Detecting the Minerals' Ore Grade Using the Emotional Network and Image Processing Techniques

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ABSTRACT

The image processing has widely delved into mining activities for years. The image processing is actually a simulation of the human eye which is able to distinguish differences. This agent empowers any neural network or intelligent system to detect valuable minerals of any given gangue. Similarly, morphology is defined as an extensive set of image processing algorithms that processes the images based on geometric shapes. Morphological operations refer to insertion of a structure element to an input image in order to create an equal output image. In the morphological operations, the value of each pixel in the output image is taken into account in relation to a corresponding pixel in the input image along with its neighbors. Having selected a local size and shape, you may run morphological operations which are sensitive to certain shapes in the structure of input images. Since it has been argued that dilation and erosion are the most basic morphological operations, they are discussed in this article. The texture features of images have been used in image processing. These features, which are called Haralick texture features, are characterized with specific definitions and matrix formula. In this paper, it has been attempted to examine the minerals' ore grade using the emotional network and image processing techniques. This method is fundamentally based on emotional learning and temporal difference learning. Besides, it is characterized with a fuzzy-neural structure.

Key words: Image processing, morphology, ore grade, emotional networks, fuzzy-neural structure, temporal difference learning.

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1. INTRODUCTION

It seems that detection of ore grade has recently involved the mining craftsmen. In this line, image processing science and emotional networks are among the methods used to detect the ore grade. The image processing is actually a simulation of the human eye which is able to distinguish differences. To do this end, digital photos of the ore are firstly taken and it is assumed that there is a fixed amount of light and camera location for all samples. Besides, all samples must be dried at room temperature until the moisture content may not affect the image quality (Haralick, Shanmugam and Dinstein, 1973). Today, the application of emotional network in engineering is growing and managers should learn how to use such networks. Since the characteristics of the emotional networks, such as high speed, noise immunity, reliability, generalizability and resistance against changes, we are going to enhance the accuracy of measuring the ore grade through emotional networks in image processing science.

In fact, it can be said that image processing means any type of signal processing with image inputs such as photographs or scenes from a movie. The image output processing can be an image or a set of specific symptoms or factors related to an image. Most of the image processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques thereof. Haralick, Shanmugam and Dinstein (1973) firstly introduced the textural features of the image. These features, which were originally used in the cinema, medical sciences and video machines, were included entropy, contrast, energy and uniformity. These features were mostly used to measure the particle size of ore.

In the most recent efforts in this regard, Singh and Rao (2005) classified minerals as high-grade or low-grade ores. They have used the image processing science and radial neural network in their study. Today, an important application of radial neural network is in remote sensing of satellite images and classification of these pictures. More recently, Al-Thyabat, Miles and (2007) investigated the usage of neural network and image processing science in sizing ores on conveyor. Particle size and size distribution are important variables in many industry sectors. Tasdemir, Ozdag and Onal (2011) focused on the mining and minerals processes. The majority of mineral processing operations in

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measuring the size distribution focus on a key factor in improving process efficiency. Many problems such as image acquisition, image segmentation algorithm, particle size parameters and error correction system have been addressed widely in recent years (Xia et al., 2012). However, all the concerned parameters have not been compared and, thus, conducting and analyzing the related agencies are still not recommended.

2. AGENT-BASED CONTROL

Figure 1 shows the structure of the control agent used to determine the ore grade in this article. First, digital photo which is taken from minerals is delivered to the agent. Then, the agent (through its sensors), detects the output signals of system (pixels received from the photo) and gains the image of the delegated controlled status. Then, the necessary control signals (diagnosis of ore grade) are applied to the system controller through the stimulus. Also, the controller maps the input signals into output signals (diagnosis of ore grade in the former case compared to diagnosis of ore grade in the latter case).

The learning element updates the knowledge stored in the controller according to an external performance indicator so that the operating performance may be optimized. The performance of the learning element is based on a signal initiated by a critical unit (Tobias, 2012; Shafieardekani and Hatami, 2013). The critic undertakes the task of system checking. Given the performance of the relevant local agent and the temporal difference learner, the critic provides the appropriate signal (proper diagnosis) which indicates good or bad performance of control system. The signal will underlie the learning element in updating the structure of controller (Zhang, Yang, Ding and Zhao (2012). Other agents can also make use of this signal to update their stored knowledge. Given the uncertain nature of the environment, the fuzzy-neural structure was selected for the controller. The learning element also has the capability of emotional learning (Zhang, Yang, Ding and Zhao (2012).

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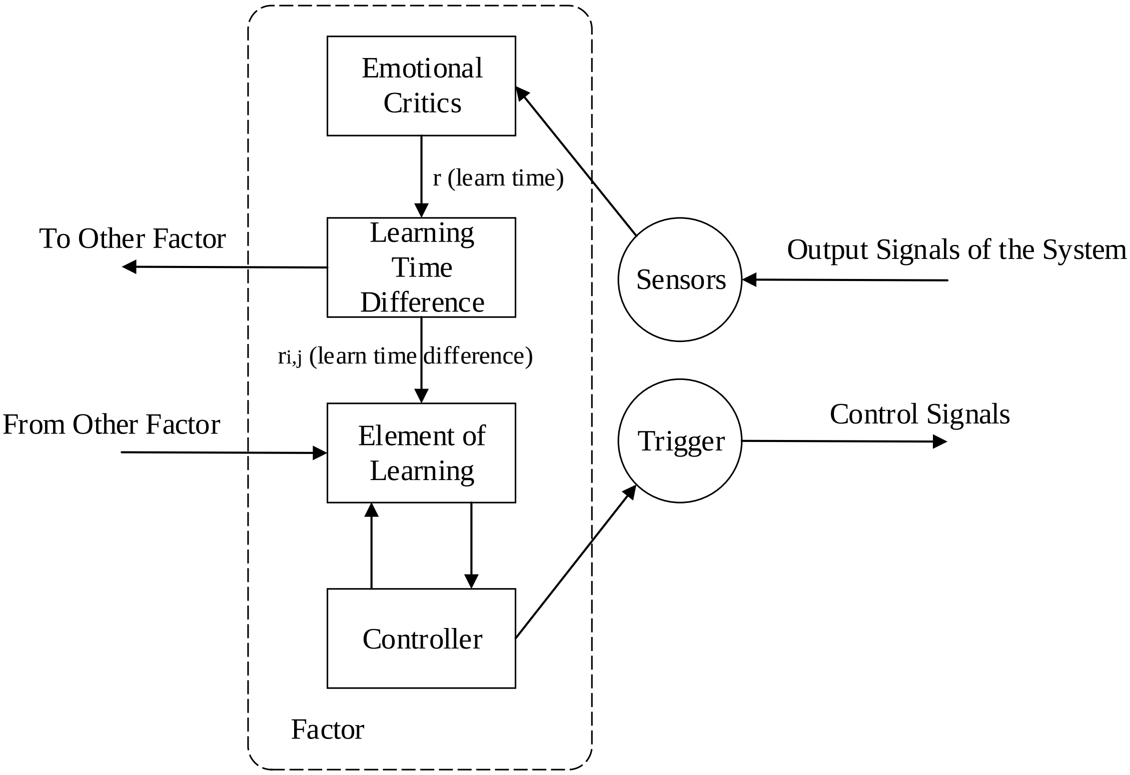

Figure 1. The structure of the control agent

3. EMOTIONAL CONTROLLERS OF TEMPORAL DIFFERENCE

The proposed structure includes the following sections:

Critic: it designates the emotional signals (diagnosis of ore grade) based on the level of control.

Fuzzy-neural controller: it provides a control signal for the device.

Temporal difference controller: it designates weights to each control signal in terms of signals of current reward and past reward (diagnosis of ore grade in the normal case compared to diagnosis of ore grade in the latter case).

4. CRITICAL STRUCTURE EMBEDDED WITH LEARNING TEMPORAL DIFFERENCE

The definition of critic and the design of its structure are directly correlated with that parts of the control system which is reviewed by the critic. In this paper, the designed critic is charged with the task of evaluating the error signal with the signal of the control effort and, hence, it is called the multifunctional critic (Yang, Liu, Xie, Xu, Sun and Wang, 2013). This critic evaluates the output and generates continuous emotional signals (it is located between -1 and +1 in such a way that r+1 (or r-1) represents a complete failure of

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controller and the closer the emotional signal to zero, the more successful control effort). The control system does not wait for a complete failure in order to access relearning. Conversely, as it exerts control signal, it continues its learning process (Tootoonchy, 2016; Hatami and Ameri Siahooei, 2013). Actually, the continuous assessment of the current situation in terms of the possibility of total success or failure is not another type of conditional link but it close to definition of cognitive and adaptive control change and, thus, it is referred to as emotional learning.

The structure of this critic is considered similar to a PD fuzzy controller with five tags for each input {PL (+large), PS (+small), ZE (zero), NS (-small) and NL (-large) and seven tags for output {PL (+large), PM (+medium), PS (+small), ZE (zero), NS (-small), NM (-medium) and NL (-large) (Laura, 2016). In this paper, the collection of proposed critics had four critics whose total output (according to the weights assigned to them) was involved in initial emotional signal.

Overview of this critic is shown in Figure 2. Two critics undertake to review the first and second errors and their inputs as follows: the first output error and its derivative and the second output error and its derivative error as well as their corresponding outputs (C_1 and C_2). Two other critics are assigned to examine the signal of the first and second attempts whose inputs are as follows: signal of the first output error and its derivative and the second output error and its derivative error as well as their corresponding outputs (C_3 and C_4). The weighted sum of these signals prepare the following emotional signals for temporal difference learning: r_{11}, r_{12} and r_{21}, r_{22}. The Rule of Maximum Multiplicity and Center of Gravity are used in terms of deduction and defuzzification.

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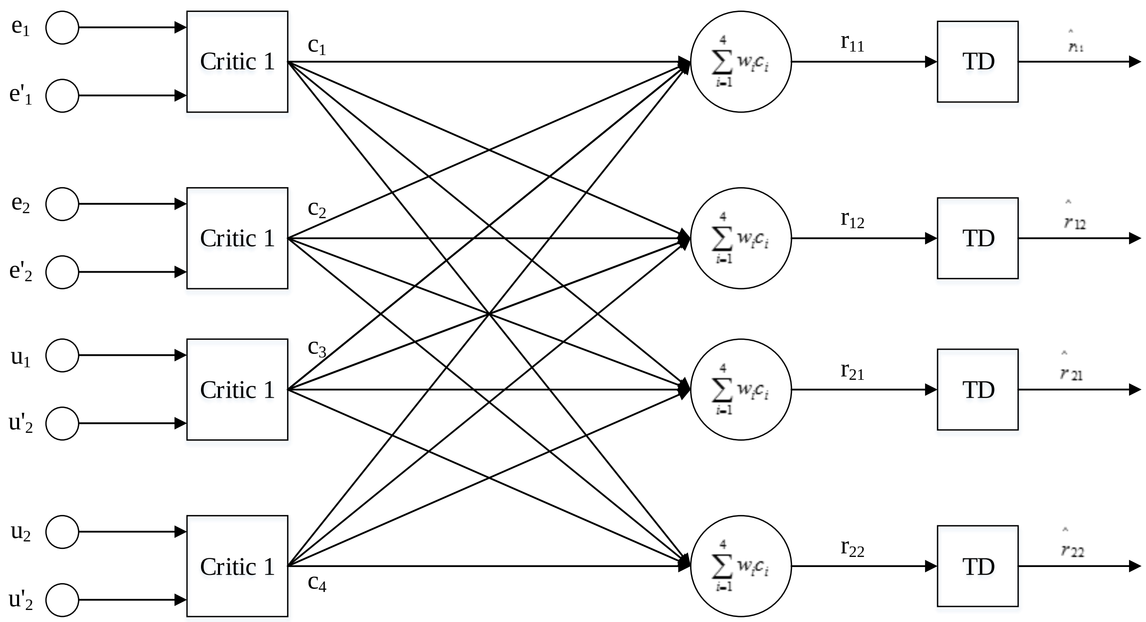

Figure 2. Structure of designed critic

Reinforcement Learning Algorithm (RL) based on the Temporal Difference (TD) is used to define the original interaction between learning agent and its environment. At each "t" time step, the current state of the environment (x_t) is observed and "at" operation is done. Then, it receives an "rt" value or reward reinforcement and the environment is changed to "x_t+1". Learning is a cognition without any prior knowledge of the environment and if it is embedded with a policy-making decision (for example, a depiction of the states to actions), it leads to an increase in the amount of amplification coefficient experienced by an agent during the period his/her life.

$$E[\sum_{t=0}^{\infty} \gamma^t r_t] \quad (1)$$

Where,

$TD(\lambda)$ is a reduction coefficient which adjusts the relative importance of long-term rewards to short-term rewards.

The most extensive studies on the reinforcement learning algorithms are based on the notion of temporal differences proposed ($TD(\lambda)$) by Satin. This general rule of learning based on reinforcement learning and temporal differences learning can be written as follows:

$$update^{\beta}(U, \mathrm{x_t}, \mathrm{r_t} + \gamma \mathrm{U_t}(\mathrm{x_{t+1}}) - \mathrm{U_t}(\mathrm{x_t})) \quad (2)$$

Where,

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U is the status evaluation function. The function assigns any given "x" status an estimated value of awarded reinforced rewards from the beginning of the status to the current policy. In the above equation, $U_t(x_t)$ is to predict the total reduction of future rewards:

$$Z_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k} \tag{3}$$

Where,

Z_t is the response of TD at time "t". The symptoms for updating inserted in the abovementioned equation point to this fact that the value of U for x_t should be determined using the error rate $\Delta = r_t + \gamma Ut\ (xt + 3) - Ut\ (x_t)$. It means that the settings of $Ut\ (x_t) + \Delta$ must be accomplished with regard to the learning rate "β".

$$Update\beta\begin{pmatrix} Q, x_{t,} a_t, r_t + \\ \gamma \max_a Q_t(x_{t+1}, a) - Q_t(x_t, a_t) \end{pmatrix} \tag{4}$$

Where,

Q, which is attributed to any given pair of status (x, a), is used to predict the received reinforcement after "a" is accomplished in "x" status. In this vein, it pursues a greedy policy to achieve current values of "Q". When the optimal values of Q are fully learned, an optimal greedy policy should be taken in this line. The total values of new ʎ of law updating TD (ʎ) for each state "x" at time step "t" can be depicted as follow:

$$\text{update}^{\,\beta}(U, x_t, (r_t + \gamma U_t(x_{t+1}) - U_t(x_t) e_x(t)) \tag{5}$$

$$ex(t) = \sum_{k=\cdot}^{t} (\gamma\lambda)^{t-k} x_x(k)$$

Incidence of the suitability for all the status is updated in accordance with the updating rule in terms of temporal steps:

$$ex(t) := \gamma\lambda e_x\ (t - 3) + x_x(t) \tag{6}$$

5. TESTS

100 iron ore samples were prepared and, then, they were powdered, solved and analyzed thereof. Each sample was reduced to a thickness of 30 microns by a series of grinding process. Polishing process was done to remove the last thin layer of the deformed metal for a smooth reflective surface and finally sealed with a cover slip and the thin-sections were subsequently examined under a combination of plane and cross-polarized light using a petrographic microscope.

After determining the grade of the samples, some pictures were taken in the studio by a professional photographer using a camera with a resolution of 13 megapixels "FUJI

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S7000 model", we using USGS spectral library for assembled for the purpose of advancing spectroscopy and remote sensing for identification and mapping of materials. A fixed amount of light and camera locations for all samples were very important in this regard. In addition, all samples were dried at room temperature so that the moisture content might not affect the quality of pictures. Figure 3 shows an example of the photo taken from the samples.

Figure 3. Picture of a sample with iron grade of 66.3%

Then the captured photo was transmitted to emotional network in order to detect iron (Fe_2O_3) ore grade. Having analyzed and simulated the process, the following conclusions were drawn:

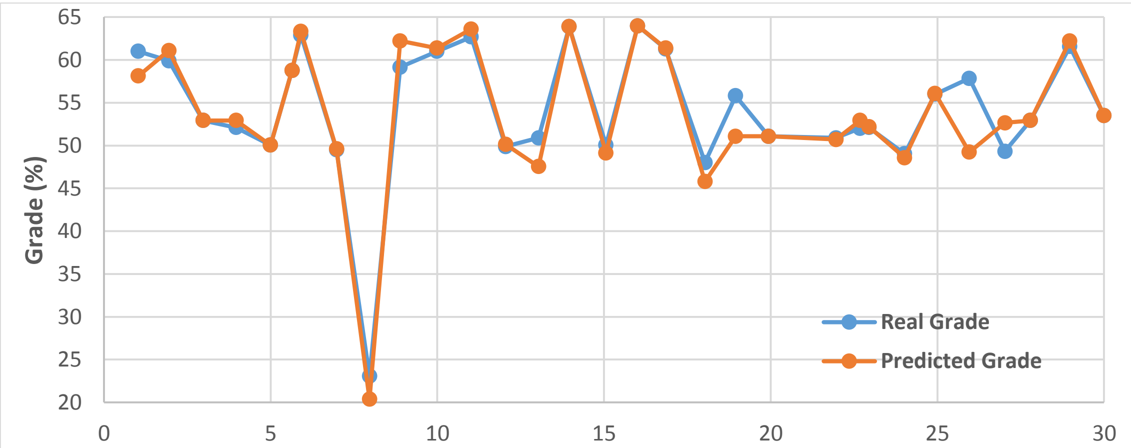

Figure 4. Comparison between actual and predicted grade in the Figure 3

As can be seen in Figure 4, the emotional network method worked well and it could predict close percent of ore grade. In fact, it was embedded with powerful precision and accuracy in diagnosing and detecting ore grade.

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6. CONCLUSION

In this paper, it was attempted to examine the minerals' ore grade using the emotional network and image processing techniques. Then, it was tried to take photographs of powdered samples using a professional digital camera. Next, photographs taken from the minerals were transferred to the emotional network system. After that, a certain emotional process accurately determined the minerals' ore grade. Although there might be some errors in this estimation, it is possible that they stemmed from photographing error or those errors occurred in determining the ore grade through chemical techniques. As such, some more comprehensive and intensive studies should be conducted on different samples in order to evaluate the relationship between errors and sample grades.

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Caption List

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