

Classification of GIS Image using GLCM and Neural Network

Prof. Dr. Tawfiq A. Alasadi

Babylon University , Dean of Computer Technology College

Wadhah R. Baiee

Babylon University, College of Science ,Computer Department

Abstract:

GIS can hold agricultural regions data like forest, fruit covered lands and/or cultivate lands, these lands have been managed inside GIS by receiving a selected region remotely sensed image, so GIS users must have an appropriate digital map that represents these lands each one according to its owner, status, and some other data. Normally, in such system, these lands will be classified by the users according to agricultural status depending on human vision. So, hardly to the users to classify these lands manually, and this become a great problem which take a long time depending on human efforts, especially if there is a huge number of lands. The suggested study creates a new ArcMap GIS tool which classifies these given lands automatically. Thus, this tool runs the developed system application; it will gather required information for each one of selected land, by sampling sub-images from their centers depending on the digital map, and gathers related status information from attribute database. On the next stage, the system will extract a vector of textural features for each one of the selected lands from their image samples using second order statistics Gray Level Co-occurrence Matrix (GLCM) and calculate eight textural features for each one of three visible bands (RGB) for each land sample. That vector of features will become the input to supervised multi-layer perceptron with backpropagation neural network classifier which be learned depending on recommended GIS user training data set. As a result the system has accuracy near to 75%; these results were achieved by comparing the classification results from system test trials with desired user classification data.

Introduction:

Geospatial data has both spatial and thematic components. Conceptually, geographic data can be broken up in two elements: observation or entity and attribute or variable. GIS have to be able to manage both elements. Spatial

component, the observations have two aspects in its localization, absolute localization based in a coordinates system and topological relationship referred. A GIS is able to manage both while computer assisted cartography packages only manage the absolute one. The aim of classification is to link each object or pixel in the study area to one or more elements of a user-defined label set, so that the radiometric information contained in the image is converted to thematic information, The process can be regarded as a mapping function that constructs a linkage between the raw data and the user-defined label set. Two types of classification are commonly performed. Supervised classification methods which are based upon prior knowledge of the number and certain aspects of the statistical nature of the spectral classes with which the pixels making up an image are to be identified, and unsupervised classification methods which are performed by running a classification algorithm without any predefinition of spectral classes of interest. Texture is also an innate property of objects. It contains important information about the structural arrangement of surfaces. The use of texture in addition to spectral features for image classification might be expected to result in some level of accuracy improvement, depending on the spatial resolution of the sensor and the size of the homogeneous area being classified. R. Methre et al. [38] investigated the texture retrieval using combination of local features of Haralick derived from one level discrete wavelet transform coefficients and global statistical features computed from three level wavelet transformed images. Y. Zhang et al. [44] proposed a hybrid classifier for polarimetric SAR images, the feature sets consist of span image, the H/A/ α decomposition algorithm, and the GLCM-based texture features. Then, a probabilistic neural network (PNN) was adopted for classification. E. S. Flores et al [11] used GIS techniques to improve the classification capabilities of a feature extraction algorithm for land use/cover change detection in a deciduous forest environment.

Proposed System Environment:

For programming issues, the proposed system application was programmed using C#.NET. The agricultural lands classification tool which is the proposed system application tool, it was added to ArcMap GIS as a new GIS dll this file contains the application classes code for the proposed system and also, the application interface windows codes to be run into ArcMap GIS software, it become a portable application; it can be used by any machine which has installed ArcMap GIS software.

The agricultural lands had been covered by polygons vector layer previously. These lands represented now by real world satellite image in the raster layer. The user entered only 20 lands information to the database according to his classification decisions to be the recommended data set for learning purpose, and the remaining lands without information; the system will classified them later.

Information Gathering from GIS database:

The system will clip a colored image with three bands from underneath the polygon to be the raster image sample of that polygon (region) and will go to the textural feature extraction stage, we proposed in this research to clip an image window of size equal to (100 * 100) pixels for each studied lands. The sample is clipped from the center of the related polygon. The information from database is required for the classification learning reason, so this information is located in attribute database table. Collected values represent the agriculture status for each land, this value will become the classifier learning desired output for each related extracted land object. Now we have gathered information for each studied land represented by (Land ID, Image Sample, and Current Status). Figure (1) illustrates the block diagram of the proposed system .

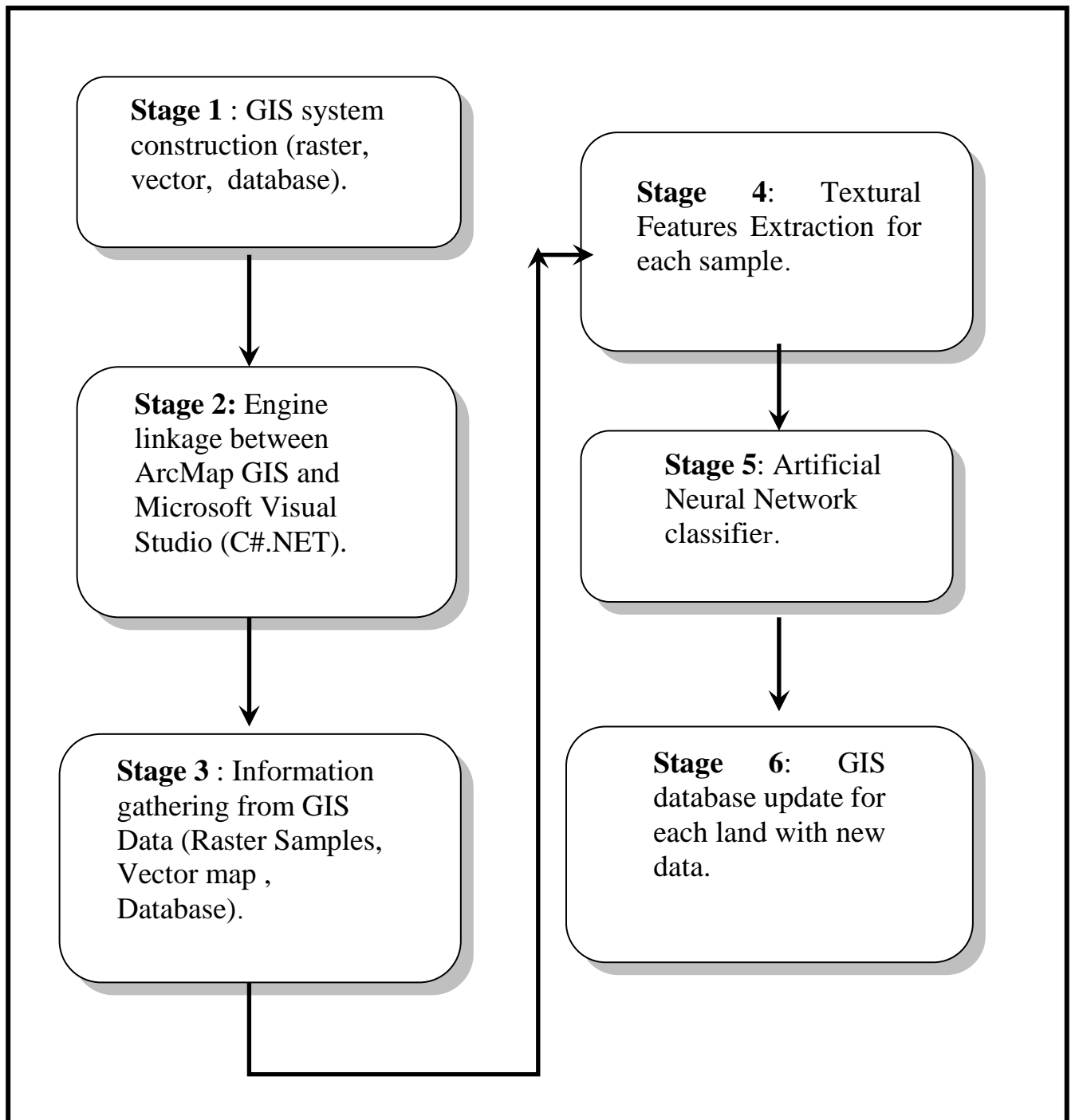


Figure (1) : Block diagram of the proposed system.

GLCM and Textural Features:

Texture feature extraction technique based on the gray-level co-occurrence matrix (GLCM), sometimes called the gray-tone spatial-dependency matrix. The principal concept of GLCM is that the texture information contained in an image is defined by the adjacency relationships that the gray tones in an image have to one

another. The matrix element $P(i, j | d, \theta)$ contains the second order statistical probability values for changes between gray levels i and j at a particular displacement distance d and at a particular angle θ . Instead of using the frequency values in a GLCM directly, it is common practice to normalize them to the range $[0, 1]$ to avoid scaling effects.

Eight textural features was extracted in proposed system for each visible band from each land sample to be the vector of features which represented the entire land sample.

Mathematically, those features can be represented as follows:

- Angular Second Moment

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2 \dots \dots \dots (Eq. 1)$$

- Contrast

$$CONTRAST = \sum_{n=0}^{G-1} n^2 \{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) \}, \quad |i - j| = n$$

$$\dots \dots \dots (Eq. 2)$$

- Inverse Difference Moment

$$IDM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i, j) \dots \dots \dots (Eq. 3)$$

- Entropy

$$ENTROPY =$$

$$- \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) \times \log_2(P(i, j)) \dots \dots \dots (Eq. 4)$$

- Correlation

$$CORRELATION = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu_i)(j - \mu_j) P(i, j)}{\sigma_i \sigma_j} \dots \dots \dots (Eq. 5)$$

- Cluster Shade :

$$\text{SHADE} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i + j - \mu_i - \mu_j\}^3 \times P(i,j) \dots \dots \dots (\text{Eq.6})$$

- Cluster Prominence :

$$\text{PROMINENCE} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i + j - \mu_i - \mu_j\}^4 \times P(i,j) \dots \dots \dots (\text{Eq.7})$$

- Haralick Correlation

$$\text{HARRALICK} = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (ij)P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \dots \dots \dots (\text{Eq.8})$$

ANN Classifier:

Each land object has its own vector of textural features that describes the properties of object. These features become the input to the ANN classifier. The neural network which be used in the system is multilayer perceptron with supervised backpropagation algorithm. ANN classifier consists of three main layers (Input layer, one Hidden layer, and Output layer), it can be shown as 24|52|2 completely connected net. Input layer has 24 input nodes each node take one feature of the textural features contained in input vector. Hidden Layer has 52 hidden nodes (This number is practically chosen by made many training trials on system classifier even to reach to highest system accuracy). Output nodes have 2 nodes (Selected lands has 4 classes (types)). 20 recommended samples were chosen to learn the classifier.

Test and Results:

The system collects lands information from GIS. The collected data are saved in system database buffer for 240 lands which covered by polygons in GIS pre-built user system. These lands data are also sampled, and the system calculated their textural features and save them in system database buffer and they were ready to test by the classifier. Here we describe the practical way which be used to choose the appropriate parameters to be applied on system classifier raising the accuracy of classification. All trials have been applied on the system classifier using different parameters with each trial will be list, these parameters are the ANN parameters such as : momentum , learning rate, sigmoid alpha value , error limit , number of hidden layer's nodes, threshold value, and the angel of the GLCM of related textural features..Table (1) lists the extracted texture features from one land, and table (2) lists all trials and their specifications.

Table (1): Example of 24 features extraction for one selected land sample.

| Features / Bands(Angle) | Red 90 | Green 90 | Blue 90 |
|--------------------------------|---------------|-----------------|----------------|
| Entropy | 0.5604390 | 0.5069230 | 0.5701910 |
| Correlation | 0.9642070 | 0.9657530 | 0.9599290 |
| Haralick | 0.0227320 | 0.0147750 | 0.0159920 |
| IDM | 0.4424280 | 0.5288610 | 0.4242930 |
| Cluster Shade | 0.0001710 | 0.0001110 | 0.0001130 |
| Cluster Prominence | 0.0004850 | 0.0005730 | 0.0003210 |
| ASM | 0.0005730 | 0.0003210 | 0.0006050 |
| Contrast | 0.0006370 | 0.0010780 | 0.0005210 |

Table (2): Training-Test trials for ANN classifier.

| Trial No. | Momentum | Learning Rate | Sigmoid alpha | Error Limit | Iteration | Threshold | Hidden Nodes | GLCM angle | Accuracy % |
|-----------|----------|---------------|---------------|-------------|-----------|-----------|--------------|------------|-------------|
| 1 | 0 | 0.1 | 2 | 0.1 | 1128 | 0.5 | 12 | 90 | 62.10045662 |
| 2 | 0 | 0.1 | 2 | 0.1 | 1189 | 0.5 | 6 | 90 | 65.75342466 |
| 3 | 0 | 0.1 | 2 | 0.1 | 1117 | 0.5 | 20 | 90 | 65.29680365 |
| 4 | 0 | 0.1 | 3 | 0.1 | 1117 | 0.9 | 20 | 90 | 69.8630137 |
| 5 | 0.1 | 0.1 | 2 | 0.01 | 4334 | 0.9 | 12 | 90 | 68.03652968 |
| 6 | 0.1 | 0.01 | 2 | 0.01 | 38754 | 0.9 | 12 | 90 | 73.05936073 |
| 7 | 0.1 | 0.01 | 2 | 0.01 | 38754 | 0.5 | 12 | 90 | 70.77625571 |
| 8 | 0.1 | 0.01 | 2 | 0.01 | 40212 | 0.9 | 20 | 90 | 72.60273973 |
| 9 | 0.1 | 0.01 | 2 | 0.01 | 38094 | 0.9 | 20 | 0 | 66.21004566 |
| 10 | 0.1 | 0.01 | 2 | 0.01 | 40028 | 0.9 | 20 | 45 | 66.66666667 |
| 11 | 0.1 | 0.01 | 2 | 0.01 | 40321 | 0.9 | 20 | 135 | 63.47031963 |
| 12 | 0.1 | 0.01 | 2 | 0.01 | 40321 | 0.5 | 20 | 135 | 57.99086758 |
| 13 | 0.2 | 0.01 | 2 | 0.01 | 42066 | 0.9 | 30 | 90 | 71.68949772 |
| 14 | 0.3 | 0.01 | 2 | 0.01 | 49432 | 0.9 | 30 | 90 | 72.60273973 |
| 15 | 0.05 | 0.01 | 2 | 0.01 | 36323 | 0.9 | 30 | 90 | 73.05936073 |
| 16 | 0.1 | 0.005 | 2 | 0.001 | 424922 | 0.9 | 20 | 90 | 73.05936073 |
| 17 | 0.1 | 0.01 | 5 | 0.01 | 6530 | 0.9 | 12 | 90 | 70.77625571 |
| 18 | 0.1 | 0.01 | 2 | 0.01 | 41190 | 0.9 | 12 | 90 | 71.68949772 |
| 19 | 0.1 | 0.01 | 2 | 0.01 | 36299 | 0.9 | 100 | 90 | 72.60273973 |
| 20 | 0.001 | 0.02 | 2 | 0.01 | 17928 | 0.9 | 12 | 90 | 71.68949772 |
| 21 | 0.0001 | 0.01 | 2 | 0.01 | 35815 | 0.9 | 12 | 90 | 70.3196347 |
| 22 | 0.5 | 0.01 | 2 | 0.01 | 78009 | 0.9 | 12 | 90 | 69.40639269 |
| 23 | 0.1 | 0.01 | 2 | 0.01 | 37887 | 0.9 | 12 | 90 | 73.05936073 |
| 24 | 0.1 | 0.01 | 2 | 0.01 | 41724 | 0.9 | 10 | 90 | 70.77625571 |
| 25 | 0.1 | 0.01 | 2 | 0.01 | 41593 | 0.9 | 9 | 90 | 69.8630137 |
| 26 | 0.1 | 0.01 | 2 | 0.01 | 38362 | 0.9 | 15 | 90 | 72.60273973 |
| 27 | 0.1 | 0.01 | 2 | 0.01 | 38963 | 0.9 | 13 | 90 | 73.51598174 |
| 28 | 0.1 | 0.02 | 2 | 0.01 | 19982 | 0.9 | 13 | 90 | 71.23287671 |
| 29 | 0.1 | 0.005 | 2 | 0.01 | 75138 | 0.9 | 13 | 90 | 72.14611872 |
| 30 | 0.1 | 0.005 | 2 | 0.01 | 85791 | 0.9 | 15 | 90 | 69.8630137 |
| 31 | 0.1 | 0.01 | 2 | 0.01 | 37677 | 0.9 | 50 | 90 | 71.68949772 |
| 32 | 0.1 | 0.01 | 2 | 0.01 | 37677 | 0.9 | 50 | 90 | 71.68949772 |
| 33 | 0.1 | 0.01 | 2 | 0.01 | 37677 | 0.8 | 50 | 90 | 74.42922374 |
| 34 | 0.1 | 0.01 | 2 | 0.01 | 37677 | 0.7 | 50 | 90 | 72.14611872 |
| 35 | 0.1 | 0.01 | 2 | 0.01 | 37677 | 0.81 | 50 | 90 | 74.42922374 |
| 36 | 0.1 | 0.01 | 2 | 0.01 | 37677 | 0.82 | 50 | 90 | 73.97260274 |
| 37 | 0.1 | 0.02 | 2 | 0.01 | 18447 | 0.8 | 50 | 90 | 73.97260274 |
| 38 | 0.1 | 0.01 | 2 | 0.01 | 37091 | 0.8 | 52 | 90 | 74.93771732 |

The test with following data was chosen and produced system accuracy \cong 75% : Momentum = 0.1, learning rate = 0.01 , sigmoid alpha value = 2 , error limit = 0.01 , number of hidden layer's nodes = 52 , threshold value = 0.8 , and the angel of the GLCM = 90° , learned with 37091 iterations. These values with heist accuracy and low iteration of ANN learning is taken from table (1) above. Table (3) illustrates a comparison details between the classified types and shows the identical accuracy of each land type with user classification decisions.

Table (3): Results accuracy for each land type.

| | | Proposed System Classification | | | | | |
|---------------------|----------|--------------------------------|----------|--------|------|-------|-------------|
| | | Land Type | not used | houses | used | trees | total |
| User Classification | not used | 45 | 6 | 10 | 2 | 63 | 71.42857143 |
| | houses | 5 | 36 | 0 | 2 | 43 | 83.72093023 |
| | used | 12 | 1 | 66 | 7 | 86 | 76.74418605 |
| | trees | 0 | 6 | 3 | 19 | 28 | 67.85714286 |
| | total | 62 | 49 | 79 | 30 | 220 | 74.9377 |

System accuracy is 74.94% compared with user classification data, these ratios were recommended by the test trials table, it is a higher accuracy test ratio among the others and depend it as a recommended results. And the details of each type are shown in table (3) above, the system has a higher accuracy 83.72% with houses covered lands ,and 76.44% with used lands , and 71.43% with not used lands , finally, 67.86% with trees lands. Figure (2) illustrates a compression between system classification on studied lands and the user classification, where figure (2.a) shows classified lands after apply the proposed system on the test lands and picture (2.b) shows manually user classification on same selected lands.

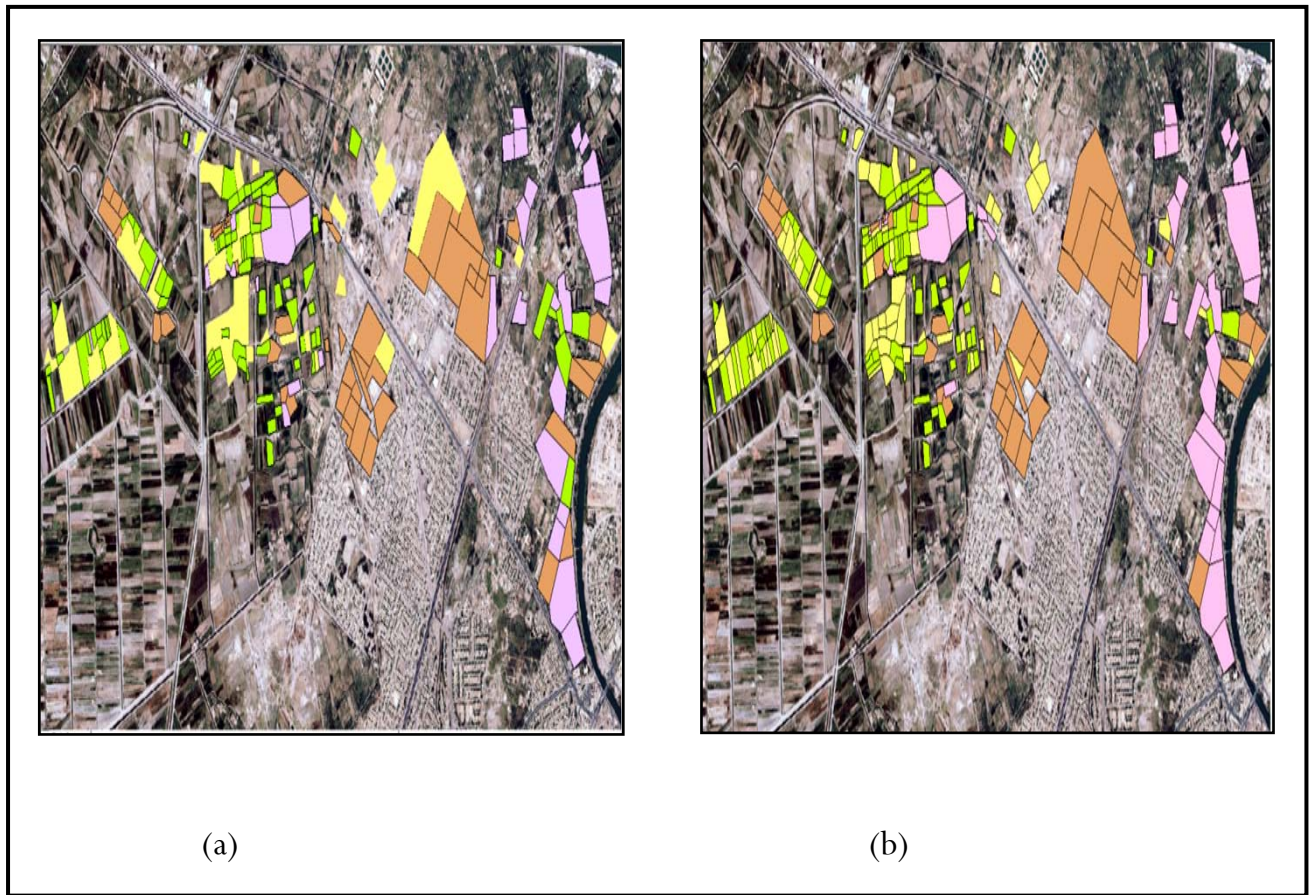


Figure (2): (a) System Classification , (b) User Classification.

Conclusions:

The classification method that used in the proposed system doesn't depend on the pixel color values for classification reasons, instead; GIS data (raster, vector, and database) is appointed all together to complete the classification requirements. Using textural features that extracted from grey level co-occurrence matrix for each land samples as the input to the supervised neural network classifier is more efficient than using classical way depending on individual pixel color values only. GLCM with angel 90° is the best among GLCMs with other angels (0° , 45° , 135°) for extraction features to be used later in supervised classification with multilayer perceptron with backpropagation classifier.

References:

1. A. K. Sinha et al., "Fuzzy Neural Network Modeling of Land-Use /Cover using IRS-1D Satellite Image", Map India Conference, 2004.
2. A. M. Coleman, "An Adaptive Landscape Classification Procedure Using Geoinformatics and Artificial Neural Networks", MSc. Thesis; Faculty of Earth and Life Sciences Vrije University, Amsterdam The Netherlands, 2008.
3. B. Booth et al., "Getting Started with ArcGIS", Environmental Systems Research Institute, 2001.
4. B. Tso et al., "Classification Methods for Remotely Sensed Data", Taylor & Francis Group, 2009.
5. C. H. Chen et al., "The Handbook of Pattern Recognition and Computer Vision", World Scientific Publishing Co., 1998.
6. C. Tucker, "ESRI using Arctoolbox" , Environmental Systems Research Institute, 2000.
7. D. Decker, "GIS Data Sources", John Wiley & Sons, 2001.
8. D. I. Verbila, "Practical GIS analysis", Taylor & Francis Group, 2003.
9. D. L. Fitzgerald, "Landing Site Selection for UAV Forced Landing Using Machine Vision", PhD Thesis; School of Engineering Systems; Queensland's University of Technology; Australia, 2007.
10. E. Gose et al., "Pattern Recognition and Image Analysis", Prantice Hall, 1997.
11. E. S. Flores et al., "GIS Improved Object-Based Classification For Land Use/Cover Change Detection In Human Altered Deciduous Forest", The American Society for Photogrammetry & Remote Sensing 2009 Annual Conference; Baltimore; Maryland, 2009.
12. E. Stefanakis et al., "Geographic Hypermedia: Concepts and Systems", Springer, 2006.
13. E. W. Tennant, "Using ArcGIS to Create Living Documents with Archaeological Data", MSc. Thesis; Michigan Technology University, 2005.
14. F. Aguera et al., "Using Texture Analysis to Improve Per-pixel Classification of Very High Resolution Images for Mapping Plastic Greenhouses", ISPRS Journal of International Society for Photogrammetry & Remote Sensing (63) 635–646 , 2008.
15. F. Albrechtsen, "Statistical Texture Measures Computed from Gray Level Co-occurrence Matrices ", University of Oslo, 1995.
16. F. Bachmann et al., "An Architecture Based on Class Dependent Neural Networks for Object-based Classification", Institute for Mine-Surveying and Geodesy, 2009.
17. F. Harvey, "A primer of GIS fundamental geographic and cartographic concepts", The Guilford Press, 2008.
18. G. E. Sherman, "Desktop GIS: Mapping the Planet with Open Source Tools", The Pragmatic Bookshelf, 2008.
19. G. H. Landeweerd et al., "The Use of Nuclear Texture Parameters in The Automatic Analysis of Leukocytes", Pattern Recognition; Vol. 10; Pages (PP) 57-61, 1978.
20. I. N. Ahmed, "Digital Image Classification", MSc Thesis; College of Science; University of Babylon, 1999.
21. I. T. Service, "Introduction to GIS using ArcGIS", Durham University, 2006.
22. J. A. Anderson, "An Introduction to Neural Networks", PHI Learning Private Limited, 2009.

23. J. L. Harris, "A Hierarchical Document Description and Comparison Method", Msc. Thesis; Purdue University, 2003.
24. K. C. Clarke et al., "Geographic Information System and Environmental Modeling", Prentice Hall, 2009.
25. K. T. Changg, "Programming ArcObjects with VBA", Taylor & Francis Group, 2008.
26. L. Fausett, "Fundamentals of Neural Networks: Architectures Algorithms and Applications", Prantice Hall, 1994.
27. M. Cheong et al., "An Approach to Texture-Based Image Recognition by Deconstructing Multispectral Co-occurrence Matrices using Tchebichef Orthogonal Polynomials ", IEEE, 2008
28. M. F. Insana et al., "Analysis of Ultrasound Image Texture via Generalized Rician Statistics," Optical Engineering , 1986.
29. M. S. Nixon et al., "Feature Extraction and Image Processing", Elsevier, 2008.
30. N. R. Chrisman, "Exploring Geographic Information Systems", John Wiley and Sons, 1997.
31. O. Dassau et al., "GIS for Educators Topic 3: Vector Attribute Data", Spatial Planning & Information; Department of Land Affairs; Eastern Cape; South Africa (DLA), 2009.
32. O. Engler et al., "Introduction to Texture Analysis", Taylor & Francis Group, 2010.
33. P. Croswell, "GIS Design and Implementation Services", IT Consultants—GIS Design and Implementation Services Brochure, 2010.
34. P. Ohanian et al., " Performance Evaluation for Four Classes of Textural Features", Pattern Recognition 25; 819-8133, 1992.
35. R. C. Ghonzaliz et al., "Digital Image Processing", Prentice Hall, 2000.
36. R. Kok et al., "Analysis of Image Objects from VHR Imagery for Forest GIS Updating in The Bravian Alps", ISPRS, Vol. XXXIII; Amsterdam, 2000.
37. R. M. Haralick et al., "Textural Features for Image Classification", IEEE Transiction on Systems Vol. SMC-3 No. 6, 1973.
38. R. Methre et al., "Exploring Spatial Information in Spectral Features for Texture Image Retrieval", International Journal of Computer and Network Security Vol. 1; No. 3, 2009.
39. S. Arivazhagan et al., "Texture Classification Using Wavelet Transforms.", Pattern Recognition Letters 24; 2003
40. S. Carver, "Innovations in GIS", Taylor & Francis e-Library, 2005.
41. S. Haykin, "Neural Networks and Learning Machines", PHI Learning Private Limited, 2009.
42. S. K. Shah et al., "Image Classification Based on Textural Features using Artificial Neural Network", IE (I) Journal ET, 2004.
43. Y. C. Chen et al., "Texture Features for Classification of Ultrasonic Liver Images", IEEE ransactions on Medical; Vol.11; No. 2; Pages 141-151, 1992
44. Y. Zhang et al., "Remote-Sensing Image Classification Based on an Improved Probabilistic Neural Network", Sensors 9; pages 7516-7539, 2009.