Classification of GIS Image using GLCM and Neural Network

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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 theses 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 .

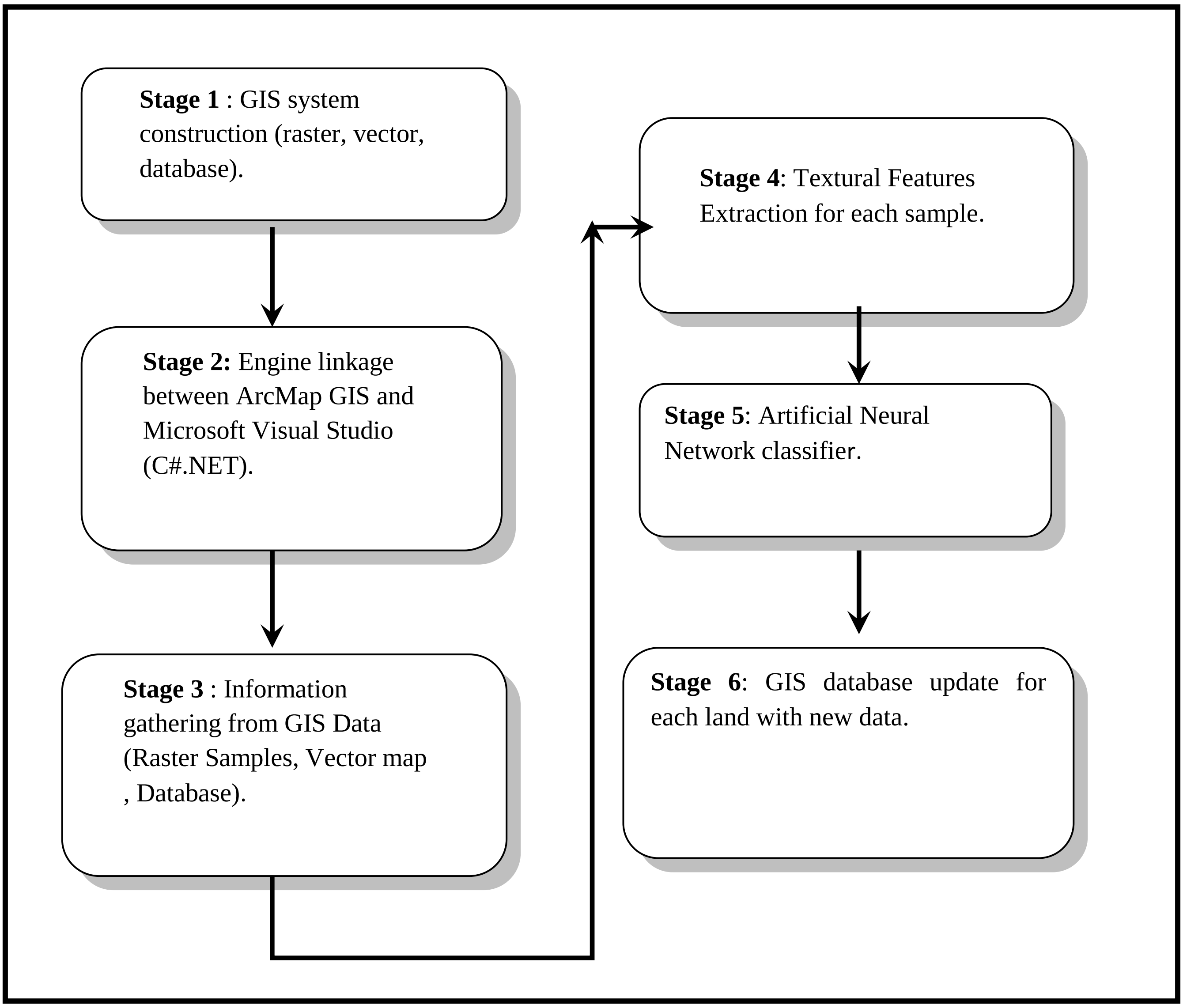


Figure (1) : Block diagram of the proposed system.

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 $(i, j \mid d,\theta)$ 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

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

Contrast

$$\text{CONTRAST} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j)\right\},\quad |i-j| = n \qquad \ldots\ldots\ldots\; (Eq.2)$$

Inverse Difference Moment

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

Entropy

$$\text{ENTROPY} = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times \log(P(i,j) \;\ldots\ldots\ldots\; (Eq.4)$$

Correlation

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

Cluster Shade :

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

Cluster Prominence :

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

Haralick Correlation

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

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

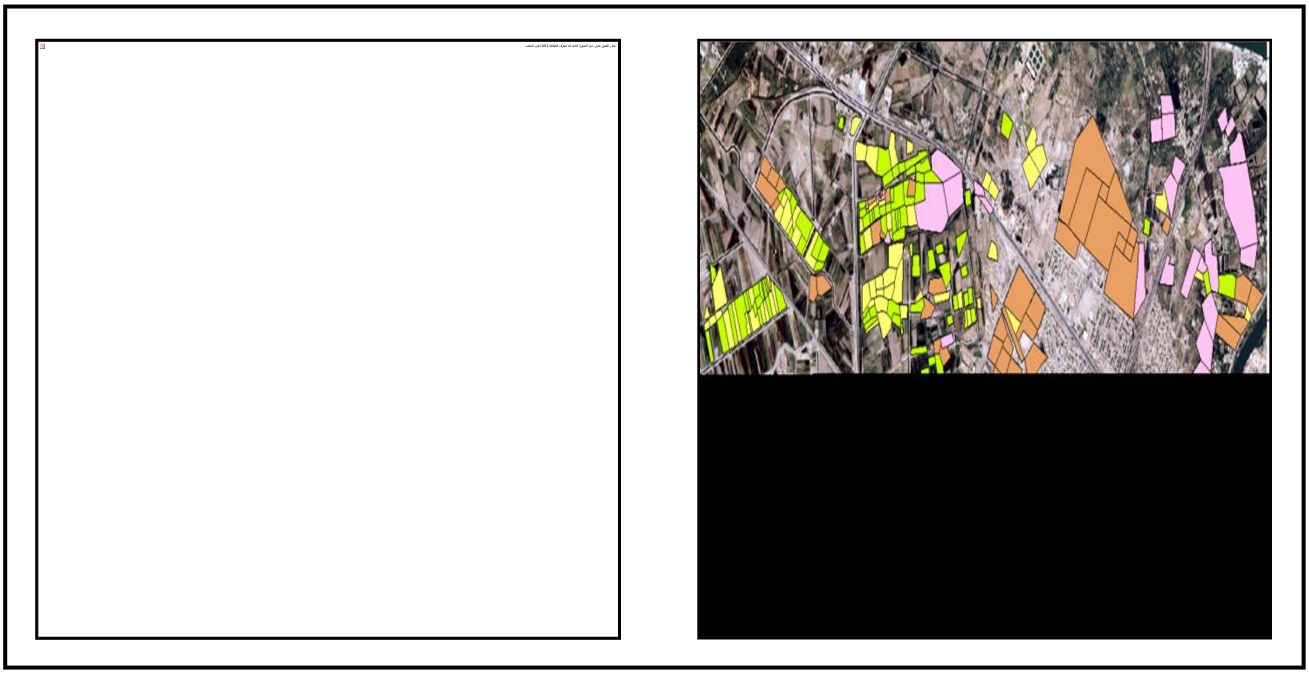
The test with following data was chosen and produced system accuracy ≅ 75% : Momentum = 0.1, learning rate = 0.01 , sigmoid alpha value = 2 , error limit = 0.01 , number of hidden layer's nodes = 52 , threshold value = 0.8 , and the angel of the GLCM = 90^o , learned with 37091 iterations.

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**	**Accuracy%**
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.



(a) (b)

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^o is the best among GLCMs with other angels (0^o, 45^o, 135^o) for extraction features to be used later in supervised classification with multilayer perceptron with backpropagation classifier.

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