An Intelligent System for Mineral Identification using Unsupervised Learning Approach

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Abstract— KSOM is being used to identify classes of mineral in a hyperspectral data. To achieve this, Characterization map was obtained which was clustered using c-means clustering to obtain the characteristics cluster center. The network was trained using KSOM (an Unsupervised Neural Network) with the cluster centers used as input. The system was able to identify six classes of minerals and give the likely amount that is present in each group.

Keywords— KSO; Mineral; Hyperspectral data; Unsupervised learning; Cluster

I. INTRODUCTION

A. BACKGROUND OF THE STUDY

Artificial intelligence may be defined as the branch of computer science that is concerned with automation of intelligent behaviour [11]. However, this definition suffers from the fact that intelligence itself is not very well defined or understood. Although, most of us are certain that we know intelligence behaviour when we see it, it is doubtful that anyone could come close to defining intelligence in a way that will be specific enough to help in evaluation of a supposedly intelligent computer program, while still capturing the validity of the human mind.

Thus, the problem of defining artificial intelligence becomes one of defining intelligence itself. What is intelligence?

Intelligence is a capacity of a system to achieve a goal or sustain desired behaviour under conditions of uncertainty [12]. Intelligent systems have to cope with sources of uncertainty like occurrence of unexpected event such as unpredictable changes in the world in which the system operate and incomplete, inconsistent and unreliable available to the system for the purpose of deciding what to do next. Intelligent system exhibits intelligent behaviour. Intelligent behaviour if exhibited is capable of achieving specified goals or sustaining desired behaviour under conditions of uncertainty even in a poor structured environment. Such environment includes an environment where various characteristics are not measurable or where several characteristics changes simultaneously and in an unexpected way and where it is not possible to decide in advance how the system should respond to every combination of events [12].

According to Nikola Kasabov [9], an intelligent system exhibits the following behaviour:

(i) They should from time to time accommodate new problem solving rules.
(ii) They should be able to analyze themselves in term of behavior error and success.
(iii) Once they are to interact, they should learn and improve through interaction with the environment.
(iv) They should learn quickly from large amount of data.
(v) They should have many base exemplar storage and retrieval capability.
(vi) They should have parameter to present.
Agris Nikitenko [1] also summarized basic features of intelligent system as follows:

(i) They have the ability to generate a new knowledge from already existing one.
(ii) They have ability to learn.
(iii) They have ability to sense environment.
(iv) They should have ability to act.

A lot of research works have been carried out in the area of intelligent system. For instance, Paul [10] has developed an intelligent system to determine the best soil for different type of crops using artificial neural network. Also, there is an intelligent system to predict weather condition in South Korea using Neuro-fuzzy method [8]. Despite series of research in the area of intelligent system, enough has not been done in term of developing an intelligent system in geoinformatics most especially in the area of mineral prospecting. This research work is to develop an intelligent system for mineral prospecting using unsupervised learning.

B. STATEMENT OF THE PROBLEM

Mineral prospecting and exploration is a multidisciplinary task requiring a simultaneous consideration of numerous disparate geophysical, geological and geochemical dataset [4]. The size and complexity of regional exploration data available to geologist are increasing rapidly from variety of source such as remote sensing, airborne geophysics, large commercially available geological and geochemical data [2]. This demands more effective integration and analysis of regional and various geospatial data with different format and attribute so as to be able to generate sufficient information for locating and exploring minerals. Unfortunately, various method used by different researchers are not sophisticated enough to handle this important task.

This problem is better handled with an intelligent system. The system will be implemented with hyperspectral data to provide numerical solution as well as map to locate the classes of existing minerals and the ones yet unknown or unidentified. It will also determine the quantity of the class of mineral so as to decide whether is it sufficient enough for mining.

C. SIGNIFICANCE OF THE STUDY

Mining industry is very important in the development of any nation. The industry obviously employs reasonable number of the nation workforce.

It is perhaps not surprising that its importance to everyday life is still poorly understood and appreciated by people.

Mining is not confined to large scale ore operations, nickel and gold production from goldfields, or bauxite mining to produce alumina. It also includes the mining of silica for the glass industry to produce drinking glasses, car windscreens and window panes, it includes the aggregate used to build roads, clay for house bricks, roof tiles and crockery, copper for electrical wire, and the exotic element like tantalum and yttrium necessary for capacitors and other products essential for modern semiconductor technology [13].

To maintain our living standard, we must continue mining and this requires continued exploration for new deposit of all types. Mineral location or exploration is like looking for a needle in a haystack. So it is important to keep searching. Moreover, everyone in the modern world, depend heavily on the product of mining. The development of commercially viable mineral deposit is also a key factor in achieving a sound economy.

To ensure a continued supply of mining products, it is necessary to discover new mineral deposit to replace those currently being mined. Successful exploration therefore ensures the future of the individual and the world economic well being.

Mineral location or exploration is a scientific investigation of the earth crust to determine if there are mineral deposits present that may be commercially developed. To be able to find new deposit, explorers must have access to land. This will only be permitted if exploration can be carried out with negligible impact on the natural environment.

Modern location methods like the proposed one should be capable of discovering deeply concealed deposits which have eluded earlier explorers.

Almost everything that we eat, drink, live in, fly in depends on the products of the mineral industry for either its components, its production or its source of energy. The exploration, mining and mineral processing industry exist because we as consumers demands these product. Mineral occur in earth crust in rare concentration known as mineral deposit.

Mineral is the process of removing these deposits from the ground.

Every deposit, no matter how large, has a finite life and will one day be exhausted. To ensure a continue supply of mineral to meet the need of a growing population, different types of methods have previously been applied to solve the problem of mineral location/ exploration. For instance, previous authors have used Evidence Weight Method, Bayesian Theory, Tree diagrams, Neural Network, GIS e.t.c.

Obviously, most of these methods are statistically based method which may bring a lot of inaccuracies and bias in the result obtained. The GIS method also depends purely on database. In other words, the results generated are not producing enough information for the mining industry to locate minerals. This calls for further research work.

New advances in satellite and information technology have enabled the gathering of hyperspectral data about the earth crust using zero impact spectrometry. This produces large amount of data that requires computational intelligence methods to process.
Therefore, an attempt is being made to use unsupervised learning method with fuzzy c-means and wavelet transform to solve the problem of mineral prospecting. This is expected to produce a better result and therefore better information for mineral industry. If the mining industries are boosted, it provides the basic needs for the people, they will be good source of income for the government, individuals, parastaters etc. this will also provide better job opportunities for the citizen. In fact, it will go a long run to boost the economy of the country at large.

D. SCOPE OF THE WORK

The research work is restricted to the location of minerals in any part of the world where hyperspectral data is available.

II. SELF ORGANIZING MAP

A. FEATURES OF KOHONEN’S SELF-ORGANIZING MAP (KSOM) - AN UNSUPERVISED LEARNING NEURAL NETWORK

According to Prof. Teuvo Kohonen from Finland in 1981, systems could be built to organize input data without being supervised or taught in any way. He studied that topological mappings of sensory and motor phenomena exist on the surface of the brain. The system was able to perform mapping of an external signal space into the system’s internal representational space, without human intervention. He called this process a self-organizing feature map and showed how it could be performed by a neural network. Similarities among patterns are mapped into closeness relationships on the competitive layer grid.

Generally, Kohonen’s later publications in 1995 [6] and 2001[7] are regarded as the major references on SOM. Kohonen’s description is “it is a tool of visualization and analysis of high-dimensional data”. Additionally, it is useful for clustering, classification and data mining in different areas.

SOM is an unsupervised learning method, the key feature of which is that “there are no explicit target outputs or environmental evaluations associated with each input”. During the training process, there is no evaluation of correctness of output or ‘supervision’ [5].

First, it is different from other neural networks, and it only has two layers which are input layer and output layer (or called competition layer). Every input in input space connects to all the output neurons in the map. The output arrangements are mostly of two dimensions. The Fig 1 shows below conventional 1Dimentional (1D) and 2Dimentional (2D) arrangements

![Fig 1(a,b): Conventional 1D and 2D arrangement](image)

In Fig 1, xn represent the input neurons in input space, yn represents the outputs in the output space. Fig 1a shows a one dimensional arrangement in form of a line layout. Fig 1b shows a two-dimensional arrangement in form of rectangular layout. The Fig 1 shows that compared to general Neural Network (NN), SOM has no hidden neurons and the discrete layout of the inputs map to output space in a regular arrangement. Besides the rectangular layout, 2D SOM also has the form of hexagonal arrangement.

The main process of Self-Organizing Maps (SOM) according to Prof. Teuvo Kohonen is made up of three main phases, which are competition, cooperation and adaptation. He also explained with series of mathematical equations as follows:

**Competition:** The output of the neuron in self-organizing map neural network computes the distance (Euclidean distance) between the weight vector and input vector. Then, the competition among the neurons is based on the outputs that they produce, where \( i(x) \) indicate the optimal matching input vector \( x \), the Equation can be represented:

\[
\text{i}(x) = \text{arg min}_{j} ||x - w_j||, \quad j = 1,2,...,l
\]

In Equation 1 above, \( x \) is the input vector, \( w_j \) is the \( j \)th neuron’s weight vector. It uses “Nearest neighbor search”, which is interpreted as proximity search, similarity search or closest point search, consists in finding closest points in metric spaces. The neuron \( j \) which satisfies the above condition is called the “winning neuron”.

**Cooperation:** The winning neuron is located at the center of the neighborhood of topologically cooperating neurons. The winning neuron tends to activate a set of neurons at lateral distances computed by a special function.

The distance function must satisfy two requirements: 1) it is symmetric; 2) it decreases monotonically, as the distance increases. A distance function \( h(n,i) \) which satisfies the above requirements is Gaussian:

\[
h(\{j\},i) = \exp \left[-\frac{d_{ji}^2}{2\sigma^2}\right]
\]

In “(2)”, \( h(j,i) \) is the topological area centered around the winning neuron \( i \). The \( d_{ji} \) is the lateral distance between winning neuron \( i \) and cooperating neuron \( j \), and \( \sigma \) is the radius influence.

**Adaptation:** It is in this phase that the synaptic weights adaptively change. Since these neural networks are self-adaptive, it requires neuron \( j \)’s synaptic weight \( w_j \) to be updated toward the input vector \( x \). All neurons in the neighborhood of the
The following Equation state the weights of each neurons in the neighborhood of the winner are updated:

\[ w_j = w_j + \eta h(j,i) (x - w_j) \]  

...(3)

In Equation 3, \( \eta \) is a learning rate, \( i \) is the index of winning neuron, \( w_j \) is the weight of the neuron \( j \). The \( h(j,i) \) function has been shown in "(2)".

These three phases are repeated during the training, until the changes become less than a predefined threshold.

B. BASIC PRINCIPLES OF THE KSOM

- The KSOM neural network is basically a single-layer feed forward network.
- When an input pattern is presented, each unit in the 1st layer takes on the value of the corresponding entry in the input pattern.
- The 2nd layer units then sum their inputs and compete to find a single winning unit.

C. THE KSOM ALGORITHM

Step 1: Set up input neuron matrix, \( \text{In}_X \) and \( \text{In}_Y \).

Thus, total number of input neurons,
\( I = \text{In}_X \times \text{In}_Y \).

\( i = 0 \) to \( I-1 \) for numbering the neurons in this layer.

Eg., \( X_j \) is the label for the input neurons i.e. \( X_0 \) to \( X_{I-1} \)

Step 2: Set up competitive layer matrix, \( \text{Out}_X \) and \( \text{Out}_Y \).

For simplicity \( \text{Out}_X = \text{Out}_Y \)

Therefore, total number of competitive neurons,
\( J = \text{Out}_X \times \text{Out}_Y \)

\( j = 0 \) to \( J-1 \) for numbering the neurons in this layer

Step 3: Initialize connection weights (randomize) between input layer neurons and competitive layer neurons, \( W_{ij} \).

Set initial topological neighborhood parameters, \( d_0 \).

Usually,
Set initial learning rate parameter, \( \alpha_0 \)
(usually between 0.2 to 0.5)
Set total number of iterations, \( T \) (usually 10,000).
Start with iteration \( t = 0 \).

Apply the first pattern to the input of the KSOM.

Step 4: Compute the winning neuron \( (j_c) \) in the competitive layer which is the minimum Euclidean distance from input layer to competitive layer such that:

First, for each \( j \) (from \( j = 0 \) to \( J-1 \)), compute the Euclidean distance as follows:

\[ \|E[j]\| = \sqrt{\sum_{k=0}^{n-1} (x_k - f[k])^2} \]  

...(4)

Then compare all these distances i.e., from

\[ \|E[0]\| \leq \|E[1]\| \leq \|E[J]\| \]  

...(5)

and find the minimum distance \( \|E[j_c]\| \) which is the winner neuron, \( j_c \).

\[ \|E[j_c]\| = \min \|E[j]\| \]  

...(6)

Calculate Euclidean distance for each Competitive layer neuron

\[ \|E[j]\| = \sqrt{\sum_{k=0}^{n-1} (f[k] - x_k)^2} \]  

...(7)
Step 5: Update weight for each connections i.e. For all neurons \( j \) within a specified neighbourhood of \( J \), and for all \( i \):
\[
W_{ij}(new) = W_{ij}(old) + \Delta W_{ij}(new)
\]
where
\[
\Delta W_{ij} = \begin{cases} 
\alpha_t (v_i - W_{ij}(old)) & \text{if unit is in neighborhood } d_i \\
0 & \text{otherwise}
\end{cases}
\]
...(8)

Step 6: Update learning rate \( \alpha_t \) such that:
\[
\alpha_t = \alpha_0 \left(1 - \frac{t}{T}\right)
\]
...(9)

Step 7: Reduce radius of topological neighborhood at specified times:
\[
d_{ij} = \text{int} \left[ d_0 \left(1 - \frac{t}{T}\right) \right]
\]
...(10)

Step 8: Increase iteration \( t: t = t+1 \)
Repeat Steps 5 to 8 until \( t = T \)

Step 9: Repeat with next pattern chosen randomly
(Do Steps 4-9)

D. COMPUTER SIMULATIONS OF SELF-ORGANIZATION IN THE KSOM
1. Initialize weights to \( 0.5 + 10\% \) randomized value.
2. 2 input vectors, \( X_1 \) and \( X_2 \) with several scores of entries between the range of 0 and 1.
3. The Fig 3 given shows a plot of initial weights, \( w_{ij} \).
4. Each unit in the competitive layer shows a point on this graph.
5. The coordinate values of this point are the values of the incoming weights for the unit, thus \( w_{i1}, w_{i2} \) are plotted for each competitive unit \( j \).
6. All pairs of units in the competitive layer that are adjacent are connected.
7. This will allow us to see how the pattern of weights changes as the network organization evolves during training.

E. SOME APPLICATIONS OF THE KSOM
KSOM has been used for solving a variety of pattern classification problems. Also, Prof. Teuvo Kohonen has used the KSOM in developing a phonetic typewriter, a speech recognition device. Other applications include classification of images for remote sensing application, character recognition, etc.

F. ADVANTAGES OF KSOM
- The KSOM (unsupervised learning ANN) is trained without teaching signals or target.
- Based on a series of input patterns, KSOM learns by itself to cluster the patterns according to their similar features.
- It can discover the existence of unlabelled data cluster.

G. LIMITATIONS OF KSOM
- It cannot give the unlabelled data cluster meaningful names nor can it associate different clusters.
III. SELECTION OF INPUT DATA

Hyperspectral images can be defined as images whose pixels contain a fine sampling of the light spectra. Therefore each pixel is a high dimensional vector, whose components received radiance values inside a fine wavelength band of the spectra.

Most of the hyperspectral sensors cover the visible light spectrum and the near infrared (NIR) spectrum is shown in figure 4. This shows the structure of a hyperspectral image from a computational point of view. It consists of a 3D matrix, whose third dimension corresponds to the radiance spectra sampled at the pixel. The first two dimensions correspond to the spatial coordinates in the image plane.

Another view of the data in a hyperspectral image is given in figure 5. In figure 6, an illustration of the band (slice) of hyperspectral image capture in a remote sensing setting is shown. A high altitude device, either an airplane or a satellite, goes over the land, picking the images. On board sensors often capture one line of the image, so that the motion of the device gives the second spatial dimension. The figures shows that different land covers produce different spectra in the corresponding image pixels. This additional spectral information has the promise of allowing image automated detection of materials highly efficient and robust without resorting to spatial processing.
IV. DATA

The test data consists of specter data for Cuprite, Nevada. The data consists of 600 by 320 pixels with 357 band spectrum ranging from 0.4 μm to 2.5 μm. Fig 5 shows the hyperspectral data cube while Fig 6 shows a colormap slice (a band) of the given data. Fig 8 shows the 3D plots of some band data.

An interface for the implementation of the intelligent system for mineral identification is shown in Fig 7 below.

Figure 8: 3D Plot of some bands of the input data
V. PROCESSING OF SPECTRUM FOR EACH PIXEL

The spectrum for each pixel is selected in turn, displayed in figure 9 and turned into characterization map. The characterization map for a particular pixel is shown in figure 10. The characterization map is then clustered to obtain 3 cluster centers marked in red in figure 10.

The cluster center data for each pixel is thus calculated in turn and stored in a cluster center data structure for file storage or further processing. The cluster center data distill the essential features for classification and recognition of mineral classes in the given data. Figure 11 shows the 3D plots of the cluster center data.

![Figure 9: The spectrum of a pixel](image1.png)

<table>
<thead>
<tr>
<th>CLUSTER CENTER</th>
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</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>X</td>
</tr>
<tr>
<td>Y</td>
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</tbody>
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![Figure 11: 3D Plots of the cluster center data](image8.png)

Fig 12 indicates the plot of learning for KSOM after implementing the system with hyperspectral data. Where, Fig 13 is the count plots which gives an impression of the amount of minerals that are present in each class identified.

![Fig 12: Plot of learning SOM](image9.png)

Fig 14 shows the six (6) classes of mineral identified by KSOM.

![Fig 13: Class count plot of trained SOM](image10.png)
VI. CONCLUSION

The concept of KSOM as a type of unsupervised Neural Network was discussed. An intelligent system was developed using KSOM to identify different classes of minerals. To achieve this, Characterization map was obtained which was clustered using c-means clustering to obtain the characteristics cluster center. The network was trained with KSOM (Unsupervised NN) with cluster centers used as input. The system was able to identify six classes of minerals and give the likely amounts that are present for each class. Novel minerals were also identified. Any class of mineral that do not belong to the identified classes will be treated as Novel mineral i.e. not part of the presently existing mineral. The research will be a useful tool in mining and related industries.

REFERENCES


**AUTHOR'S PROFILE**

Olanloye, Dauda Odunayo received B.Sc. Mathematical Science with option in Computer Science from University of Agriculture, Abeokuta in 1994 and M.Sc. Computer Science from Nnamdi Azikwe University, Awka in 2002. He is currently a lecturer in the Department of Computer Science, Emmanuel Alayande College of Education, Oyo. His area of interest is Artificial Intelligence.