB to HSL spaces, Eq. 1-3 are used:

$$\begin{aligned} Max &= \max(R, G, B) \\ Min &= \min(R, G, B) \\ L &= (\max + \min) / 2 \end{aligned} \quad \text{Eq. 1}$$

$$S = \begin{cases} (\max - \min) / (\max + \min) & L < 0.5 \\ (\max - \min) / (2.0 - \max - \min) & L \geq 0.5 \end{cases} \quad \text{Eq. 2}$$

$$H = \begin{cases} (G - B) / (\max - \min) & , R = \max \\ 2.0 + (B - R) / (\max - \min) & , G = \max \\ 4.0 + (R - G) / (\max - \min) & , B = \max \end{cases} \quad \text{Eq. 3}$$

Due to limitations of microscope optics, the boundaries in captured images of a polished section are usually blurred. This problem can affect the efficiency of the filtering process. To eliminate the mentioned problem and improve the performance, small portions of image boundary are clipped. The performed experiments show that clipping 5% to 20% of the image has no effect on the results.

5.3. Segmentation and filtering

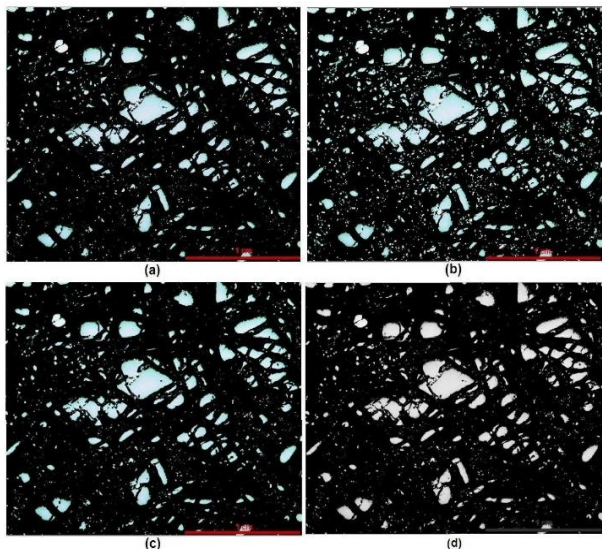


Fig. 4. (a) HSL image subjected to (b) dilation and (c) erosion, (d) is binary black and white image of filtered image Two polished

Image segmentation is performed based on color and luminance after converting the image to the HSL color space. The algorithm performance greatly depends on a correct segmentation of image features since either vigilant selection or accurate extraction of features certifies the reliability of the methodology. In this step, the image is subjected to some special filters so that the noteworthy parameters of the image are separated from the other parts of the image. For each image, the following steps should be done to discriminate between chromite minerals and gangue parts. Try-and-error examinations show that a hue value between 160 and 280 and a luminance value between 0.6 and 1 give the best results (Fig. 4(a)). These steps are codified and attached to the end of this manuscript as Appendix A. After the filtering process, little holes may emerge in the result. The morphological dilation filter with a 3×3 kernel is utilized to eliminate these holes and

extend the boundary pixels (Fig. 4(b)). The last operation in this step is the erosion filter with a 3×3 kernel for noise elimination and boundaries clarification (Fig. 4(c)). Finally, the image is converted to a gray scale image in which light intensity of pixels ranges from 0 to 255. This process is done for all 49 captured images of each polished section, and then the images are arranged using a mosaic system, as mentioned before.

5.4. Determination of directional densities in mosaic image

The segmented image shows chromite and non-chromite minerals in two easily recognizable white and black groups of pixels, respectively. Studying the directional density of chromite minerals is possible in this image. Fig. 5(a) shows a mosaic image of a polished section, while its edges are cut to make the image the same as it can be seen from the microscope lens. Distinguishing pixels belonging to chromite in this image is easy for human eyes but it is still impossible for computer due to a variety of image feature intensities. To tackle this problem, the image should be converted to a binary image. The binary image is an image with just two groups of pixels including white and black. In the proposed algorithm, white areas representing the pixels related to chromite bear areas and black pixels show the gangue minerals (Fig. 5(b)).

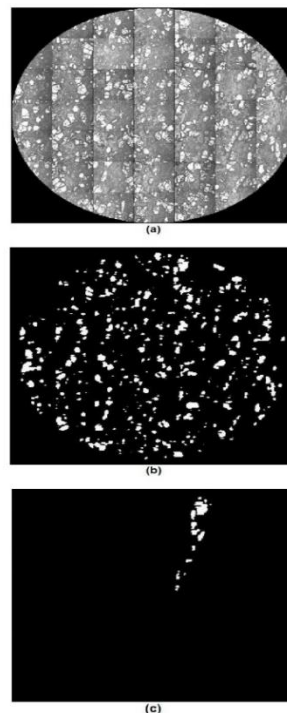


Fig. 5. (a) A mosaic image of a polished section under microscope lens. (b) A binary image of the mosaic image. (c) A sector of binary image shows directional density between 70 and 80 degree.

After image division into sectors, the algorithm starts counting the white images in each sector. The abundance of white pixels for each sector is shown by an array, and the while length of each array denotes the number of white pixels in a particular sector. The direction of highest number of white pixels is shown by a red array, while the green and white arrays represent the directions of sectors in which the number of white pixels is larger and smaller than the average number of white pixels in all sectors, respectively. Fig. 7 shows an example of the final output of the algorithm. It can be easily found that the main inclination of chromite minerals is toward SW of the area. All steps of this process are codified and attached to this manuscript as Appendix B.

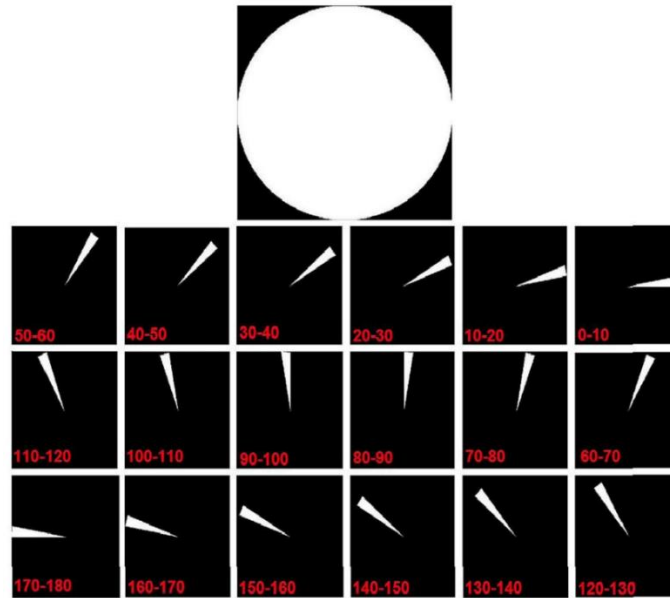


Fig. 6. Eighteen parts of sector division for a hypnotic image.

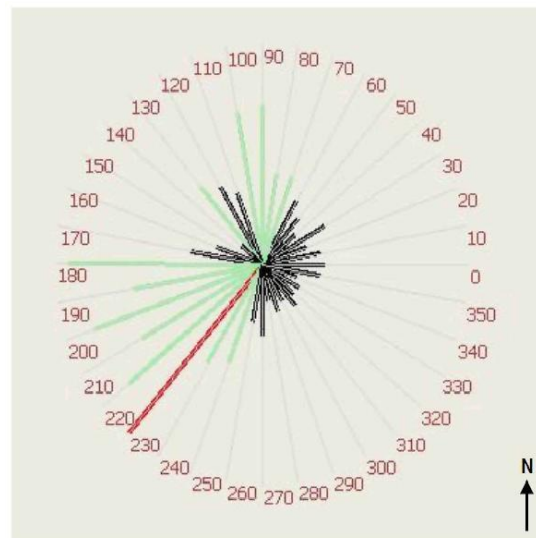


Fig. 7. An example of final output of algorithm in which the trend of dominant distribution of chromite minerals is shown by a red array.

5.5. Graphic user interface (GUI) of program

6. All discussed steps for the proposed algorithm are codified in MATLAB programming environment. A graphic user interface (GUI) is also designed, helping the users to use the capabilities of the algorithm in an easy-going environment. All options of the algorithm are included in GUI. The user can load the image and also compare the original polished section with its corresponding segmented image. The pre-processing options are included as a separate part, where the user can change the percentage of the image that should be cropped before analysis. Morphological filters of dilation and erosion are designed as arbitrary options, while the user should mark them if they are necessary for the understudied image. Also, the size of each sector is changeable, in scale of either degree or percentage, from a special box.

7. The developed GUI can be easily executed without MATLAB programming software. It just needs NET Framework which can be downloaded automatically by the downloader package attached to the setup file of GUI. Figure 7 illustrates an image of the GUI environment.

6. Case study

Various inner structures and morphological types of chromite have formed in Iran based on the conditions and mechanism of crystallization, dynamic processes, and transport of chromite segregation. Numerous deposits and occurrences of high-quality chromite ores in the Faryab area, SE of Iran, are related to the Alpine-type dunite–harzburgite ultramafic rocks which were formed in early Jurassic to late Cretaceous. The folding and metamorphic activity within the area is not very widespread, but if present, the grades of ore as well as the thickness of the chromite horizon increase significantly. The enclosing rocks are structurally undisturbed, and as a result, mineral indications are located easily. The Faryab mines are located in an area where the major geological divisions of Iran change their trends from NW-SE to NS. The area is at the conjunction of two main fault zones trending in NS and NW-SE directions; they play a pivotal role in the formation of structural features of the area [28].

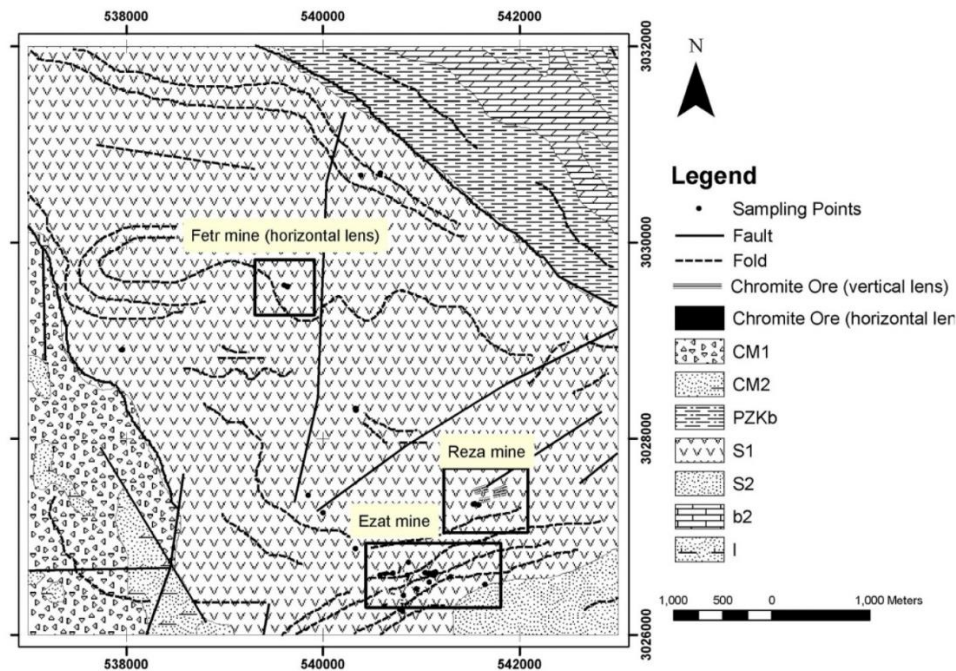


Fig. 9. Simplified geological map of the study area (adapted from McCall, G.J.H. (1995)). Black dots represent chromate mineral deposits/mine (CMI; sedimentary association, CM2; basic association-basalt and basaltic andesite pillow lava with minor pelagic sediment and phyllite, PZKb; metamorphic unit (upper cretaceous), S1; well layered dunite, pyroxenite, harzburgite, websterite, wehrlite, and chromitite. S2; poorly-layered dunite, harzburgite, and minor clinopyroxenite. b2; recrystallised limestone with marble and minor polytic schist. I; Rudan Ultrabasics; Harzburgite with minor websterite and serpentinised dunite. An open

The chromite ore mineralization is characterized by extremely complicate localization conditions and wide variability of typomorphic features. Various viewpoints on genesis and formation conditions of chromite mineralization have made it difficult to have an unequivocal judgment on the potential of particular ultramafic massifs. The existing geophysical methods do not yield an adequate effect [29]. Most geologists suggest a magmatic or late magmatic origin of different chromites crystallized directly from magma or by interaction of host dunite with penetrative melts.

The OGIA methodology was used in Ezat Mine, which is one of the subsets of the Faryab Mine. The Faryab Mine is one of the richest chromite mines of Iran. It was explored in 1960, located 120 km away of Bandar-Abbas in the south of Iran. Chromite is the main mineral ore of the mine, while manganese, limestone, and silica are the by-products. Concentration of Cr_2O_3 in some parts of the mine is as high as 45%. The amount of chromite extraction from this mine gradually increased in early years of exploration so that it ranked as the second large chromite mine of the world in 1996. Lithological intervals of the area are mainly composed of basaltic and ultramafic strata. Amphibolite and schist are the second dominant lithologies in the area. Primary investigation, before 1979, on the area proved a reserve of two million tons of chromite, while further studies showed that the actual reservoir of the mine can be considerably larger than the previous explorations. After 1979, the exploration operations continued and nowadays more than 30 open pits and underground mines are active in the area, while their reserve varies between 0.5 to 1 million tons. However, the exploration activities have proved that it is necessary to invest on exploration activities in order to preserve the total production level of the mine. Drilling exploration borehole with a depth of 150 m is one of these activities. However, recent drilled boreholes showed no reserves, and it seems that it is difficult and expensive to detect the trends of chromite growth. Therefore, the authors aimed to solve the trend of chromite ores in the area and introduce the most susceptible parts of the mine for drilling exploration boreholes. There are 23 mining localities in the area, the most important ones are Shahryar, Amir, Ebrahim, Nazafarin, Nader, Majid 1 and 2, Yasmin, Sarhang, Baharsang, Ezat, Reza, Dastgerd, and Kuh-e Sorkh. Chromite lenses in Faryab were generally developed

in three main separated horizons. These lenses are parallel with each other, while their dip has diversely changed by faults. In addition, the chromite concentration of these mines was different, and they were classified as high and low concentrations. Madah, Fetra, Rubaz and Shahryar are in the category of high concentration, and exploration activities were focused on these mines. Among the aforementioned mines, Ezat was selected for verification of the OGIA approach. Ezat Mine includes three main chromite layers with low dip, while two layers were exploited by two open pits [30]. Figure 8 shows one of these open pits using exploitation of chromite.



Fig. 8. An open pit of Ezat mine using exploitation of chromite from layers 1 and 2.

The third layer of this mine is still unexplored and its trend is unknown. An exploration tunnel with a length of 400 m was drilled but it just cut layers 1 and 2, and showed nothing related to layer 3. To solve this ambiguity, several samples of outcropped layer 3 were taken and prepared for studying through the OGIA approach (Fig. 9).

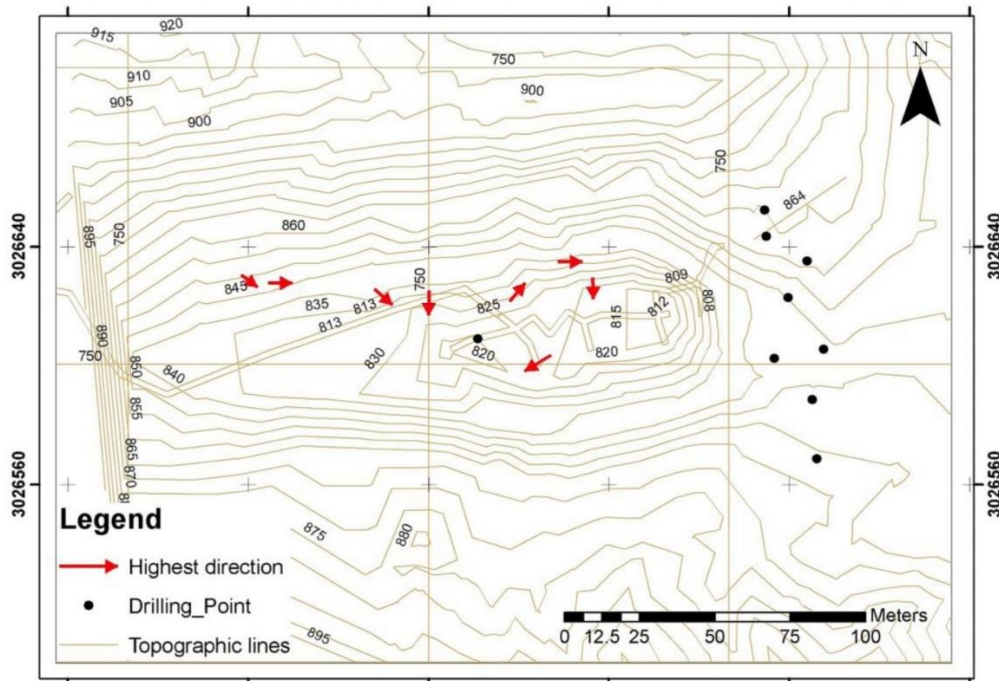


Fig. 10. Red fletchers and black dots illustrate trend of chromite growth and location of exploration boreholes in Ezat mine. Simplified geological map

Fig. 10 illustrates the dominant distribution of chromite minerals in the studied samples. The results suggest that extension of this layer reduced toward the east, and exploratory activities in this direction leads to nothing. This fact was verified by eight exploration wells drilled in the eastern part of the mine. These wells did not cut the prospected trend of chromite. On the other hand, the drilled well in the suggested trend of OGIA algorithm led to exploration of chromite layer 3 of Ezat Mine.

6. Case study

8. This paper presents a novel methodology using the advantages and capabilities of the image processing and analysis techniques for identification of chromite mineral inclinations in mine scale. The proposed method reduced the cost and time of metallic mineral exploration considerably. Studying outlines of chromite ore inclination, suggested by the algorithm in scale of thin section in Ezat chromite deposit, demonstrated the presence of a close agreement with the results of exploration boreholes in the area. Considering the negligible costs of core plug preparation from outcrops compared to drilling exploration boreholes, this technique can be a milestone in exploration of metallic minerals such as chromite and cobalt. Such ore minerals slowly precipitate in the magma chamber, and their inclination is not affected by fault system during this step. However, secondary tectonic processes affect chromite mineral ore in microscopic and macroscopic scales. Studying the microscopic changes can be a hint for finding the macroscopic inclination of chromite, which helps geoscientists in exploration of chromite veins and boundaries.

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Appendix A

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For each pixel
If (pixel . HUE <minHUE and pixel.HUE>maxHUE)
Set pixel value to 0
Else If (pixel. LUMMINANCE <minLUM and pixel. LUMMINANCE
>maxLUM)
Set pixel value to 0
Else If pixel's. GreyValue < GreyThreshold
Set the pixel value to 0
Else
Set the pixel value to MaxGrayValue
End

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Appendix B

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N = number of directions = 360/ direction degrees
Directional densities = an array with N elements
For all elements in directional densities
Set the initial value to 0;
Set Center X = image Width/2, Center Y = image Height/2
For all pixels
If pixel Value = 1
xDif = current X – CenterX;
yDiff = -1 *(Current Y – CenterY);
Set  $\theta = \arctg(ydiff/xdiff)$ ;
Directional Densities  $[\frac{\theta}{N}] = \text{Directional Densities} [\frac{\theta}{N}] + 1$ 

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