APPLICATION OF FUZZY LOGIC AND NEURAL NETWORK: A REVIEW

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Abstract: Image classification is one of the crucial techniques in detecting the crops from remotely sensed data as mapping of crops is a complex activity which in turn is an important parameter for planning and management of irrigation command area. Classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image-processing and classification approaches, may affect the success of a classification. Up-to-date and accurate classification results are required for analyses, which provide basis for deciding and implementing policies and plans for management of agricultural crops in local, regional and global scale. Successful identification of crops requires knowledge of the developmental stages and appearance of each crop in the area to be inventoried. The crops thus identified from the remote sensing data can be utilized to estimate crop water requirements for irrigation planning and management. Supervised and unsupervised classifications have been in common use in remote sensing for many years which are known as hard classification. Supervised and unsupervised classifications rely on classical set theory in assigning pixels into discrete classes based on training sets and some statistically determined criteria. Conventional classification methods such as Supervised and Unsupervised classification techniques are often incapable of performing satisfactorily in the presence of mixed pixels, the pixels which are not completely occupied by a single homogeneous category. Soft computing techniques are useful for tackling these real-world problems based on fuzzy systems, artificial neural networks, and evolutionary algorithms. These techniques are widely used nowadays by researchers. Nevertheless, each model has its own advantages and disadvantages. Contrary to hard classifiers, fuzzy classifier does not make a definitive decision about the land cover class to which each pixel belongs. Rather, they develop statements of the degree to which each pixel belongs to each of the land cover classes being considered. It is achieved by applying a function called "membership function" on remotely sensed images. Artificial Neural Networks are computer programs that are designed to simulate human-learning processes through establishment and reinforcement of linkages between input data and output data. Artificial neural network is used as a powerful tool for pattern classification and have been found to be accurate in the classification of remotely sensed data. The paper reviews application of different soft computing classification techniques for crop mapping which is necessary for estimating crop water requirements with the help of satellite images.

Keywords: Crop Classification; Remote Sensing; Soft Computing; Fuzzy Logic

I. INTRODUCTION

Mapping of natural vegetation, as well as that of natural resources, is a complex activity. The availability of remotely sensed images and the advances in digital processing and analysis techniques have enabled research scientists to have information about the type, condition, area, and the growth of agricultural crops. Remote Sensing plays a significant role for crop classification, crop health and yield assessment. Accurate classification results are required for analyses, which provide basis for deciding and implementing policies and plans for management of agricultural crops in local, regional and global scale and also required for estimating crop water requirement for irrigation purpose. Supervised and unsupervised classifications have been in common use in remote sensing for many years which are known as hard classification. Hard classification techniques rely on classical set theory in assigning pixels into discrete classes based on training sites and some statistically determined criteria. The classification of remotely sensed imagery relies on the assumptions that the study area is composed of a number of unique, internally homogeneous classes and that classification analysis based on reflectance data and ancillary data can be used to identify these unique classes with the aid of ground data [3]. However, such assumptions are often not valid in areas with significant fuzziness. Fuzziness often occurs due to the presence of mixed pixels which are not completely occupied by a single, homogeneous category. This problem has lead to the concepts of soft classification techniques like fuzzy classification, sub-pixel classification. Conventional classification methods such as maximum likelihood classification are often incapable of performing satisfactorily in the presence of mixed pixels. Fuzzy logic attempts to address this problem by applying different classification logic. Artificial Neural Networks are computer programs that are designed to simulate human-learning processes through establishment and reinforcement of linkages between input data and output data. Artificial neural network is used as a powerful tool for pattern classification and have been found to be accurate in the classification of

remotely sensed data. In this paper, application of different hard and soft computing classification techniques i.e. fuzzy logic and artificial neural network in crop mapping is reviewed.

II. CROP CLASSIFICATION

Vegetation classification is the most fundamental thing to separate vegetated from non-vegetated regions or forested from open lands. Such distinctions can have great significance in some contexts, especially when data are aggregated over large areas or are observed over long intervals of time. A plant community is an aggregation of plants with mutual interrelationships among each other and with the environment. Among the vegetation classification crop-classification is the important part because in many setting crops are usually observed planted in Uniform district fields with a single crop to a field. Crop classification through visual image interpretation is based on the spectral response pattern and image texture of a specific crop. Successful identification of crops requires knowledge of developmental stages of each crop. Because of changes in crop characteristics during growing season it is often desirable to use satellite images acquired on several dates during the growing cycle. Often crops that appear very similar on one date will look quite different on another date, and several dates of image acquisition may be necessary to obtain unique spectral response patterns from each crop type (Lillesand, 2007).[3] Various researchers have worked on the classification of crops using the conventional hard computing techniques out of which a few of them are represented here. Daly (2001) developed a process to identify major crops during cultivation season using Land sat-TM satellite images and GIS in eastern Washington area. Multi temporal classification used field training sets, multi-temporal images and field boundaries to classify thirteen crops. Overall classification accuracy was 84% and for several crops exceeded 93%. Jeff. et al. (2001) describes in their project of “Central Valley Crop Classification Processing Using Remote Sensing and GIS Technologies” which is intended to demonstrate the applicability of crop mapping procedures used in the Lower Colorado River Basin for classifying crop types in the Central Valley of California. A case study of interpreting paddy distributions of three counties on Northern Taiwan during two crop seasons on year 2000 using multi temporal imageries together with cadastre GIS by Bayesian posteriori probability classifier has been presented by Lau and Hslao (2002). Temporal change of NDVI from different growth stages pass through rice's life cycle has been measured and it has been seen that two stage images make significant improvement on classification results. Overall accuracy was high. Kozan et al. (2002) produced new maps classifying landuse and cropping pattern using satellite derived vegetation indices and surface meteorological data in the Huaihe river basin, Japan. Agricultural statistic data of 187 prefectures in Henan Province have been used for validation. [1] performed mapping of summer crops using a multi-temporal masking technique together with the parcel-based analyses of the classified images. First, a supervised per-pixel classification of the three images (May, July, and August 2000) was performed using a maximum likelihood classifier algorithm. The masking technique was applied to overcome the problems caused by the spectral overlaps between the information classes. The classified output of the August image was analyzed in a field specific manner. Reddy et al. (2004) applied remote sensing to estimate cotton growth and developmental parameters in the Mississippi State, USA. They investigated seasonal patterns of canopy reflectance and also determined relationship between plant growth and reflectance parameters. Shakoor (2004)[2] estimated cropped areas for individual crops using satellite image classification in an area in Pakistan. Crop water requirements at various stages of crop growth have been calculated, temporal behavior of canal water supply patterns have been studied. Crop areas calculated from classified image showed reasonable similarity with actual areas. Ortiz et al. (2010) investigated crop classification results using two methodologies i) maximum likelihood classification technique, with the standard technique coupled with a tabular database(e.g., crop types and cultivars, crop age in each used scene date, planting date, harvesting date, soil type, etc.) integrated in a GIS framework ii) conventional maximum likelihood classification method. The former method was proved to be better than the later one. Not only the average global performance index was better (73´65 per cent against 57´12 percent) but also the Kappa statistics was assigned as `very good’ against `good’, respectively.

III. IMAGE CLASSIFICATION TECHNIQUE

Remote-sensing classification is a complex process and requires consideration of many factors. The major steps of image classification may include determination of a suitable classification system, selection of training samples, image pre-processing, and feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment. In general, image classification approaches can be grouped as supervised and unsupervised, or parametric and non parametric, or hard and soft (fuzzy) classification, or per-pixel, sub pixel, and per field. Based on whether output is a definitive decision about land cover class or not the classifiers are of two, hard classifiers and soft classifiers. This section focuses on the various image classification techniques.

A. Hard Computing

Hard classifiers make a definitive decision about the land cover class that each pixel is allocated to a single class. The area estimation by hard classification may produce large errors, especially from coarse spatial resolution data due to the mixed pixel problem. Most of the classifiers, such as maximum likelihood, minimum distance, decision tree etc. are basically hard classifiers.

B. Unsupervised Classification

It can be defined as the identification of natural groups, or structures, within multispectral data. The notion of the existence of natural, inherent groupings of spectral values

within a scene may not be intuitively obvious, but it can be demonstrated that remotely sensed images are usually composed of spectral classes that are reasonably uniform internally in respect to brightness in several spectral channels. The algorithm identifies clusters or groups of these similar data and the analyst identifies the individual clusters.

C. Supervised Classification

In this type of classification the image analyst "supervises" the pixel categorization process by specifying the computer algorithm, numerical descriptors of the various land cover types present in a scene. Representative sample sites of known cover types, called training areas, are used to compile a numerical "interpretation key" that describes the spectral attributes of each feature type of interest. Each pixel in the data set is then compared numerically to each category in the interpretation key and labeled with the name of category it looks most similar. Usually the analyst begins by assembling and studying maps and remote sensing images of the area to be classified and by investigating selected sites in the field. The objective is to identify a set of pixels that accurately represent spectral variation present within each informational region. The algorithm generates decision boundaries. Various supervised classification methods may be used to assign an unknown pixel to one of a number of classes. The choice of a particular classifier or decision rule depends on the nature of the input data and the desired output. Among the most frequently used classification algorithms are the maximum likelihood, Bayesian, minimum distance and parallelepiped algorithms.

D. Soft Computing

Soft classifiers provide for each pixel a measure of the degree of similarity for every class. Soft classification provides more information and potentially a more accurate result, especially for coarse spatial resolution data classification. Artificial Neural Networks, Fuzzy Logic, Decision Tree, Genetic Algorithms come under Soft Classification Techniques.

E. Fuzzy Logic

Most classification approaches are based on per-pixel information, in which each pixel is classified into one category and the land-cover classes are mutually exclusive. Due to the heterogeneity of landscapes and the limitation in spatial resolution of remote-sensing imagery, mixed pixels are common in medium and coarse spatial resolution data. The presence of mixed pixels has been recognized as a major problem, affecting the effective use of remotely sensed data in per-pixel classifications. Sub pixel classification approaches have been developed to provide a more appropriate representation and accurate area estimation of land covers than per-pixel approaches, especially when coarse spatial resolution data are used. A fuzzy representation, in which each location is composed of multiple and partial memberships of all candidate classes, is needed. To overcome the mixed pixel problem fuzzy classification is used. Fuzzy logic has application in many fields, but has special significance for remote sensing. Fuzzy logic permits partial membership, a property that is especially significant in field of remote sensing, as partial membership translates closely to the problem of mixed pixels. So for example, whereas traditional classifier must label pixels as either “Forest” or “Water”, a fuzzy classifier is permitted to assign a pixel a membership grade of 0.3 for “Water” and 0.7 “Forest”, in recognition that the pixel may not be properly assigned to a single class. Membership grade typically vary from 0 (non-membership) to 1.0 (Full membership) with intermediate values signifying partial membership in one or more other classes.

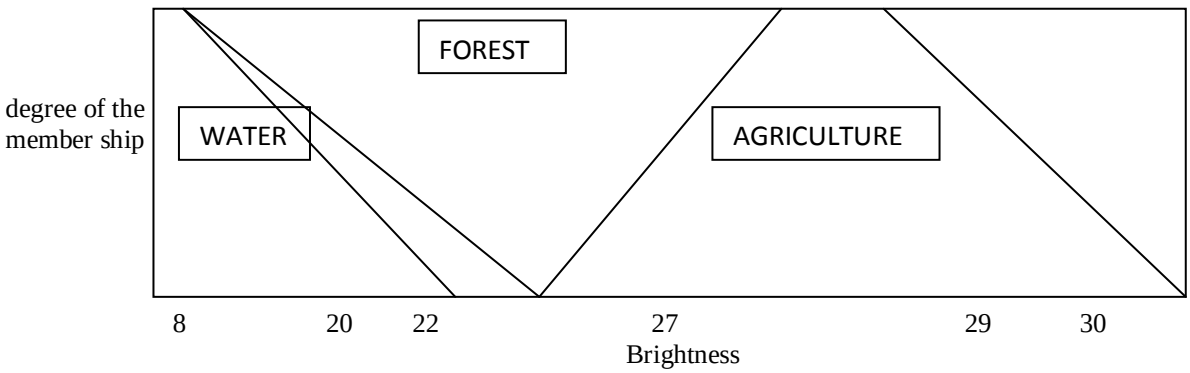

Fig. 1: Membership functions for fuzzy clustering

This example illustrates membership functions for the simple instance of three classes considered for a single band, although the method is typically applied to multiple bands. The horizontal axis represents pixel brightness; the vertical axis represents degree of membership, from low near the bottom to high at the top. The class "Water" consists of pixels darker than brightness 20, although only pixels darker than 8 are likely to be completely occupied by open water. The class "Agriculture" pixels are found only in the range 27 to 29. A pixel of brightness28, for example, can only be "Agriculture" although a pixel of brightness 24 could be partially forested, partially in agriculture. Unlabeled areas on this diagram are not occupied by any of the classes in this classification (Campbell 2002). Fuzzy-logic technique has been utilized for

classification of crops during the years by various scientists. Console and Mouchot (1997) applied techniques based on fuzzy logic where the fuzzy membership values of Land sat image pixels were calculated and a buffer area was defined around map field data for each considered class. The membership values were then modulated using spatial information derived from known targets. The accuracy of the classification was also assessed. Multi temporal ERS SAR PRI images were utilized to delineate map areas under different rice cropping system by Balababa et al. (1998). It was seen that radar images are capable of detecting the differences in the ground vegetation cover manifested by the different magnitude and trends of the backscatter profile at various acquisition dates. Chi-Chen and Yueh Li (2000) made an attempt to use the fuzzy training method to avoid repeated selection of training data in each image. The classification map generated from the first-period image was used as fuzzy training sites for second-period image. The proposed approach was also tested by a series of simulated multi-temporal images. The results indicate that the method has great potential for practical applications. Kahubire (2002) used fuzzy logic to improve statistical distributions by incorporating expert knowledge in order to produce final crop area distribution maps. The validation of the final maps indicates that compared to the available land cover and land use map of Ghana, distributed crop area statistics fall within areas that were mapped out for possible crop production. The method proved a cheap, rapid and efficient method for mapping crop distribution over large areas in tropical environments where in situ information is limited or incompatible with satellite data. McMahan Ben (2002) used fuzzy classification to better characterize the complexity and heterogeneity of vegetation. Unlike supervised classification where pixels are classified into discrete categories, fuzzy systems classify each pixel into multiple categories based on estimated membership in each class. The results showed that fuzzy classification produces more accurate predictions of sagebrush and grass cover compared to supervised classification of Land sat 7 imagery. Nedeljkovic (2003) [4] classified SPOT image in fuzzy logic classification procedure using Matlab Fuzzy Logic toolbox. The results were compared with supervised classification. It was concluded that fuzzy logic takes advantage of already created simple rules and image classification in equal or even less time consuming with satisfactory classification accuracy. Tapia (2004) optimized sampling schemes considering remote sensing data by fuzzy c-means classifier. The confusion index was used to quantify the uncertainty. Two sites of natural vegetation were selected. The first was used to pose a sampling scheme for model validation. The second area was selected for accuracy assessment. Qinghan et al. (2008) demonstrated the application potential of remote sensing to estimate large crop areas using hard as well as soft classification techniques. Hard classification of high resolution imagery can produce spatial cropping details but inefficient for crop mapping at large scale, because of low temporal resolution and the limited swath width of the sensor. However sub-pixel classification of low spatial resolution imagery applying neural network helped to get better result and also cost effective. The effect of various indices SR, NDVI, TNDVI, SAVI and TVI to identify cotton crop using temporal multi-spectral images was investigated by Musande et al. (2012). The fuzzy set theory based sub-pixel classification technique was used for classification. It has been observed that the flower to open ball and harvesting stage respectively, are optimum dates to discriminate cotton crop from other crops/vegetation and found that temporal data base from SAVI index has outperformed other indices with 93.12 % overall classification accuracy.

F. Artificial Neural Networks

Artificial neural networks (ANNs) are computer programs that are designed to simulate human learning processes through establishment and reinforcement of linkages between input data and output data. It is these linkages, or pathways, that form the analogy with the human learning process in that repeated associations between input and output in the training process reinforce linkages, or pathways, that can be employed to link input and output, in the absence of training data. ANNs are often represented as composed of three elements. An input layer consists of the source data, which in the context of remote sensing are the multispectral observations, perhaps in several bands and from several dates. The output layer consists of the classes required by the analyst. Included are training data in which the association between output labels and input data are clearly established. During the training phase, an ANN establishes an association between input and output data by establishment of weights within one or more hidden layers. In context of remote sensing repeated associations between classes and digital values, as expressed in the training data, strengthen weights within hidden layers that permit the ANN to assign correct labels when given spectral values in the absence of training data. Artificial neural networks have been employed to process multispectral remote sensing images and have achieved improved accuracy compared to those obtained from traditional statistical methods. Applications of neural network or neuro-fuzzy models in crop mapping have been explored by many researchers Li R. et al. (2002) demonstrated the ability of the feature-weighted detector (FWD) that enables the classification of patterns and as well the selection of features. The proposed network attempts to select important features from among the originally given plausible features, while maintaining the maximum recognition rate. The resulting value of weight connection represents the degree of importance of feature. FWD provides interpretable rules that are of if– then form. These properties of the FWD suggest that it will be a promising method for pattern recognition. Experiments have been carried out using Land sat-TM data and the results are compared to those obtained by the conventional neural network classifier. The results showed an improvement in classification performance comparing to the conventional neural network algorithm. Qiu Fang (2008) developed Gaussian Fuzzy Learning Vector Quantization (GFLVQ), which is a supervised image classifier that makes use of a priori knowledge in the training data to update a

single neuron without complete retraining. When configured with multiple competitive neurons for each class, GFLVQ is able to self-organize the training samples into natural spectral cluster, taking advantage of the unsupervised competitive learning ability embedded in the system. A geo visualization tool is also developed to help to visualize and understand the fuzzy expert system and its "if-then" rules through fuzzy spectral profile plots, allowing users to interact with individual pixels to explore sampling distributions. Verbeiren et al. (2006)[5] studied potential of sub-pixel classification for regional crop area estimation using time series of monthly NDVI-composites. Two different methods were investigated: the linear mixture model and neural networks. Both algorithms were trained with part of the reference data and validated with the remainder. The best results are obtained with the NN estimates, for the most of the classes. The method is effective for wide-scale, regional area estimation in data-poor countries. Wang, Y. and Jamshidi, M. (2007) proposed Hierarchical Fuzzy Neural Network (HFNN) classifier in remote sensing data classification. In the HFNN classification, each FNN system is composed of the FNN classifier and further FNN systems need inputs from the outputs of previous FNN systems. In this experiment FNN classification without the hierarchical structure needed 1152 rules. However in HFNN classifier by combining more input bands, 40 rules is used totally with the same membership functions but with improved accuracy. Wui, W. and Guanglai, G., (2008) presented neuro-fuzzy model to classify landuse/landcover using Landsat 7 ETM+ images. It combines neural networks and fuzzy systems to learn from the training data and generate conditional linguistic rules. NEFCLASS starts without rules and inserts fuzzy rules into the system during a first run through the training data. Howard, Daniel M., (2012) developed a regression tree classification model based on training data points derived from the National Agricultural Statistics Service Cropland Data Layer in relation to a variety of other relevant input environmental variables for crop type prediction. This vast database was then analyzed with RuleQuest Research's data mining software (RuleQuest 2011) to identify NDVI patterns, phonological signatures and other site characteristics for each crop type. The model rules consist of if–then conditional statements. The results showed that the model produced crop classification maps that closely resembled the spatial distribution trends observed in the NASS CDL.

IV. DISCUSSION

Crop classification is important for planning and management of agricultural crops. Satellite image plays a significant role on it. The success of an image classification depends on many factors. The availability of high quality remotely sensed imagery and ancillary data, the design of a proper classification procedure, and the analyst's skills and experiences are the most important ones. For a particular study, it is often difficult to identify the best classifier due to the lack of a guideline for selection and the availability of suitable classification algorithms to hand. In the conventional unsupervised classification method, the analyst has limited control over the menu of classes and their specific identities which causes the use of unsupervised classification unsatisfactory. The advantage of supervised classification relative to unsupervised classification is the operator can detect errors and often remedy them. The disadvantage of this approach are training data can be time consuming and expensive and tedious undertaking, even if ample resources are in hand. Also training data selected by the analyst, may not be representative of conditions encountered throughout the image. Another disadvantage of supervised classification is it is prone to human error. Crop classification has also been done by various scientists using supervised classification technique as well as soft computing techniques. The combination of different classification approaches has shown to be helpful for improvement of classification accuracy (Benediktsson and Kanellopoulos 1999, Steele 2000).

V. CONCIUSION

From the present review of crop classification using different techniques, the following points can be highlighted in brief:

- Fuzzy classification has been utilized to better categorize the area where vegetation is heterogeneous. Some of the results have been compared with supervised classification and found to be better.
- Fuzzy logic takes advantage of already created simple rules and image classification resulting in equal or even less time consuming than the other conventional methods.
- The fuzzy c-means classifier proved to be a promising tool to build models for multivariate studies by identifying proper parameters and making use of the interpretation of remotely sensed data.
- Neural networks or neuro-fuzzy models have also been applied in few studies where the performance was better than the other classification techniques. The improved neuro-fuzzy image classification system is based on the synergism between neural networks and fuzzy expert systems which incorporates the best of both technologies. So along with hard techniques, we can adopt soft classification techniques for a better output.

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