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Big Data Analysis: Hyperspectral Image Processing for Agriculture Applications

Sahar A. El_Rahman[1,2]

[1] *Electronics, Computers Systems and Communication, Electrical Department, Faculty of Engineering-Shoubra, Benha University, Cairo, Egypt*
[2] *Computer Science Department, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia*

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Abstract: Hyperspectral imaging is employed in a broad array of applications. The usual idea in all of these applications is the requirement for classification of a hyperspectral image data. Where Hyperspectral data consists of many bands - up to hundreds of bands - that cover the electromagnetic spectrum. This results in a hyperspectral data cube that contains approximately hundreds of bands - which means BIG DATA CHALLENGE. In this paper, unsupervised hyperspectral image classification algorithm, in particular, Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA) algorithm used to produce a classified image and extract agricultural information, using ENVI (Environment of Visualizing Images) that is a software application utilized to process and analyze geospatial imagery. The study area, which has been applied on is Florida, USA. Hyperspectral dataset of Florida was generated by the SAMSON sensor. In this paper, the performance was evaluated on the base of the accuracy assessment of the process after applying Principle Component Analysis (PCA) and ISODATA algorithm. The overall accuracy of the classification process is 75.6187%.

Keywords: Hyperspectral Imaging, ISODATA algorithm, Image Classification, Unsupervised Classification

1. INTRODUCTION

Hyperspectral imaging is typically defined as a spectral sensing technique which takes hundreds of contiguous narrow waveband which provide spectral information to identify and distinguish spectrally unique materials [1]. Hyperspectral imaging, is concerned with the measurement, analysis, and interpretation of spectra acquired from a given scene (or specific object) at a short, medium or long distance by remote sensing [2].

Hyperspectral sensors look at objects using a broad portion of the electromagnetic spectrum. Hyperspectral imagers utilize hundreds of wavelength channels that can record even the subtlest variations in the surface-reflected solar energy allowing for efficient and unequivocal identification of the observed targets. The technology offers the capacity to observe and discriminate unique characteristics of materials and features, much like a fingerprint or DNA have unique characteristics and structures [3]. Each object like oil causes a unique fingerprint (signature) across the electromagnetic spectrum. A material that makes up the scanned object identified using the signature. Each pixel in a hyperspectral image has a spectral signature [4][5].

Hyperspectral sensors are expected to improve our ability to observe the earth surface. Such as increasing the classification accuracy in contrast to multispectral imaging systems, where hyperspectral imagery provides opportunities to elicit more detailed data than is possible using traditional multispectral data. The distinction between hyper- and multi-spectral is mainly based on an arbitrary (number of bands) or on the type of measurement, where hyperspectral imaging system provides detailed spectral information that enables the observer to detect and classify a pixel based on its spectral characteristics. However, in many cases, the spatial resolution of these systems is lower than a multispectral imaging system that has less spectral channels [6].

Multispectral satellite remote sensing technologies have been commonly used for remotely sensed classification of vegetation since the early 1960s [7][8]. In a single observation, multispectral sensors generate three to six spectral bands of data that range from the visible to NIR of the EMS [8]. This small window of spectral bands

E-mail: sahr_ar@yahoo.com, saismail@pnu.edu.sa

is a primary disadvantage to multispectral sensors. During the last decade, advances in imaging spectrometers have begun to fill the gap in multispectral sensor limitations providing better performance in object detection, classification, and identification of earth features [9][10][11]. Hyperspectral sensors commonly collect more than 200 spectral bands that set out from the visible to short wave infrared (SWIR) section of the EMS. Hyperspectral sensors not only produce detailed spectral data consisting of hundreds of bands in a single collection [8]. Therefore, these advantages have contributed to recent scholarly and governmental explorations of classification and mapping of ground cover and vegetation with the application of hyperspectral imagery [9][12].

Furthermore, multispectral imaging deals with several images at discrete and somewhat narrow bands, but hyperspectral deals with imaging narrow spectral bands over a continuous spectral range, and produce the spectra of all pixels in the scene, as shown in Figure 1. Hyperspectral data consists of many bands - up to hundreds of bands - that cover the electromagnetic spectrum. The imaging spectrometer collects data within the 380nm to 2510nm portions of the electromagnetic spectrum within the bands that are approximately 5nm in width. This results in a hyperspectral data cube that contains approximately 426 bands - which means BIG DATA CHALLENGE.

The primary advantage of hyperspectral remote sensing is the amount of spectral detail it provides [13]. The disadvantages are cost and complexity. Faster computers, sensitive detectors, and heavy information storage capabilities are needed for analyzing hyperspectral data. Significant data storage capacity is necessary since hyperspectral cubes are great, multidimensional datasets, potentially exceeding hundreds of megabytes. All of these factors greatly increase the monetary value of getting and processing hyperspectral data. Also, one of the hurdles researchers has had to face is finding ways to program hyperspectral satellites to sort through data on their own and transmit only the most important images, as both transmission and storage of that much data could prove difficult and costly. Horizons as a relatively new analytical technique, the total potential of hyperspectral imaging has not even been recognized [14].

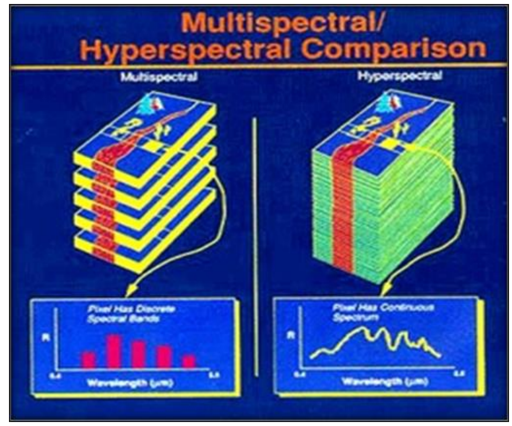


Figure 1. Hyperspectral and Multispectral differences

2. HYPERSPECTRAL IMAGING APPLICATIONS

The hyperspectral imaging used in many areas, including medical domains, security and defense areas, monitoring and target recognition, mining and oil exploration, agriculture fields, and food safety areas.

A. Security

Detection the changes of the optical characteristics of material surfaces that can not be observed by the human eye, such as discrimination of the zero added with a different ink in document forgeries as shown in Figure 2 [15], and monitoring of changes in historical documents caused by aging process and conservation treatments as shown in Figure 3 [16].

Fingerprint recognition, which supply an accurate visualize of details, even on complex, patterned, or interfering backgrounds, such as fingerprint revealed on a counterfeit $10 bill, dark background extracted as shown in Figure 4 [17].

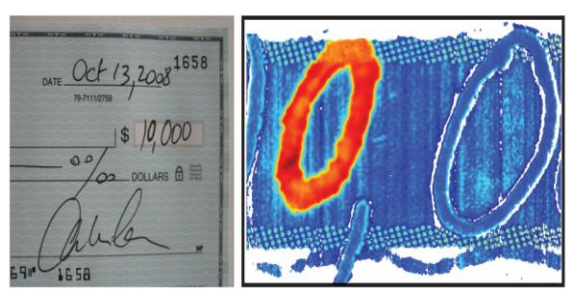


Figure 2. Forgery Detection (a) Original Copy (b) Hyperspectral Copy

B. Geological Applications

The Mineral exploration with which different minerals can be distinguished using spectral characteristics, as shown in Figure 5, the white arrow in the frame indicates the locations of the oil seeps using hyperspectral data [19].

Characterization of the coastal zone environment to elicit information about the coastal ocean utilized for multiple purposes such as bathymetry, water clarity, harmful blooms and bottom characteristics as shown in Figure 6 [20].

Hyperspectral imaging used in defense and military applications for target detection and recognition, mapping applications, and marine mapping applications such as penetrating the barriers to detect troop and vehicles as evidenced in Figure 7 [18].

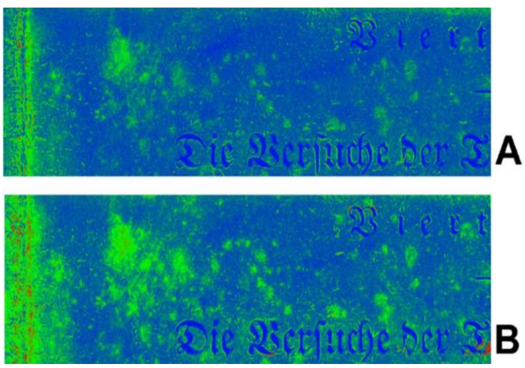


Figure 3. Monitoring of Changes in Historical Documents

Figure 4. Fingerprint Recognition

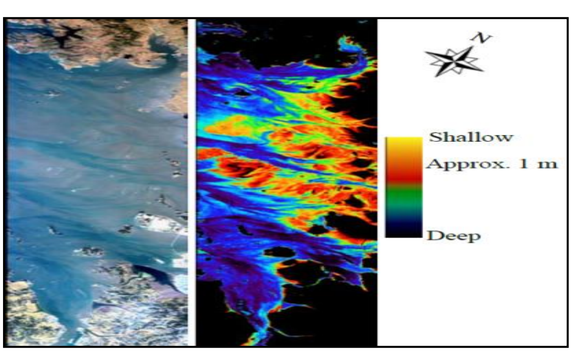


Figure 5. The Oil Seeps Location

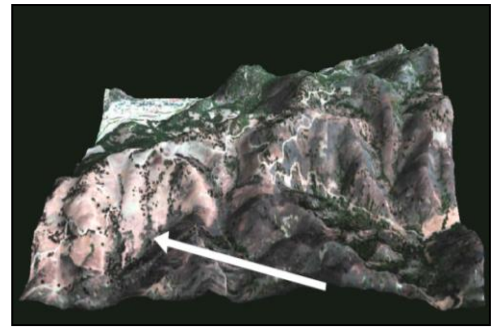


Figure 6. Bathymetry Map of South Korea Coast

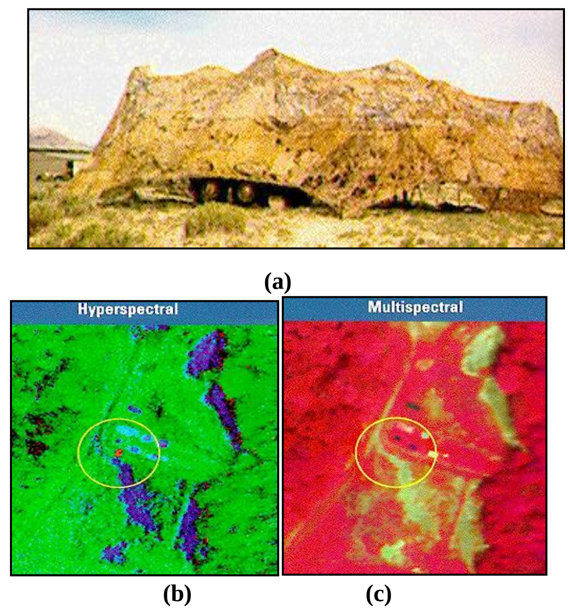


Figure 7. Penetrating the Barriers (a) Original (b) Hyperspectral (c) Multispectral Copy

C. Vegetation Analysis

Hyperspectral imaging used in wide areas such as agriculture, food safety, and forestry; to identify plant health, early phase detection of infestations, and soil properties such as the Forestry Department of Sarawak State in Malaysia used hyperspectral image to map the health condition in individual palm trees, and identify fungus infection in oil palm forests as shown in Figure 8 [21], and using hyperspectral imaging to provide the state of the fish freshness as shown in Figure 9 [22]..

D. Medical Imaging Applications

Hyperspectral imaging used in non-invasively disease detection to distinguish healthy tissue from diseased tissue [23], as exhibited in Figure 10 [24].

Drug discovery process, identifying substances, analysis the compounds, and scanning multiple batches of tablets medicine simultaneously when move across a process line [25].

E. Environment Monitoring

Detection of environmental change such as pollution investigation of land areas [19].

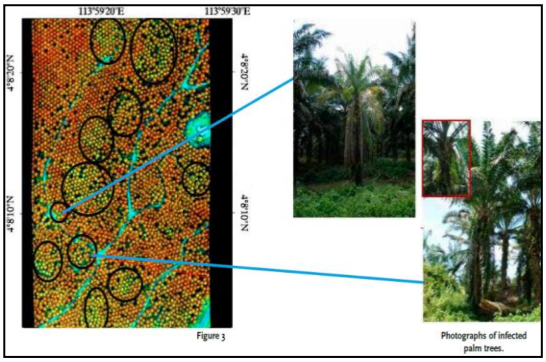


Figure 8. Mapping the Health Condition and Identifying Fungus Infection

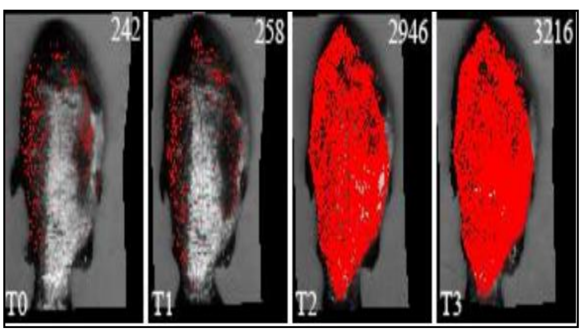


Figure 9. Providing the State of the Fish Freshness

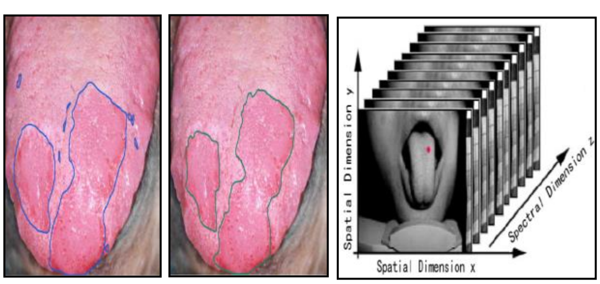


Figure 10. Detecting Tongue Tumor. (a) Tumor Region Labeled by an Expert. (b) Tumor Region Classified by Classifier Prediction Using Hyperspectral Image.(c) 3D Hyperspectral Image of Tumor Region

3. CLASSIFICATION METHODS

The Classification of remotely sensed image means categorizing all pixels in a digital image into groups. Alternatively, it means assigning objects with the same level to a class with homogeneous characteristics. It is a process to recognize the geographical features in the digital remotely sensed images. Depending on the aim and the characteristics of the image data, the classification classes should be delineated clearly. Some mathematical programs can cause the classification process automatically. These programs usually treat each pixel as the smallest single unit with a group of values combined in various spectral bands [26][27].

There are two principal cases of image classification which are supervised classification and unsupervised classification. When the analyst interact with the program or guide the classification by identifying each class, the classification is called supervised but when the interaction of the analyst with the program is minimal, the classification is called unsupervised [28]. However, when the classifier shares the characteristics of both supervised and unsupervised strategies, the classification called hybrid classification [26][29].

A. Supervised Versus Unsupervised Classification

The Supervised Classification and Unsupervised Classification have many disputes and each holds its own advantages and disadvantages as shown in Table I and also in Figure 11 [27][30].

B. Clustering

The Clustering (or cluster analysis) is grouping the similar data items into a cluster or group such that the items in a cluster have more similarity than the items in others. One of the optimization problems is clustering pixels in multidimensional space. Clustering is a very important technique in the unsupervised classification since there is no information available about to which class the pixel belongs [31].

C. Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA)

The ISODATA algorithm is one of the most utilized methods in unsupervised classification. It is an extension of the K-Means algorithm, but ISODATA select the number of clusters automatically with some heuristics [32]. And normally assumes that each class obeys a multivariate normal distribution, so requires the class means and covariance matrices for each year. It abides by an iterative process. Initially, this approach assigns arbitrary cluster centers and the cluster means and covariance are calculated. Each pixel is then classified to the nearest cluster. New cluster means and covariance are then calculated based on all the pixels in that cluster. This procedure is iterated until the change between iterations is "low enough". The modification can be quantified either by measuring the distances the cluster mean has changed from single iteration to the next or by the percentage of pixels that has changed between iterations [33].

In more particular, the steps in ISODATA clustering are as follows:

a) Enter number of clusters.

b) The clustering first selects arbitrary initial cluster centers and then doles out the pixels between the cluster centers using (1):

$$x \in i \ \text{if} \ |\omega(x) - \omega_i| < |\omega(x) - \omega_j| \ \text{for all} \ j \neq i \tag{1}$$

where ωi and ωj are cluster centres for cluster i and j respectively and ω(x) is the feature vector at position x .

c) The new cluster center for class i is computed by averaging the values of the pixels assigned to the class (i.e. A new class mean is computed by (2)):

$$\omega_i = \frac{1}{Q_i} \sum_{x \in i} \omega(x), \quad i = 1, 2, \ldots, K \tag{2}$$

Where K is the number of clusters and Qi is the number of pixels in class i. At the same time, the cluster covariance is computed.

d) The pixels are then classified to the nearest cluster, and the new cluster mean and covariance are calculated.

e) If the change between the initial cluster and the new cluster is not small enough, steps 4 to 5 are repeated otherwise, the clustering process ends [33].

1) ISODATA Advantages

- There is no need to know much about the data in advance.
- The required user effort is less.
- ISODATA algorithm is really efficient for identifying spectral clusters.
- It has self-organizing capabilities.
- Flexibility in eliminating clusters that have very few samples.
- The ability to segment clusters that are too dissimilar.
- The ability to merge clusters that are sufficiently similar [32][33].

2) ISODATA Limitations

- There Data must be linearly separable because of long, narrow or curved clusters not handled properly.
- Hard to know the optimal parameters.
- Performance is highly dependent on these parameters.
- ISODATA is less effective than other linear methods for big datasets and large number of clusters.
- Although ISODATA appears to play well for non-overlapping clusters, convergence are unknown [32] [33].

D. Iterative Principle Component Analysis (PCA)

It is a technique in data analysis used to reduce the dimensions. It reduces a set of high dimensional vectors into a set of lower dimensional vectors [34]. The matrix method and the data method are two types of methods for performing PCA. The four general steps to compute PCA is given below:

a) Find the mean vector in x-space.

b) Assemble covariance matrix in x-space.

c) Compute eigenvalues and corresponding eigenvectors.

d) Form the components in y-space.

All information of a number of bands is compressed by PCA into number of new bands that called principal components, to decrease redundancy and increase the covariance to achieve lower dimensionality (see Figure 12).

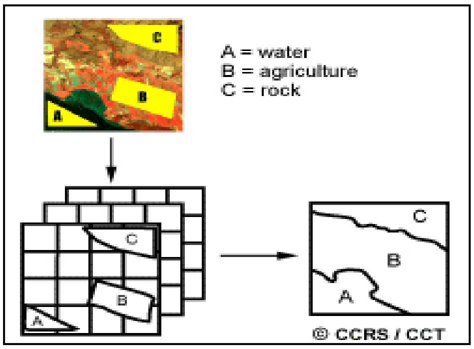
4. Results and Discussion

The study area was located in Florida , USA. Hyperspectral dataset of Florida was generated by the SAMSON hyperspectral sensor. Unsupervised classification was applied to the hyperspectral image using ENVI [35][36]. Figure 13-a shows the original hyperspectral image of Florida as an input image. The result of applying Principle Component Analysis (PCA) using PC Band 141 in R, PC Band 88 in G, and PC Band 20 in B (see Figure 13-b).

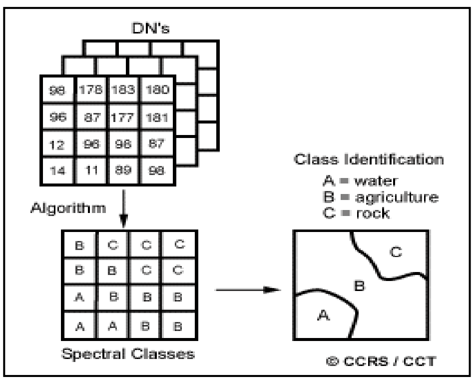
After applying PCA, ISODATA algorithm was applied to the result of PCA. Number of classes range is from 4 to 6 and the maximum iterations is 3 are chosen as ISODATA parameters. The classified image of Florida after applying the ISODATA algorithm (see Figure 13-c).

In this work, the performance was evaluated on the base of the accuracy assessment of the process of the ISODATA algorithm as unsupervised hyperspectral image classification. Accuracy of the process of unsupervised hyperspectral image classification and Assessment of landscape properties are two features to be tested. Table II shows the class distribution summary and Table III shows a summary of the Class Confusion Matrix.

The result of applying ISODATA algorithm is a classified image where the time for processing is increased when the number of iterations is increased to get the classified image. The statistical information calculated from the classified image data and show that ISODATA algorithm is accurate since each pixel in the image is classified into a class that is not Unclassified Class. The overall accuracy of classification process using ISODATA algorithm is 75.6187% .



(a) Supervised Classification



(b) Unsupervised Classification

Figure 11. Supervised and Unsupervised Classification

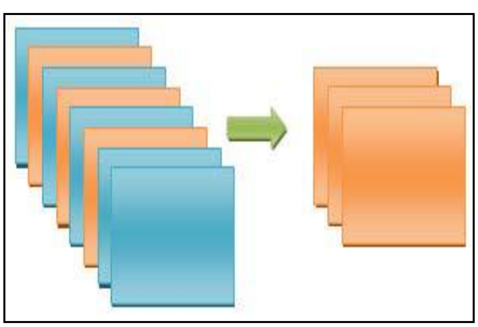


Figure 12. PCA is a dimension reduction technique

TABLE I. A COMPARISON BETWEEN SUPERVISED AND UNSUPERVISED CLASSIFICATION METHODS

	Supervised Classification	**Unsupervised Classification**
Are there needing to label the training data?	Yes.	No.
Type of Decision	Prior.	Posterior.
Difference between Prior and Posterior	Supervised Prior Decision: from informational classes (ex. water) in the image to spectral classes in the feature space.	Unsupervised Posterior Decision: spectral classes in the feature space to informational classes (ex. water) in the image.
Advantages	▪ It has to be controlled. Therefore, it is proper for the comparison of areas or dates. ▪ It is bound to specific areas (training areas). ▪ All production classes are meaningful to mankind. ▪ There is no problem of matching spectral categories with the information categories. ▪ It sustains the ability of deleting serious errors by analyzing the training information.	▪ There is no demand for detailed prior knowledge of the area, but for interpreting the results, the cognition of the area is required. ▪ The probability of human errors is minimized. ▪ Unique classes recognized as discrete units.
Disadvantages	▪ The analyst forces the classification structure. ▪ The training area depends on informational classes then refers to the spectral properties. If this classifier applied to forests, it will ignore the differences in density, age and shadowing. ▪ If the area to be classified is large, the training area may not representative of the condition. ▪ Selecting good training areas are tedious, expensive and takes longer time.	▪ Classes are classified depending on the spectral values similarities, so that some pixels are classified to informational classes that the pixels are not related to them. ▪ Unsupervised classification is not suitable to create a specific menu of informational classes since the analyst limits the menu of the informational classes. ▪ The relationships between the spectral classes and the informational classes are not constant because of the change of the spectral properties of specific informational classes over time.

TABLE II. CLASS DISTRIBUTION SUMMARY

Unclassified	0 points (0.000%) (0.0000 Meters²)
Water	428,038 points (47.229%) (428,038.0000 Meters²)
Shadow	33,145 points (3.657%) (33,145.0000 Meters²)
Wet	60,587 points (6.685%) (60,587.0000 Meters²)
Fertile soil	175,146 points (19.325%) (175,146.0000 Meters²)
Land	141,172 points (15.577%) (141,172.0000 Meters²)
Forest	68,216 points (7.527%) (68,216.0000 Meters²)

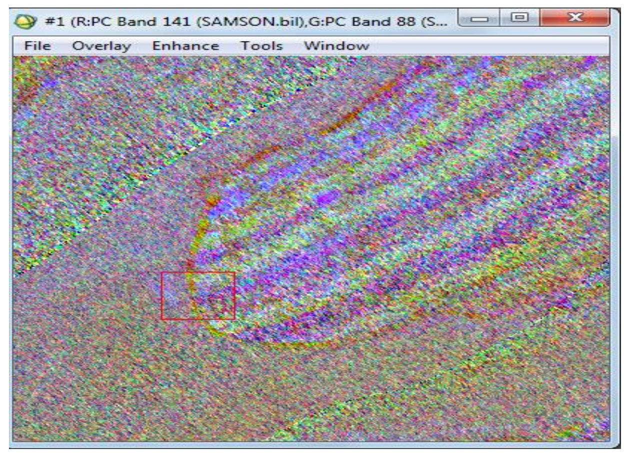
5. CONCLUSION

Hyperspectral images have broad spectral information to identify and distinguish materials spectrally unique. Classification of hyperspectral image means assigning objects with the same level to a class with homogeneous characteristics. In this paper, unsupervised classification algorithm (ISODATA algorithm) is applied using ENVI tool. The analysis of ISODATA algorithm has been performed to classify pixels. Principle Component Analysis (PCA) is used before the classification process as a technique in data analysis to reduce hyperspectral image dimensions. From the classified image data, Statistical information calculated.

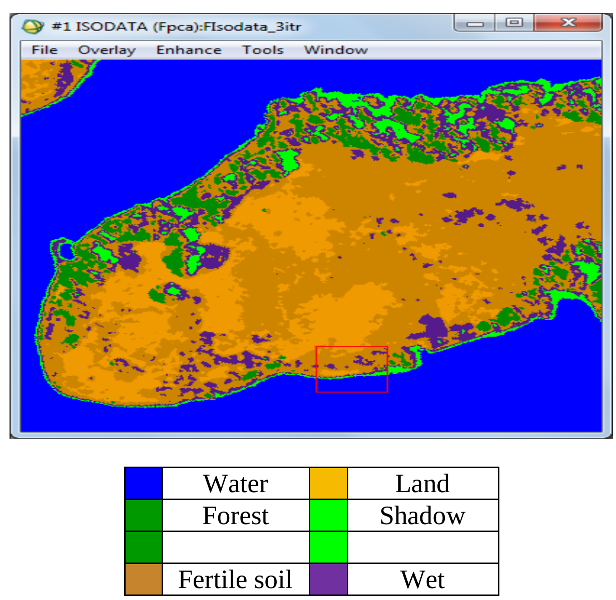
ACKNOWLEDGMENT

Apart from the efforts of myself, the success of any work depends largely on the encouragement and guidelines of many others. Our thanks to the people who have been instrumental in the successful completion of this work.

(a) Input hyperspectral image



(b) After applying PCA



(c) After ISODATA Clustring

Figure 13. Experimental Results using PCA and ISODATA

TABLE III. SUMMARY OF THE CLASS CONFUSION MATRIX

Overall Accuracy = (685335/906304) 75.6187%								
Kappa Coefficient = 0.6580								
Ground Truth (Percent)								
Class	**Unclassified**	**Water**	**Shadow**	**Wet**	**Fertile soil**	**Land**	**Forest**	**Total**
Unclassified	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Water	0.00	100.00	56.08	0.00	0.00	0.00	0.00	47.23
Shadow	0.00	0.00	43.92	45.68	0.00	0.00	0.00	3.66
Wet	0.00	0.00	0.00	54.31	4.75	0.00	73.56	6.69
Fertile soil	0.00	0.00	0.00	0.00	88.33	17.34	26.21	19.33
Land	0.00	0.00	0.00	0.00	6.92	54.46	0.23	15.58
Forest	0.00	0.00	0.00	0.00	0.00	28.20	0.00	7.53
Total	0.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

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Sahar Abd El_Rahman was born in Cairo, Egypt, B.Sc. Electronics & Communication Branch, Electrical Engineering Department, Faculty of Engineering- Shoubra, Benha University (previously Branch from Zagazig University) – Cairo, Egypt in May 1997. She had the first rank over all graduates in all academic evaluations. M.Sc. in an AI Technique Applied to Machine Aided Translation, Electronic Engineering, Electrical Engineering Department, Faculty of Engineering-Shoubra, Benha University – Cairo, Egypt, May2003. Ph.D. in Reconstruction of High-Resolution Image from a Set of Low-Resolution Images, Electronic Engineering, Electrical Engineering Department, Faculty of Engineering- Shoubra, Benha University – Cairo, Egypt in Jan2008.

She is Assistant Professor from 2011 till now at Princess Nourah Bint Abdulrahman University/Department of Computer Science, College of Computer and Information System. Also, She is Assistant Professor from 2008 till now at Electronics & communication, and Computer Systems Branch, Electrical Engineering Department, Faculty of Engineering-Shoubra, Benha University, Cairo, Egypt. She was a Lecture in the same location since 2003 and an Instructor in the same location in 1998.

Dr. Sahar has published many papers in national and international journals and conferences. Her research interests include Computer Vision, Image Processing, Signal Processing, Information Security, Human Computer Interaction, E-Health, Big Data and Cloud Computing. She immersed herself in conducting research in chosen area of specialization, guiding Ph.D. and M.Sc. students and teaching at undergraduate and post graduate level.

Dr. Sahar is a member of IACSIT (International Association of Computer Science and Information Technology) since 2013. A member of Internet Society (ISOC) since 2015. A member of IAENG (International Association of Engineers) since 2011. A member of the Egyptian Engineers' Syndicate since 1997.