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Determination of Alterasion Zones Using Hyperspectral Imagery Based on Spectral Unmixing

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Abstract: The remote sensing as a new technology provides data from earth with lowest cost and time. The Central Iranian Volcanic Belt is a volcano-plutonic complex which contains extrusive and intrusive rocks of Eocene to Quaternary age. In this area, the Meyduk porphyry copper deposit (55° 10′ 05″ E, 30° 25′ 10″ N) is located 45 km northeast of Shahr-e Babak city. The Cu-mineralization and associated hydrothermal alteration zones are focused on the Miocene dioritic and Eocene andesitic rocks. Today, remote sensing with having high spatial and spectral resolution, wide coverage and the lowest cost plays a key role in the field of earth sciences research (especially in the mineral ore explorations). In this case, hyperspectral images have a special status in remote sensing. Even though these images have a high spectral resolution, they have not a high spatial resolution. Because of the presence of different prospectives on a ground pixel, the amount of received energy by the receiver is the combination of multiple ground effects. Therefore, low spatial resolution of hyperspectral images can be a reason for spectral mixing in these images. The purpose of spectral separation is recognition of observed surface components and calculation of abundance of the inside component of each pixel area. The purpose of applying unmixing algorithm is estimation and extraction of presence percentage of any considered mineral ores in each pixel of the image. We applied mentioned algorithm in three steps. In the first one, estimation of a number of the mineral ore types using Hysime algorithm is done. In the next step, we extracted spectral signature of each of these mineral ores using N-finder and in the final step, we calculated vector abundance of them using FLS algorithm.

Keywords: mineral alterations, remote sensing, hyperspectral, unmixing, mineral map.

1. Introduction

Remote sensing (RS) is kind of new source of numerous applications in the field of Earth Sciences that studies one of the most important applications identified changes to the Earth's surface[1]. Today, remote sensing with having high spatial and spectral resolution, wide coverage and the lowest cost plays a key role in the field of earth sciences research and has many application[2]. These applications are: mineral mapping, disaster monitoring, urban monitoring, and wetland monitoring[3].

Recently, to development hyperspectral sensors and improvement of quality data, the using of hyperspectral dataset covert to hot subject between researchers. This theme can be seen in many applications such as: classification, anomaly detection, change detection and mineral mapping[4–7]. Most hyperspectral imagery has high spectral resolution with low spatial resolution [8,9]. Also, the complex diversity of scene caused the spectrum gained in one pixel of a hyperspectral image may mix with some material [8,9]. The spectral unmixing is a processing that decomposing each mixed pixel into a set of abundances pure endmembers. The unmixing provides details information on each pixel in the hyperspectral image in terms of abundance.

2. Proposed Method

2.1 Unmixing

The spectral Unmixing was applied in three steps: 1) Estimation of endmembers using Hysime algorithm, 2) Extraction of enmembers using Sisal and N-finder algorithms and 3) Calculation of vector abundance using fully least square error (FLS) algorithm. We explain the details of algorithm at next steps.

2.1.1. Endmember Estimation

The endmember estimation is first step for unmixing that applied by many algorithms. We used Hysime endmember estimation due to it is simple and common in spectral unmixing Hyperspectral imagery field. The main basic idea Hysime algorithm is use of correlation and noise matrix for estimation of endmember[10].

The purpose of this section is estimation of endmembers that is carried out using Hysime algorithm. This algorithm is one of the automatically intrinsic dimension estimation methods. This method starts with estimation of noise correlation matrix and signal matrix. Then a subset of Eigen vector values (corresponding to the number of endmembers) is selected so that it can represent the subspace under the least error[10].

2.1.2. Endmember Extraction

Extraction of endmembers using Sisal and N-finder algorithms were done. These algorithms are widely used in remote sensing. The main idea of the mentioned algorithms is to find pixels that can make maximum simplex volume.

These pixels are considered as endmembers. Due to complex mathematics of finding endmembers, this only be considered as an optimal estimate of the problem[11].

2.1.3. Abundance Map

The abundance of each extracted end member will be calculated using the fully least squares error algorithm for each pixel of the predictor phase. The main idea of this algorithm is to find the abundance of one of each endmember, so that the amount of positive and total abundance of each endmember from each pixel is equal to one. Each pixel is decided thorough calculating the abundance[12].

2.2. Proposed Framework

We extracted endmembers from hyperspectral dataset using spectral unmixing and assigned them to one of the mineral objects. For this purpose, we used spectral library and geological map, so that attributed the spectral signatures that have more similarity to which mineral objects in spectral library. It’s noticeable to say, we used the geological map for areas where we have more than one spectral signature. The figure 1 presents proposed method flowchart.

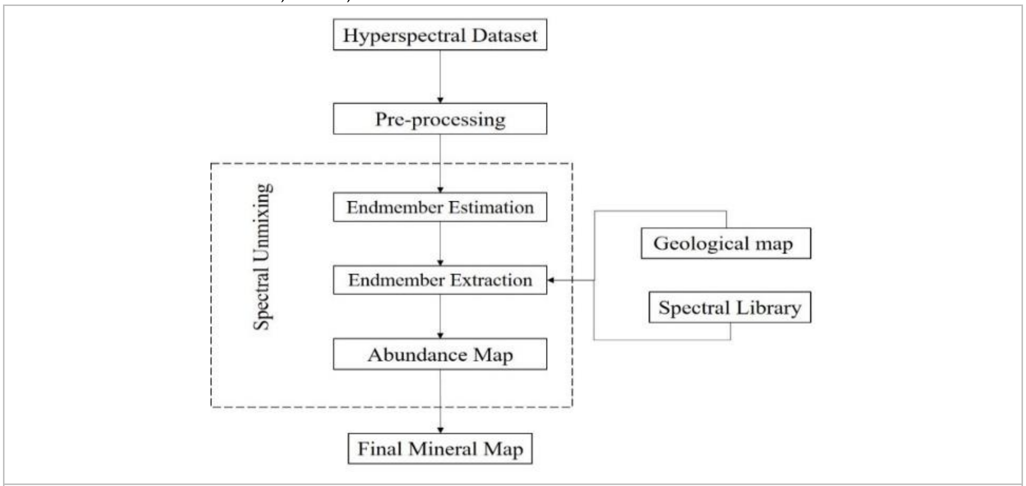


Figure 1. Overview on the proposed method.

3. Geology of the area

Meyduk (Latala) area is located in Shahre Babak (Kerman province). The rock outcrops of Meyduk exploratory (Latala) area is included a small part of the northeastern border of Shahre Babak sheet. The most significant feature of the mineralization in the study area is vein-veinlet mineralization zones which are controlled by faults and fault zones[13].

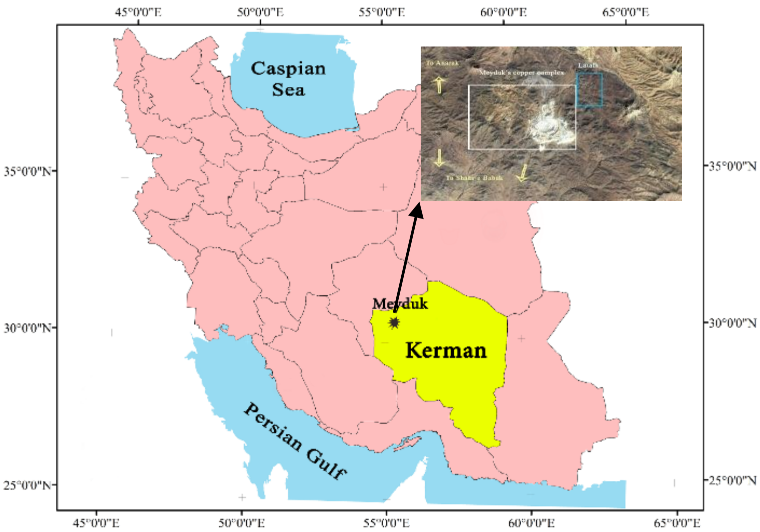
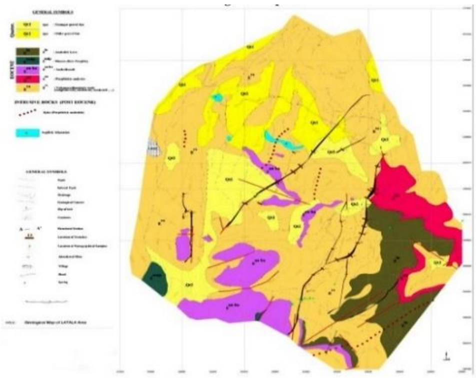


Figure 2. The location of Meyduk in Kerman province and satellite image of the area that indicates relative position of Latala.

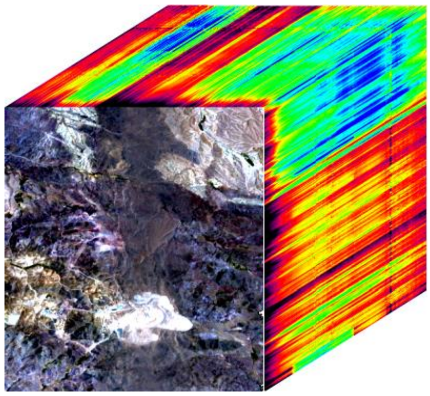
3.1 Mineralization

As we mentioned, the most important feature of the mineralization in the study area is vein-veinlet mineralization zones which are controlled by faults and fault zones. In total seven veins were detected which are along the mostly north-south to NW-SE (Figure 3-a). Width of the mineralized veins are from 20 cm to 20 m and they visible up to 1300 meters. The main mineralized veins contain quartz, goethite, hematite, calcite, clay minerals and calcite.

The figure 3-b presents false colour composite of the area.



(**a**)



(**b**)

Figure 3. (**a**) geological map of the area, and (**b**) showing false color composition that is derived from hyperspectral data in Meyduk (Latala) area at 2004.

3.2. Hyperspectral Dataset

In order to evolution of proposed method performance, the real hyperspectral dataset were used in this research that are related to Hyperion sensors. The Hyperion sensors carried by EO-1 satellite that it is first spaceborne hyperspectral instrument to acquire data in a wide of spectral bands. The characteristics of Hyperion dataset sensors has presented in table 1.

Table 1. The characteristics of hyperspectral dataset.

Parameters	Description
Spatial Resolution	30 m
Spectral Resolution	10 nm
Radiometric Resolution	16
Date Acquired	2006
Spectral bands	166

4. Implementation

4.1. Preprocessing

Due to environmental and equipment conditions, these images have to be applied preprocessing. The preprocessing are made in two steps: 1) geometric preprocessing and 2) spectral preprocessing[14].

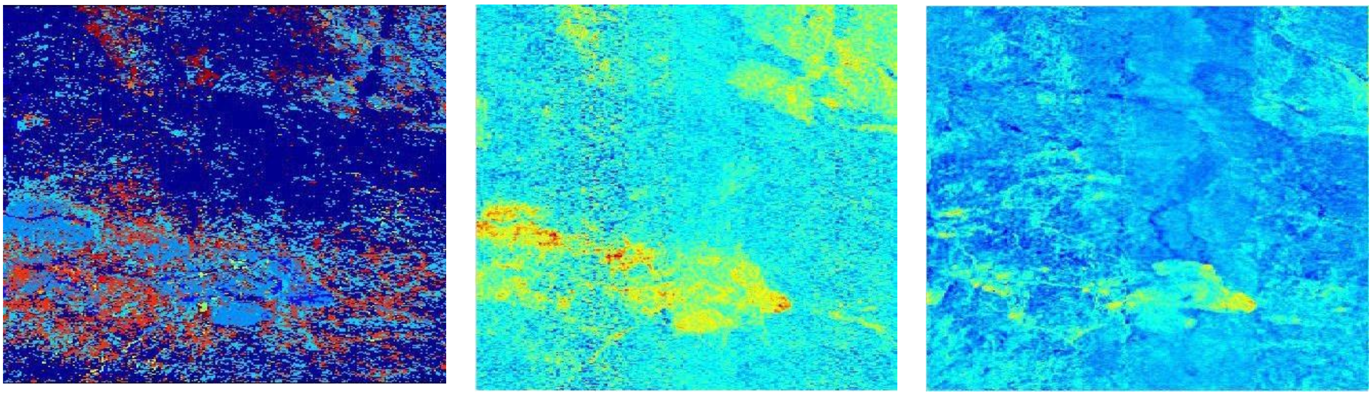
The specptral preprocessing contains: 1) remove no-data bands, 2) spatial shift correction for SWIR data, 3) destriping, 4) angular-shift correction, 5) noise reduction, 6) smile–frown detection, 7) radiometric calibration, and 8) atmospheric correction.

The hyperspectral dataset need to geo-referencing dataset to the pixels located in right position, therefore we used relative geo-referencing.

4.2. Results

After of applying preprocessing, the spectral unmixing was used for extraction of the mineral map. The spectral unmixing algorithm was applied on hyperspectral dataset to create the mineral map. The Hysime algorithm detected 11 endmember on the area. Then endmember extraction applied by Sisal and N-finder algorithms. Finally, the abundance maps were obtained. In order to determine the nature of each mineral ore exactly, we attributed the extracted spectral signatures to the spectral signatures that are in the spectral library. Finally, we compared the obtained maps to the maps that are in the geological report of Geological Survey and Mineral Exploration of Iran (GSI) in order to more validation. The all of endmembers assigned to mineral ores that are: malachite, azurite, chalcanthite, limonite and hematite.

The figure 5-a presents the result of obtained maps from abundance of mineral ores in the area. The obtained result of abundance map of copper has presented in figure 5-b. The figure 5-c presents result of iron oxide such as limonite and hematite prominently.



(**a**) (**b**) (**c**)

Figure 5. (**a**) The classification map of extracted spectral signatures, (**b**) The abundance map of copper oxide (malachite and azurite, prominently), and (**c**) The abundance map of iron oxide (limonite and hematite, prominently).

5. Conclusions

Remote sensing as a new technology can provide information about geology and mineral exploration with lowest price at least time. In this case, hyperspectral images with having rich spectral information are able to be effective for improvement in the results. Due to low spatial resolution of hyperspectral images, we applied a new technique that is based on unmixing. This technique has the ability to extract types of variety of mineral ores and alterations consequently. In this study, we used hyperspectral data that obtained by Hyperion sensor in Meyduk area and recognized some prominent mineral ores like malachite, azurite, chalcanthite, limonite and hematite. We presented the prominent abundance maps and recognized the nature of each mineral ore using spectral signature. Finally, sericite and argillic alterations were detected that have good agreement with the geological report.

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