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The Concert between Geology and Artificial Intelligence: Automatic Identification of Heavy Minerals from River Sand

HAO Huizhen[1, 2], HU Xiumian[3], GUO Ronghua[3] and GU Qing[1, 4, *]

[1] *Software Institute, Nanjing University, Nanjing, China*
[2] *School of Communication Engineering, Nanjing Institute of Technology, Nanjing, China*
[3] *School of Earth Sciences and Engineering, Nanjing University, Nanjing, China*
[4] *State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing, China*

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Heavy minerals with densities higher than 2.8 g.cm^{-3} are generally considered minor components of sand or sandstone, typically forming 1% of the weight in the samples (Mange and Wright, 2007). Heavy-mineral analysis is an effective tool for studying the sedimentary provenance of siliciclastic rocks, reconstructing sedimentary sources to sink routes, subdividing and correlating non-fossiliferous siliciclastic strata, and finds various uses in mining, exploration and forensic science (Mange and Wright, 2007). Many heavy minerals are diagnostic of particular sources and the factors affecting the distribution of heavy minerals in sediment are well understood (Garzanti and Ando, 2007). However, due to the lack of rapid and accurate analytical instruments the identification of heavy minerals still relies on visual microscopical identification. The traditional composition analysis of heavy-mineral assemblage is laborious, time-consuming, and requires a highly skilled operator, which greatly restricts the use of heavy mineral analysis (Vermeesch et al., 2017). Development of a fast and reliable heavy mineral automatic identification system would not only have great significance for the basic sedimentological research, but also important applications in the exploration of oil, gas and mining industries.

In recent years some researchers focused on the technological development of automated classification and identification for heavy minerals, but little progress has been made. Ando and Garzanti (2014) applied Raman spectroscopy as an innovative tool for the reliable identification of heavy minerals. However, this method is used as an auxiliary for single mineral identification, not automatic identification. Currently, the quantitative evaluation of minerals by scanning electron microscopy (QEMSCAN), produced by the FEI Company, is the only commercially available method for heavy mineral analysis (Gu, 2003). Generally speaking, QEMSCAN is a good choice for this purpose since it is simple and adaptable. However, Nie and Peng (2014) compared the heavy mineral assays obtained by QEMSCAN and traditional optical resolution both in Chinese loess and red clay, and found significant deviations between results. For instance, QEMSCAN yielded estimates of hornblende content three times higher than were obtained from traditional optical methods. The accuracy of rutile abundance was two times higher, and the accuracies of tourmaline, garnet, zircon, and epidote by QUESCAN reaches 97%, 54%, 51%, and 35% higher than were obtained from traditional optical method, respectively. These discrepancies arise primarily because 1) QEMSCAN cannot distinguish minerals having the same chemical composition (e.g., titanium oxides) or rock fragments; and 2) mineral composition is variable, which means that the measured mineral energy spectrum may differ greatly from that of the standard mineral database used to calibrate the QEMSCAN software.

Recently, SEM-EDS has proved to be an effective, reliable, intuitive and quantitative elemental analysis method, which has been widely used in both rock and mineral identification (Akkaş et al., 2015). However, the SEM-EDS method does not provide accurate and precise results of trace elements (Newbury and Ritchie, 2013). This makes manual mineral identification-based SEM-EDS data very challenging. Thus, the search for reliable computer-aided identification techniques goes on.

At their early stages,computer-aided techniques for mineral classification based on SEM-EDS data onlychecked look-up tables or identified minerals in the scanning electron micrograph frames using maximum likelihood classification (Tovey and Krinsley, 1991). With the development of artificial intelligence, researchers have attempted to use machine-learning methods to carry out automatic mineral identification. In a pioneering investigation, Ruisanchez (1996) used the Kohonen neural network to analyze the EDS data from 12 different minerals. Gallagher and Deacon (2002) used three different multilayer perceptrons and the Kohonen self-organizing map to automatically classify minerals based on their SEM-EDS data. These authors concluded that backpropagation and quasi-Newton algorithms perform well at mineral-identification tasks. Tsuji et al. (2010) also used the Kohonen self-organizing map to automatically classify eight minerals based on electron probe data. Akkaş et al. (2015) employed SEM-EDS data to evaluate use of a decision-tree approach to the automatic classification of 10 different minerals and obtained a good result. Ishikawa and Gulick (2013) used a backpropagation algorithm of artificial neural networks to train the Raman spectra of igneous minerals and successfully used the method to automatically identify minerals including olivine, quartz, plagioclase, potassium feldspar, mica and pyroxene with accuracy reaching up to 83-100 in percentage. Some researchers have even combined image analysis (backscattered electron, BSE) with mineral energy-dispersive *X*-ray emission spectroscopy for mineral

* Corresponding author. E-mail: guq@nju.edu.cu

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Table 1 Chemical composition of common heavy mineral in sand or sandstone and potential analysis for automatic identification

Chemical classification of heavy mineral		Mineral name	Abbre-viation	Chemical formula	Chemical analysis	Image analysis
Oxide		Rutile	Rt	TiO_2	√	
		Cassiterite	Cst	SnO_2	√	
		Spinel	Spl	AB_2X_4，A=Mg、Fe、Zn、Mn，B=Al、Cr、Fe	√	
		Chromite	Chr	$FeCr_2O_4$	√	
		Magnetite	Mag	Fe_3O_4	√	
		Ilmenite	Ilm	$FeTiO_3$	√	
		Hematite	Hem	Fe_2O_3	√	
Sulfide		Cinnabar	Cin	HgS	√	
		Pyrite	Py	FeS_2	√	
Sulfate		Barite	Brt	$Ba[SO_4]$	√	
Tungstate		Scheelite	Sch	$Ca[WO_4]$	√	
Phosphate		Apatite	Ap	$Ca_5[PO_4]_3(F,Cl,OH)$	√	
		Monazite	Mnz	（Ce, La）PO_4	√	
Silicate	Nesosilicates	Zircon	Zrn	$Zr[SiO_4]$	√	
		Titanite	Ttn	$CaTi[SiO_4]O$	√	
		Epidote	Ep	$Ca_2(Fe, Al)Al_2[SiO_4][Si_2O_7]O(OH)$	√	√
		Garnet	Grt	$A_3B_2[SiO_4]_3$，A=Mg、Fe^{2+}、Mn、Ca，B=Al、Fe^{3+}、Cr、Ti、Mn	√	√
	Inosilicates	Tourmaline	Tur	$NaR_3Al_6[Si_6O_{18}](BO_3)_3(OH)_4$，R represents Mg、$Fe^{2+}$、$Li^{+}$+Al	√	√
	Inosilicates	Amphibole	Amp	$W_{0-1}X_2Y_5Z_8O_{22}(OH)_2$，W=Na、K，X=Na、Li、Ca、Mg、$Fe^{2+}$、Mn、Li，Y=Mg、$Fe^{2+}$、Mn、Al、$Fe^{3+}$，Z=Si、Al	√	√
		Pyroxene	Px	$W_{1-p}(X, Y)_{1+p}Z_2O_6$，W=Ca、Na，X=Mn、Mg、$Fe^{2+}$、Li，Y=Al、$Fe^{3+}$，Z=Si、Al	√	√
	Phyllosilicates	Muscovite	Ms	$KAl_2[AlSi_3O_{10}](OH)_2$	√	
		Biotite	Bt	$K(Mg,Fe)_3[AlSi_3O_{10}](OH,F)_2$	√	

identification. For instance, Frei et al. (2005) and Keulen et al. (2012) have developed a computer-controlled scanning electron microscopy (CCSEM) automatic particle analysis system based on back-scattered electron and energy dispersive *X*-ray data. The Geological Survey of Denmark and Greenland used this CCSEM system to determine the elemental chemistry of both individual minerals and rock samples.

Generally, the heavy minerals can be classed into different chemical groups. We can use micro-XRF to get the relative chemical compositions (major elements larger than 1% in weight) of each heavy mineral. At this stage, most oxides (including rutile, cassiterite, spinel, chromite, ilmenite), sulfide (cinnabar, pyrite), sulfate (barite), tungstate (scheelite), and phosphate (apatite, monazite) can be recognized easily according to their specular major chemical composition (Table 1). Magnetite can be separated from hematite by its magnetism. The great challenge for automated heavy-mineral identification by their chemical composition arises in the case of those silicate minerals which share similar chemical compositions. Among these, zircon and titanite can be recognized by their chemical composition. Phyllosilicate minerals, including muscovite and biotite, are special not only in terms of their crystal shapes, but also by their potassium contents.

We have applied machine-learning techniques in classifying 22 types of heavy minerals collected from modern river sands in China based on the EDS data. Preliminary results are promising, with training accuracy higher than 97.9675% by the random forest classifier and X-ray probe times of c. 6 sec. Five silicate groups, including epidote, garnet, tourmaline, amphibole, and pyroxene, had similar chemical compositions. For the differentiation of these minerals we suggest using image-analysis techniques applied to micrographs in polarizing or binocular microscopes. By using modern image analysis procedures, augmented by artificial intelligence technologies, a new, fast method for the accurate identification of heavy mineral constituents can be achieved.

Key words: river sand, heavy mineral, artificial intelligence, image analysis

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About the first author

HAO Huizhen, female, born in 1974 in Jiaochen City, Shanxi Province; master; graduated from Chengdu University of Technology; Lecturer in the Nanjing Institute of Technology. She is now interested in pattern recognition, data analysis, computer vision. Email: haohuizhen@njit.edu.cn; phone: 18013381255.

About the corresponding author

GU Qing, male, born in 1972 in Taiyuan City, Shanxi Province; PhD; graduated in Computer Science from Nanjing University; Professor of the State Key Laboratory of Novel Software Technology, and the Department of Computer Science and Technology, Nanjing University. His research interests include software testing, machine learning, and complex network. Email: guq@nju.edu.cn; phone: 025 89686550.