Rice fields identification using multi-temporal Satellite images

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Abstract: determination of rice yield in a region needs to be done after identification of rice fields in that area. In this paper, using satellite images, rice fields identification has been performed in Mazandaran province which is located off the Caspian sea, in the North of Iran.

The research area is located at 36^o, 21'N to 36^o, 43'N and 52^o, 20'E to 52^o, 44'E (36km* 40km).

To identify rice fields in the rice growing season of the year, LISS-III sensor images of IRS-1D satellite was used. Four images; two from growing and two from non-growing season of rice were used. Geometric corrections of images were done using ground control points. Many sample areas of rice fields and different non-rice fields were chosen and their perimeters were found using GPS. With the acquired GPS information the sample areas were located on satellite images.

The field reflections in near infrared and red bands of the four images were used to train a MLP neural network for classification of rice and non-rice fields.

Principal component analysis was used to decrease the dimension of input samples to the network. The network was trained for different cases where different dimensions of input samples and different No. of neurons for the hidden layer were used.

Using validation set the optimized network was chosen. It provides an overall accuracy of %98 and a kapa coefficient of 0.96 on the test set.

Keywords : rice field identification, principal component analysis, MLP neural network.

Introduction:

With increase in the population of the world, changes in agricultural fields' use are increased. Agricultural management organizations need to have correct, accurate and up-to-date information from agriculture fields' changes, crop areas and crop yield estimation. Continuous and reliable information of varieties and areas of different crops and conditions of their growth are important components which can be used in price policy-making and imports and exports planning.

Data collection is time consuming and costly by traditional procedures. With the development of satellite technology, researchers can now use satellite images to produce earth resource information widely and quickly. Today satellites are used in earth and natural resource management efficiently. Satellite images can be used to determine crop kind, crop area, crop yield and soil fertility in agricultural fields.

During the last 20 years statistical classification methods such as minimum distance and maximum likelihood classifiers have been widely used. These methods have some limitations such as assumption of a certain distribution for data.

In the last decade artificial neural networks (ANN) were used as more powerful and more accurate classifiers than statistical classifiers in remote sensing applications [1].

Estes et.al. [2] performed preliminary studies on the use of ANN as classifiers for remote sensing information. Benediktson et.al. concluded that ANN classifiers produce more accurate results than maximum likelihood classifiers do [3]. Other researchers also confirm such conclusions [4,5,6].

Chen [7] and Hara [8] used neural networks for classification of earth surface cover in radar images. Bischof [9] and Heermann [10] used multi-spectral images in their ANN approach for the classification of earth surface cover.

The region under the research:

The research area is located at 36^o, 21'N to 36^o, 43'N and 52^o, 20'E to 52^o, 44'E (36km* 40km). It is a part of Mazandaran province which is located off the Caspian Sea in the North of Iran (Fig. 1).

To identify rice fields in the rice growing season of year, LISS-III sensor images of IRS-1D satellite were used. Four images; two from growing and two from non-growing season of rice were used. They are dated as Nov.2002, June 2003, Aug. 2003 and Feb. 2003 (Fig.2). The June and August images are from the growing season.

Non-systematic geometric corrections were done to relate satellite images with geographical co-ordinates system. The co-ordinates of the earth control points were found using GPS and the June image was corrected using co-ordinates of those points. Corrections on other images were done using the June image.

In Mazandaran province two kinds of rice are mainly grown; low-yield and high-yield. The low-yield rice has a shorter period of growth. The rice growth season starts at mid April and continues to the end of September.

Many sample areas of low-yield and high-yield rice fields and different non-rice fields were chosen and their perimeters were found using GPS. With the acquired GPS information the sample areas were located on satellite images

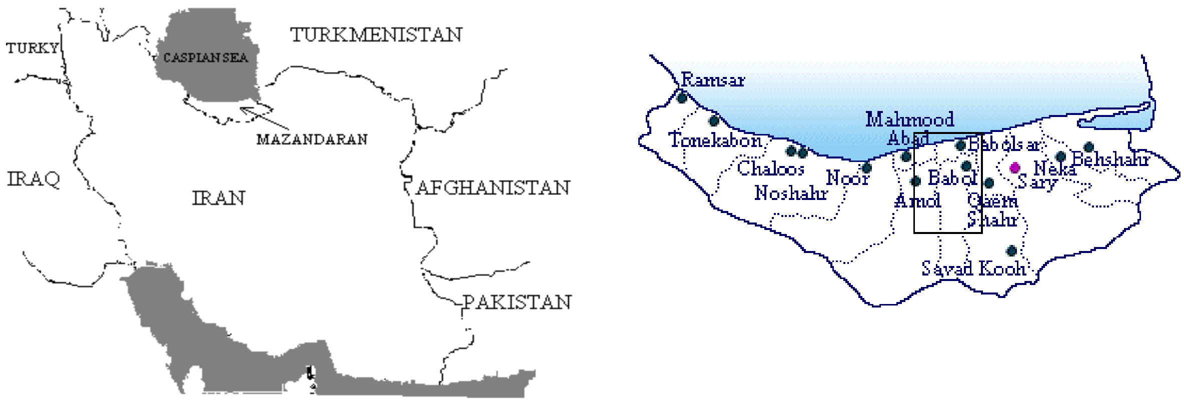
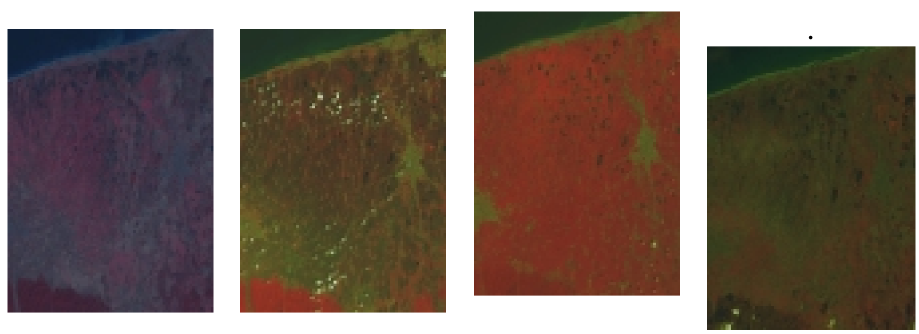


Fig. 1: The region under the research



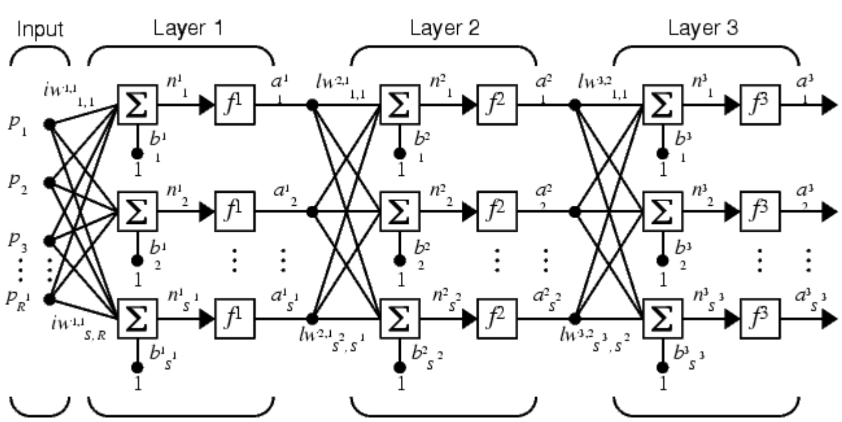
a b c d

Fig. 2: LISS-III sensor images shown with pseudo colors:

a) Nov. 2002, b) June 2003, c) Aug. 2003 and d) Feb.2003.

ANN Classifier:

A MPL neural network was used for identification of rice fields. MLP is a multi-layer feed-forward neural network which has one input layer, one or more hidden layers and an output layer. Each layer consists of a number of neurons and different transfer functions can be used for each layer (Fig. 3)



$$a^1 = f^1(IW^{1,1}p + b^1) \quad a^2 = f^2(LW^{2,1}a^1 + b^2) \quad a^3 = f^3(LW^{3,2}a^2 + b^3)$$

$$a^3 = f^3(LW^{3,2} f^2(LW^{2,1} f^1(IW^{1,1}p + b^1) + b^2) + b^3)$$

Fig. 3: Architecture of the MLP network

Feature extraction is an important issue in statistical pattern recognition. It is a process in which data is transformed to another space called feature space in a way that initial data is represented with a smaller set of data (features) which contain most of the information of the initial data. Principal component analysis (PCA) was used in work to reduce the dimension of input samples to the network. It is a method which transforms the initial data to feature space in a way that samples have maximum variance in the first few dimensions [11].

The MLP network used in this work has two classes of rice and non-rice. It has two hidden layers and one output layer. Each sample has 12 dimensions which are near infrared, red and green components of the four images.

The network was trained for several cases by changing network variables as follows and the one providing the best results was chosen as the optimal network:

1- Different network inputs:

Two kinds of input were considered for the network.

a) Color components of each image sample were used as inputs.
b) PCA Components of the train set were used as inputs; K vectors with maximum eigenvalues are chosen and projections of original samples on these vectors are derived and their values are used as network inputs. The network was trained for K ranging from 6 to 11.

2- No. of neurons in the hidden layer:

The No. of neurons in the first hidden layer was chosen equal to the input dimension and for the second layer is was changed from 2 to 12.

3- Layer functions:

The Purelin function was used for the output layer and the Logsig and Tansig functions were used for the hidden layer in two different cases.

4- Representation of classes:

In order to have better convergence for a back-propagation algorithm it is important to have desired values of classes in the range of stimulating functions [11]. Since values of Logsig functions are between 0 and 1 and values of Tansig functions are between -1 and 1, for Logsig function $\begin{bmatrix}\alpha \\ 1-\alpha\end{bmatrix}$ and $\begin{bmatrix}1-\alpha \\ \alpha\end{bmatrix}$ were considered for rice and non-rice classes and for Tansig functions $\begin{bmatrix}-1+\alpha \\ 1-\alpha\end{bmatrix}$and $\begin{bmatrix}1-\alpha \\ -1+\alpha\end{bmatrix}$were considered for those classes respectively. α Ranges from 0 to 0.3 with step size of 0.05.

In all of the above cases Levenberg Marquardt optimization method for network learning was used [12].

Results:

To choose the optimum network, mean performance of the network was calculated in each case where training was accomplished for five times. The network which resulted in maximum Kapa coefficient on the validation set was considered as the optimum network. In this network input vectors have 10 dimensions which are produced by PCA. The hidden layer has 10 neurons with Logsig function used for it. Purelin function was used for the output layer. Classes are represented by $\begin{bmatrix} 0.25 \\ 0.75 \end{bmatrix}$ for rice and by $\begin{bmatrix} 0.75 \\ 0.25 \end{bmatrix}$ for non-rice.

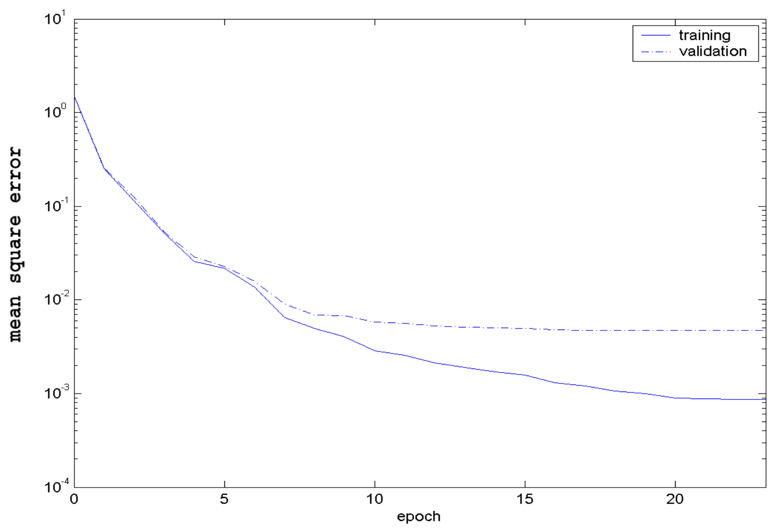


Figure 4 shows learning curve of the optimal network.

Results for the learning and performance of the network for each class are shown in table 1. Also results for the network performance for 3 different sets are represented in table 2. According to this table the overall accuracy of the network for these 3 test sets is %98.82 with a Kapa coefficient of 0.916 which is considered excellent by Landis and Koch [13]

Table 1: Results of learning and performance of the optimal network

Set	Correct identification (none-rice)	Correct identification (rice)	Overall accuracy (%)	Kapa coefficient
Train	%99.15	%99.62	99.37	0.987
Validation	%98.42	%97.46	97.97	0.959
Test	%98.24	%97.66	97.97	0.959

Table 2: Results of the rice field identification model for three new sets

Variety	No. of Samples	Non-rice	Rice	Correct identification
Non-rice	2114	2050	64	%96.27
Rice	4627	4610	17	%99.63
Rice	514	5	509	%99.53

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