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Object Based Image Analysis of High Resolution Satellite Image using Radial Basis Function Neural Network and Curvelet Transform

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ABSTRACT

Image-object extraction is one of the most important parts in the image processing Object-based image analysis (OBIA) method classify individual pixels directly, This method first aggregates image pixels into spectrally homogenous image objects by using an image segmentation algorithm and then classifies the individual objects using any classifier. Image segmentation is one of the most important pre-processing stages in computer vision to classify similar pixels to one cluster. Clustered pixels have the same attributes such as texture, color and intensity. The most famous segmentation techniques are edge based techniques, region based techniques, clustering based techniques and watershed based techniques. To overcome non continuity and non differentiability there is an introduction of a new method based on the curvelet transform, which represents edge better than wavelet. My work is related to extracting objects from images by detecting edges based on the watershed and curvelet transform.

Key words: Curvelet, Multi-resolution Analysis, Image Segmentation, Watershed Transform

INTRODUCTION

Object based image analysis provides a powerful tool for analysis and classification of high spatial resolution imagery compared to the traditional per-pixel classifiers. The best part of object based classification is that the object characteristics such as shape, texture, spatial relationship and spectral response can be used for classification. Object based image classification technique does not operate directly on single pixels, but image objects which refer to homogeneous, spatially contiguous regions. These are obtained by dividing an image, which is a challenging problem due to the fact that it is no longer meaningful to carry out this task on a pixel-by-pixel basis.

To solve the problem of complexity of high resolution image, the image is first segmented into homogeneous regions. Image classification involves three main steps Pre-processing, Feature extraction by image segmentation and classification by neural network. Among all satellite image classification methods Neural networks have the properties of parallel processing ability, adaptive capability for multispectral images, good generalization, fault tolerance and not requiring the prior knowledge of the probability distribution of the data. Although ANN classification methods are more robust, they have a few drawbacks, related in particular to the long training time requirement, and inconsistent results due to the use of random initial internodes weights. Most importantly, the structure of the network has a direct effect on training time and classification accuracy.

PROBLEM DEFINITION

In the conventional method classification units is pixels due to this image objects increases within class spectral variation and generally add the salt-and-pepper effects. The pixel-based classification produce unacceptable classification results in extracting the interest objects. In Haar Transform, it is not continuous and is not differentiable and also the segmented image curves are not accurate and sharp.

CURVELET TRANSFORM

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing. Wavelet transforms are based on small wavelets with limited duration. Wavelets locate where we concern. The wavelet transform provide a multiscale basis Althought multiscale can handle point discontinue well,but it is not optimal up to curve. Because the wavelet basis is isotropic, and the curve have direction so it take lot of coefficients to account for edges as shown in the figure

The Curvelet Transform includes four stages:

i. Sub-band Decomposition: Dividing the image into resolution layer. Each layer contains details of different frequencies:

P_0 – Low-pass filter.

$\Delta_1, \Delta_2, \ldots$ – Band-pass (high-pass) filters.

The original image can be reconstructed from the sub-bands:

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f)$$

ii. Smooth Partitioning: The windowing function w is a nonnegative smooth function. The energy of certain pixel (x_1, x_2) is divided between all sampling windows of the grid.

$$h_Q = w_Q \cdot \Delta_s f$$

iii. Renormalization: Renormalization is centering each square to the unit square $[0,1]\times[0,1]$.

$$g_Q = T_Q^{-1} h_Q$$

iv. Ridgelet analysis: Divides the frequency domain to dyadic squares

$|\xi| \in [2^s, 2^{s+1}]$

$$\alpha_{(Q,\lambda)} = \langle g_Q, \rho_\lambda \rangle$$

Fig.1 Curvelet & Wavelet coefficient

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks are commonly used in pattern classification, function approximation, optimization, pattern matching, machine learning and associative memories. They are currently being an alternative to traditional statistical methods for mining data sets in order to classify data. Artificial Neural Networks are well-established technology for solving prediction and classification problems, using training and testing data to build a model. However, the success of the networks is highly dependent on the performance of the training process and hence the training algorithm. It has training feed-forward neural networks to classify different data sets which are widely used in the machine learning community. Artificial neural networks (ANN) are very important tools for solving different kind of problems such as pattern classification, forecasting and regression. However, their design imply a mechanism of error-testing that tests different architectures, transfer functions and the selection of a training algorithm that permits to adjust the synaptic weights of the ANN. This design is very important because the wrong selection of one of these characteristics could provoke that the training algorithm be trapped in a local minimum. Because of this, several met heuristic based methods in order to obtain a good ANN design have been reported.

Supervised RB Neural Network Training

The RBF Mapping can be cast into a form that resembles a neural network. The hidden to output layer part operates like a standard feed-forward MLP network, with the sum of the weighted hidden unit activations giving the output unit activations. The hidden unit activations are given by the basis functions $\varphi_j(\mathbf{x}, \alpha_j, \sigma_j)$, which depend on the “weights” $\{\alpha_{ij}, \sigma_j\}$ and input activations $\{x_i\}$ in a non-standard manner. Intuitively, it is not difficult to understand why linear superposition of localised basis functions is capable of universal approximation.

Back Propagation Neural Networks

The network functions as follows: each neuron receives a signal from the neurons in the previous layer. Each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and passed through a limiting function which scales the output to a fixed range of values. The output of the limiter is then broadcast to all of the neurons in the next layer. So, to use the network to solve a problem, we apply the input values to the inputs of the first layer, allow the signals to propagate through the network, and read the output values.

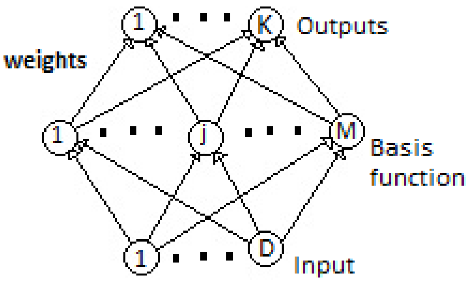

Fig.2 Radial basis function mapping

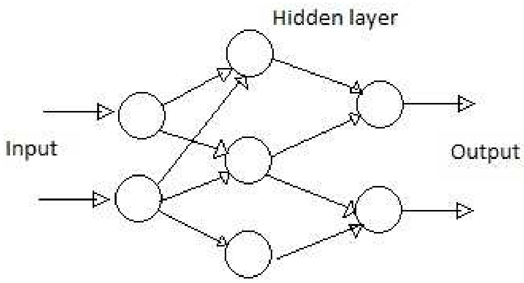

Fig.3 Back propagation neural network

The back propagation learning process works in small iterative steps: one of the example cases is applied to the network, and the network produces some output based on the current state of its synaptic weights (initially, the output will be random). This output is compared to the known-good output, and a mean-squared error signal is calculated. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated to reduce the error signal for the case in question. The whole process is repeated for each of the example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below some pre-determined threshold. At this point we say that the network has learned the problem "well enough" - the network will never exactly learn the ideal function, but rather it will asymptotically approach the ideal function. Back propagation is a form of supervised learning for multi-layer nets, also known as the generalized delta rule. Error data at the output layer is "back propagated" to earlier ones, allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications.

IMPLEMENTATION DETAILS

The methodology includes image acquisition, image segmentation data pre-processing, Artificial Neural Network training, image classification (using pixel based and object based feature extraction), post classification using accuracy assessment. It also highlights how the Curvelet transform helps in achieving the accurate Segmented Image.

Preprocessing

Gaussian filtering is done by convolving each point in the input array with a *Gaussian kernel* and then summing them all to produce the output array.

Remember that 2-D Gaussian can remember as:

$$G_0(x,y) = Ae^{\frac{-(x-\mu_x)}{2\sigma_x^2}+\frac{-(y-\mu_y)}{2\sigma_y^2}},$$

here μ is mean and σ is variance.

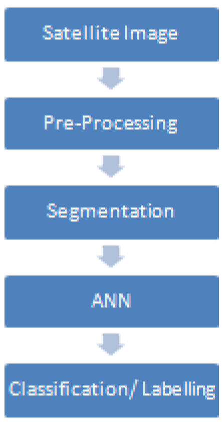

Fig.4 Implementation details

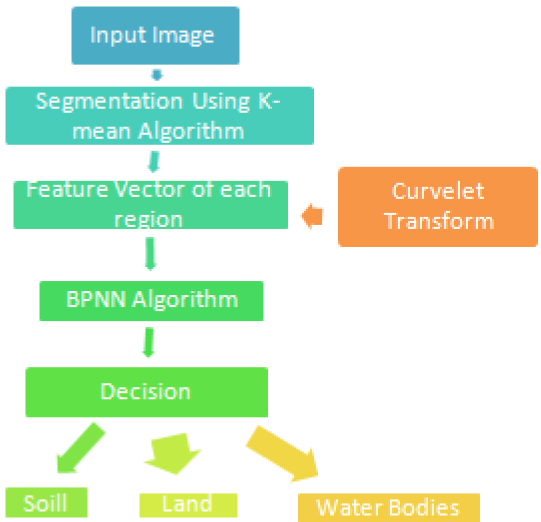

Fig.5 Flowchart

Multi-resolution Segmentation Using Wavelets

A necessary prerequisite for object oriented image processing is successful image segmentation. The multi-resolution segmentation produces highly homogeneous image objects in arbitrary resolution on different types of data.

Object-Based Supervised Image Classification

The largest common boundary between two objects should be merged which were two separate regions due to over segmentation. The output layer responses of the RBFNN are scaled by dividing each response by the sum of all the responses and used as initial label likelihoods. These likelihoods are iteratively updated using the Relaxation labeling technique by drawing support for each label from the neighboring segments.

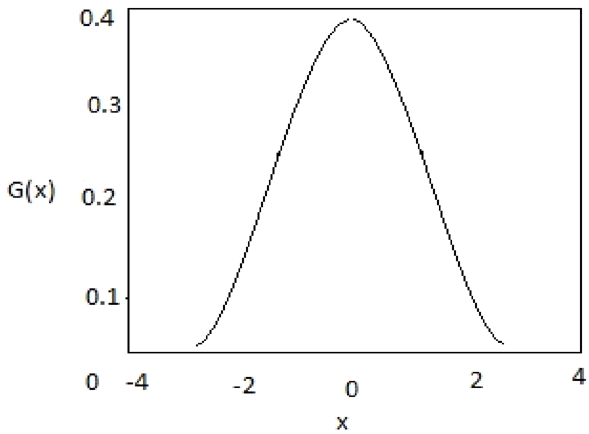

Fig.6 Gaussian Filter

Fig.7 Adaptive Gaussian Filter Output

Fig.8 Segmentation superimposed on input image

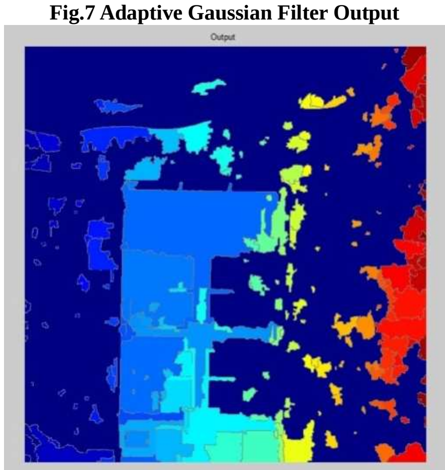

Fig.9 Segmented output

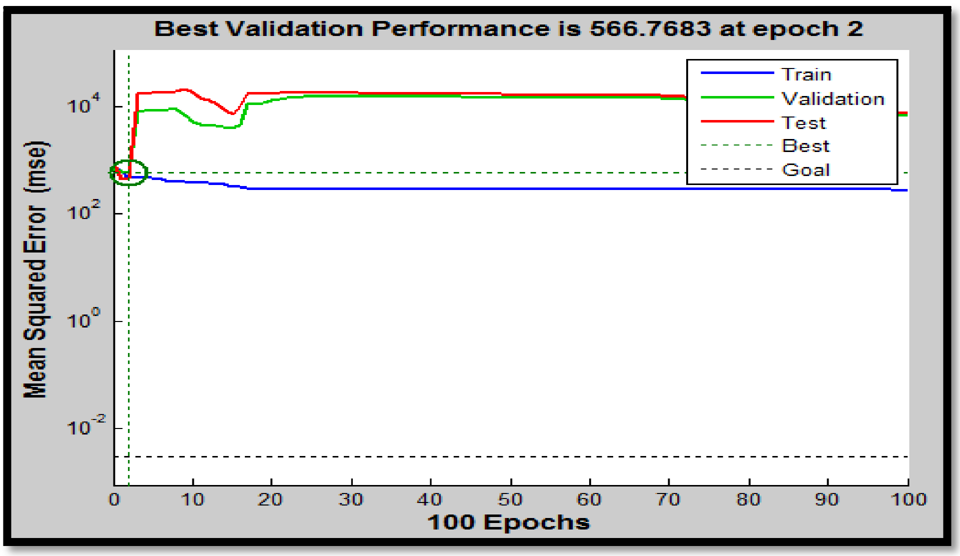

Fig.10 Training state

The Learning Process

The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms: Associative mapping in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units. The associative mapping can generally be broken down into two mechanisms:

(i) *Auto-association*: an input pattern is associated with itself and the states of input and output units coincide. This is used to provide pattern competition, i.e. to produce a pattern whenever a portion of it or a distorted pattern is presented. In the second case, the network actually stores pairs of patterns building an association between two sets of patterns.

(ii) *Hetero-association*: is related to two recall mechanisms:

- *Nearest-neighbor* recall, where the output pattern produced corresponds to the input pattern stored, which is closest to the pattern presented, and
- *Interpolative* recall, where the output pattern is a similarity dependent interpolation of the patterns stored corresponding to the pattern presented. Yet another paradigm, which is a variant associative mapping, is classification, i.e. when there is a fixed set of categories into which the input patterns are to be classified.

These are the image taken for the training of neural network.

Fig.11 Training Input

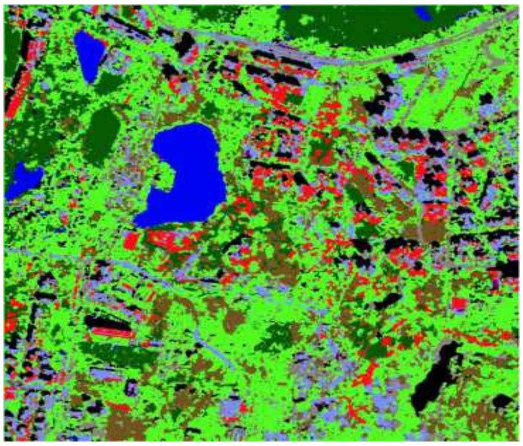

Fig.12 Training Output

CONCLUSION

In proposed image classification system a new approach using Curvelet transform, Radial Basis Neural Network and Back propagation Neural Network has been introduced. The correlation coefficient, mean and standard deviation features of the various combinations coefficients produced by Curvelet transform. A number of Texture images not considered in the work have been analyzed and have been found working within the range 86.2- 99.06% of the performance and also the segmented.

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