REDUCED COMPUTATIONAL COMPLEXITY OF HYPER SPECTRAL IMAGE USING HYBRID INTELLIGENCE

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ABSTRACT

Hyper spectral data contains both spatial and spectral information by hyper spectral sensors in remote sensing application. In this proposed method, hybrid intelligence is widely used to reduce the overall accuracy. In that, Artificial neural networks (ANNs) are used to address the dimensionality issues. Major problem of computation complexity of hyper spectral image can be reduced by using Particle Swarm Optimization (PSO) algorithm and Knowledge encoded Genetic Algorithm (KE-GA).The proposed model thus explores jointly the advantages of ANNs and Particle Swarm Optimization (PSO). This hybrid intelligence is justified in land covers classification of HSI images acquired by different remotely placed sensors.

Index term: Hyper spectral data, Artificial neural networks (ANNs), Particle swarm optimization (PSO) , Knowledge encoded Genetic Algorithm (KEGN).

INTRODUCTION

The recent development of hyper spectral sensors and image-data analysing software it is one of the most significant breakthroughs in remote sensing. Hyper spectral imaging provided by lower-cost, convenient devices that still carry premium accurate data has become a vital tool for researchers [1]. The ability of these devices to enhance and enable day-to-day monitoring promises to create a new paradigm of agricultural efficiency. Some of the benefits of hyper spectral and multispectral imaging are that these technologies are: small cost ,give steadfast results, simple to use, permit for quick assessment, non-destructive, vastly perfect, and have a lane range of applications.

Remote sensing is in general the practice of collecting information from a distance. However, the term “remote sensing” was introduced in the 60’s when the first meteorological satellites were put in range. Hence, currently it is used to illustrate the acquisition of spectral information regarding Earth’s surface using satellite or aerial technologies. The major benefit of such technology over field measurements is that they provide information in large spatial scale [2]. The sequential magnitude of such data is also very valuable. Each day acquisition of the same province gives the opportunity to produce long-term time series of multiple data that can be used to monitor dynamic processes of Earth’s surface. Such processes include vegetation phonological or biochemical behaviour.

The spectral [3] information of a satellite instrument is very important and determines its prospective applications. According to the supernatural promise, the sensors can be regarded as as multispectral or hyper spectral while hyper spectral sensors possess the power to record detailed spectral attributes of Earth's surface through many continuous narrow spectral bands. The most common VI designed from outpost instruments is the Normalized Difference Vegetation Index (NDVI):

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \quad (1)$$

where R_{NIR} and R_{RED} are the reflectance of the red and the NIR band accordingly. NDVI

takes advantage of the single spectral characteristic to absorb in the red and reflect strongly in the NIR part. NDVI and other VIs are found to be strongly correlated with Leaf Area Index (LAI) that is a key component in ecosystem modelling. Therefore, city state remote sensing can provide spatially and temporally extended information that is valuable for ecosystem modelling. There is occurrence in giving out hyper spectral data. Furthermore, an ecology principal productivity model (ModSat) that uses multispectral satellite and ground meteorological data is developed and calibrate for several ecosystems. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.The most shows potential of these is the use of Artificial Neural Networks (ANNs), which are computational models inspired by biological conclusion making structures such as the brain.

An ANN is non linear adaptive learning information processing systems comprised of an interconnected network of functional computing elements that are usually refer to as neurons. ANNS have ability to learn through adaptive to accumulate knowledge of the classification in hyper spectral image. During learning, ANN modify their own topology network by adjusting weight that act on individual neuron’s interconnection. In proposed methodology follows the genetic algorithm (GA) and PSO algorithms used to reduce major issues of high computational cost [14]. Gas belong to larger class of evolutionary algorithms(EA), which obtain solutions to optimization problems using techniques inspired by natural advancement, such as heritage, alteration, mixture and crossover. Linear mixing models the ground as being flat and incident sunlight on the ground causes the materials to radiate some amount of the incident energy back to the sensor.

RELATED WORK

A. Hyper spectral image classification

Hyper spectral image classification having the limited number of labeled and unlabeled pixels it has attracted a lot of attention. Important problem is how to explore the relations among pixels in both spatial information and spectral data. Some of the following methods are introduced like stochastic minimum spanning forest for spatial-spectral taxonomy of hyper spectral image organization. Bearing in mind the current progress on semi-supervised learning, which has shown its superiority to address issue of small training samples, it has introduced in hyper spectral image classification.

B. Semi-supervised Technique

Training Samples are classified as Supervised Classification [2] and Unsupervised Classification. In supervised classification, it identifies known a priori through a combination of fieldwork, map analysis as training sites; the spectral characteristics of these sites are used to train the classification algorithm for eventual land cover mapping of the remainder of the image. In Unsupervised Classification, the supercomputer or algorithm automatically group pixels with similar spectral characteristics (means, standard deviations, etc.,) into unique clusters according to some statistically estimated criteria. The political analyst then re-labels and combined the spectral clusters into information classes. It is unnecessary to perform transductive learning by way of inferring a classification rule over the entire input space; however, in practice, algorithms formally designed for transduction or induction are often used interchangeably.

C. Principal component analysis

The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is perceptive to the relative scaling of the original variables. Consider a data matrix, X, with column-wise zero pragmatic mean (the sample mean of each column has been shifted to zero), where each of the n rows represents a dissimilar recurrence of the experiment, and each of the p columns gives a particular kind of datum (say, the results from a particular sensor).

Mathematically, the transformation is defined by a set of p-dimensional vectors of weights or loadings $w_{(k)} = (w_1, \ldots, w_p)(k)$ that map each row vector $X_{(i)}$ of X to a new vector of principal component scores $t_{(i)} = (t_1, \ldots, t_p)(i)$, given by

$$\boldsymbol{t_{k(i)}} = \boldsymbol{X_i . w_K}. \qquad (2)$$

D. Independent component analysis(ICA)

ICA finds the independent components (also called factors, latent variables or sources) by maximizing the statistical independent of estimated components [10]. The system works as follows: at any time, if a source i is active (y_i=1) and it is connected to the monitor $j(g_{ij} = 1)$ then the monitor j will observe some activity $(x_i = 1)$. Formally we have:

$$x_i = \vee_{j=1}^{N} (g_{ij} \wedge y_i) \, , i = 1,2, \ldots, m,$$

Where Λ is Boolean AND. This approach under moderate noise levels.

PROPOSED METHOD

In this part, we introduce the proposed combination of both particle swarm optimization Knowledge Encoded Genetic algorithm and Artificial neural networks (ANNs).

A. *Artificial neural network(ANNs)*

Aspect of the artificial neural network is that there are different architectures, which requires different types of algorithms, but evaluate to other compound system, a neural network is moderately simple if handled brightly. The training procedure of the network can selected to fit the purpose, for supervised and unsupervised training types. The benefits of ANN is that the output of the network for selective number of points can be used to find out the outcome for any other new point using the same parameters for interpolation and extrapolation An ANN is typically defined by three types of parameters: The interconnection pattern between the different layers of neurons 1.The learning process for updating the weights of the interconnections 2.The activation function that converts a neuron's weighted input to its output activation.3. Mathematically, a neuron's network function $f(x)$ is defined as a composition of other functions $g_i(x)$, which can further be defined as a composition of other functions. This can be suitably represented as a network structure, with arrows depicting the dependency between variables. A widely used type of symphony is the nonlinear subjective sum, where

$$f(x) = K\left(\sum_i \omega_i g_i(x)\right) \qquad (3)$$

where K is some predefined purpose, such as the hyperbolic digression. It will be fitting for the subsequent to refer to a collection of functions $g_i(x)$ as simply a vector $g = (g_1, g_2, \dots, g_n)$.

In proposed tactic combines the continuous training of artificial neural network together with data decline and maximum feature separation techniques such as independent component analysis (ICAs) and synchronized diagonalization of covariance matrices, for swift and perfect class of large HSI. In that each pixels represents an N dimensional vector *x* (N = bands=224 for the AVIRIS sensor). Let Z be the number of classes, R_z be the number of pixels in class *k* and R be the total number of pixels where R=$\sum_{k=1}^{Z} R_k$. The mean vector of this set, n is denoted by,

$$n = E(x) = \frac{1}{R}\sum_{i=1}^{R} x_i \qquad (4)$$

Where, E(*x*) is the expectation of *x*. The covariance matrix of the data set $\sum_x$ is given by,

$\sum_x$= E {(*x*-n) $(x-n)^T$}

$$= \frac{1}{R}\sum_{i=1}^{R}(x_i - n)\ (x_i - n)^T \qquad (5)$$

Profit of artificial neuron model ease can be seen in its mathematical description below:

$$y(k) = F\left(\sum_{i=0}^{m} w_i(k).x_i(k) + b\right) \qquad (6)$$

Where, $x_i(k)$ is input value in discrete time k where i goes from 0 to m, $w_i(k)$ is weight value in discrete time k where i goes from 0 to m, b is bias, F is a shift function, $y_i(k)$ is output value in distinct time k. Situation can be described with equation is given by,

$$y = \begin{cases} 1 \ if \ w_i x_i \geq threshold \\ 0 \ if \ w_i x_i < threshold \end{cases} \qquad (7)$$

The fact that interconnection can be done in numerous ways results in numerous possible topologies that are divided into two basic classes. Fig.1 shows these two topologies; the left side of the figure represent simple feed-forward topology (acyclic graph) where information flows from inputs to outputs in only one direction and the right side of the figure represent simple recurrent topology (semi-cyclic graph) where some of the information flows not only in one direction from input to output but also in opposite direction.

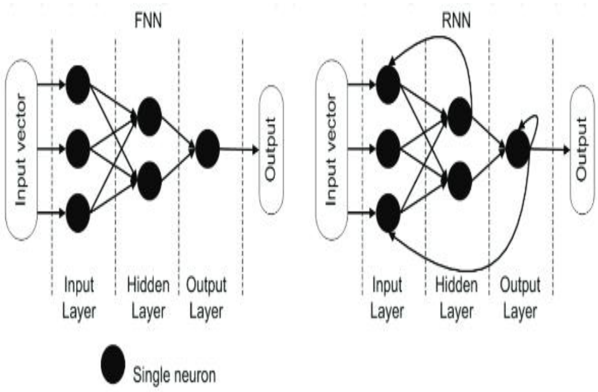


Figure1 : Feed-forward (FNN) and recurrent (RNN) topology of an artificial neural network.

B. Analysis of Genetic algorithm and PSO

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations [9]. In every iteration, each particle is modernized by following two "best" values. The first one is the best elucidation (fitness) it has achieved so far. (The robustness value is also stored.) This assessment is called pbest. Another "best" assessment that is tracked by the particle swarm optimizer is the finest value, obtained so far by any particle in the residents [11]. This best significance is a global best and called gbest. After that, gross primary productivity is determined in this hybrid method. Using this calculation accuracy of the hyper spectral image obtained.After finding the two best values, the particle updates its velocity and positions with following equation (a) and (b).

v [ ] = v[ ] + c1 * rand() * (pbest [ ] – present [ ]) + c2 * rand() * (gbest [ ] – present [ ]) (a)

present [ ] = persent [ ] + v[] (b)

where v [ ] is the particle velocity, persent [] is the current particle (solution). Pbest [] and gbest [] are defined as stated before. rand () is a random number between (0,1). c1, c2 are learning factors. Usually c1 = c2 = 2.

PSO follows the below steps: 1. First to initialize the input image. 2. After that initialize the particle of the image. 3. Evaluate the fitness of the hyper spectral image with different regions. 4. PSO and knowledge encoded genetic algorithm is applied to achieve the accuracy of an image.5. Parameters are optimized in next step. 6. If classification accuracy determined it will move on optimization separating the hyper plane. If accuracy is not cleared again this step is processed until classification accuracy might be achieved. From these procedure, we can learn that PSO shares many common points with GA [13]. Both algorithms start with a group of a randomly generated population, both have fitness values to evaluate the population. Both update the population and search for the optimium with random techniques. Both systems do not guarantee success. In particle swarm optimization, consider a fitness function:

$$f : R^n \rightarrow R \quad (8)$$

However, PSO does not have genetic operators like crossover and mutation. Particles update themselves with the internal velocity. They also have memory, which is important to the algorithm. A 3-layer ANN [8] is used to do the classification. There are 4 inputs and 3 outputs. So the input layer has 4 neurons and the output layer has 3 neurons. One can evolve the number of hidden neurons. However, for demonstration only, here we suppose the hidden layer has 6 neurons. We can evolve other parameters in the feed-forward network. Here we only evolve the network weights. So the particle will be a group of weights, there are 4*6+6*3 = 42 weights, so the particle consists of 42 real numbers. The range of weights can be set to [-100, 100] (this is just a example, in real cases, one might try different ranges). After encoding the particles, we need to determine the fitness function. For the classification problem, we feed all the patterns to the network whose weights is determined by the particle, get the outputs and compare it the standard outputs. Then we record the number of misclassified patterns as the fitness value of that particle. Now we can apply PSO to train the ANN to get lower number of misclassified patterns as possible. There are not many parameters in PSO [14] need to be adjusted. We only need to adjust the number of hidden layers and the range of the weights to get better results in different trials.

From the above case, we can learn that there are two key steps when applying PSO to optimization problems: the representation of the solution and the fitness function. One of the advantages of PSO is that PSO take real numbers as particles. It is not like GA, which needs to change to binary encoding, or special genetic operators have to be used. For example, we try to find the solution for f(x) = x1^2 + x2^2+x3^2, the particle can be set as (x1, x2, x3), and fitness function is f(x). Then we can use the standard procedure to find the optimum. The searching is a repeat process, and the stop criteria are that the maximum iteration number is reached or the minimum error condition is satisfied. There are not many parameter need to be tuned in PSO. Here is a list of the parameters and their typical values. The number of particles: the typical range is 20 - 40. Actually for most of the problems 10 particles is large enough to get good results. For some difficult or special problems, one can try 100 or 200 particles as well.

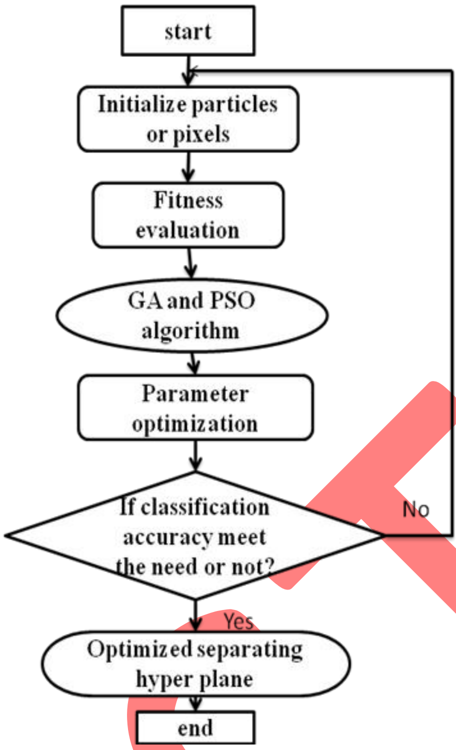


Figure 2: flow chart for PSO and GA

C. Experimental results

Without independent ground truth to validate the NN classification results, a small fraction of the ROI pixels were used to train the networks. The remaining pixels from the ROIs were then used to test the classification performance of the NN. Specifically, 8-12 randomly selected pixels from each class were used to train the NNs. As a result, a reasonable number of pixels were left in the ROIs to test the network classification accuracy. A pixel is ‘correctly ‘classified if its network activation level is the highest of all networks and exceeds the threshold. Index values can range between -1.0 and 1.0, but vegetation has values that typically range between 0.1 and 0.7. The particles' data could be anything. In the pixels example above, the data would be the X, Y, Z coordinates of each pixels. If the data is a sample or series, then entity pieces of the data would be manipulated until the pattern matches the target pattern. The velocity value is calculated according to how far an individual's data is from the objective. Vmax, it determines the maximum change one particle can take during one iteration. Frequently we set the array of the particle as the Vmax for example, the particle (x1, x2, x3) X1 belongs [-10, 10], then Vmax = 20.

The maximum number of iterations the PSO [14] execute and the minimum error requirement. For example, for ANN preparation in previous section, we can set the bare minimum error necessity is one mis-classified pattern. This stop condition depends on the problem to be optimized. An overall different approach is to find clusters based on pattern in the data matrix, frequently referred to as biclustering, which is a method frequently utilized in bioinformatics. Hyper spectral image is taken as input and image is improved using the ANNs technique to adapt to low dimensional data and clustering algorithm useful to calculate the performance effectiveness of different regions and tenancy of the region.

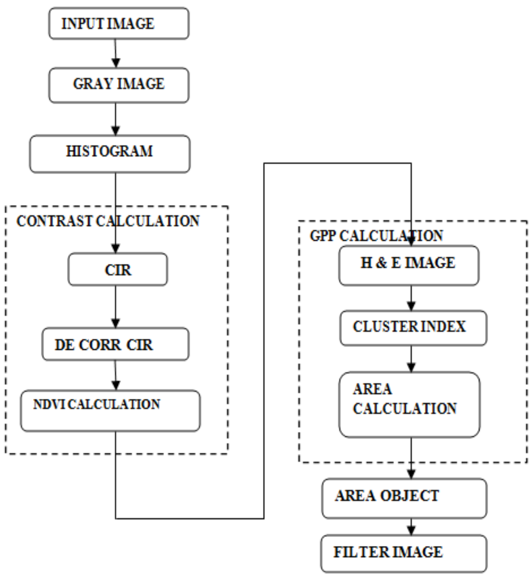
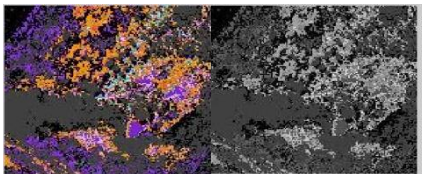
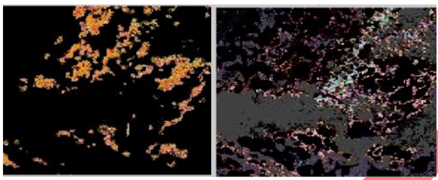


Figure 3: Proposed model

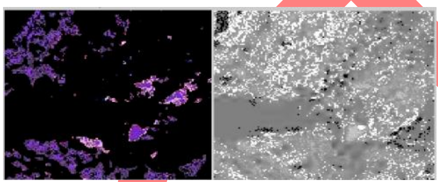
Hyper spectral image is taken as a input and image is pre-processed and enhanced. The input image consists of the different large dimension spatial and spectral bands. High dimensional input image is converted into the low dimensional data. After that, this input image is converted into gray scale image that is RGB value will be same. Then, histogram is calculated by using input of the spectral bands. This, low dimensional image is given into contrast process. In this process, hyper spectral image is evaluated following steps : CIR, DE CORR, and NDVI. The objective of Normalized difference vegetation index (NDVI) is to estimate a value indicate of certain vegetation attributes. These spectral reflectance are themselves ratios of the reflected over the incoming radiation in each spectral band independently, hence they take on ethics between 0 and 1.0. The use of NDVI itself thus varies between -1.0 and +1.0. It should be noted that NDVI is functionally, but not linearly, comparable to the easy infrared/red ratio (NIR/VIS). The advantage of NDVI over a simple infrared/red ratio is therefore generally limited to any possible linearity of its functional relationship with vegetation properties. NDVI image is given to Gross Primary Productivity (GPP) calculation. GPP is the total primary productivity of an eco system. After applying area calculation the final filtered image is obtained. The algorithm assigns a feature selection to a cluster according to a maximum weight pattern selection overall clusters. The most efficient algorithm is hybrid intelligence which is widely used to reduce the computation efficiency and also dimensionality of hyper spectral image.



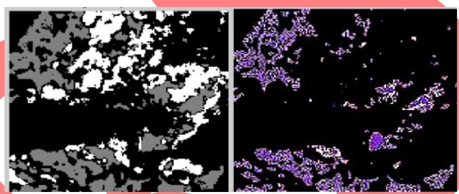
(a)Input image (b)gray image



(c) CIR (d) H&E image

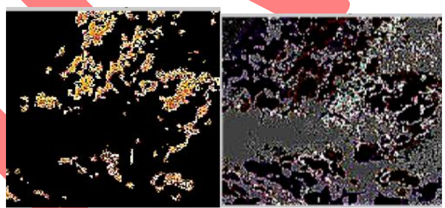


(d) DE CORR (f) NDVI



(g) cluster index (h) area object

GPP value=3981.25



(i)GPP value=3981.2 (j) filter image

Figure 4: Classification of image with different region

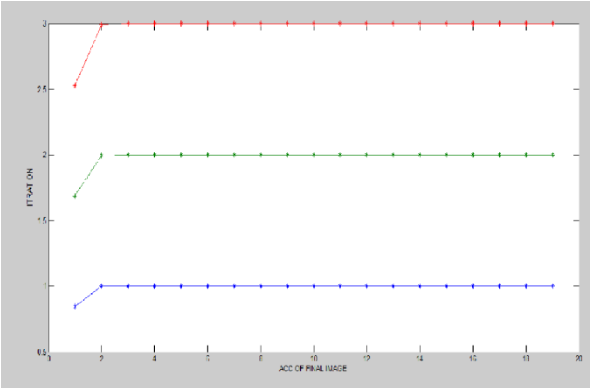


Figure 5: Accuracy graph

CONCLUSION

In this paper, we proposed a hybrid intelligence framework for hyper spectral image sensing. This algorithm shown, challenge to see how far the result becomes better by taking different number of hidden layers and nodes. So better result could be expected by taking more number of test points where the error values are more. It was observed that the parameters of ANN [8] remains fixed while the dimension can be increased by taking more test points. The learning constant used has the effect for the convergence of ascent error.The high spectral and spatial resolution hyper spectral image sensing requires correction for platform motions and this has been accomplished using PSO, GA, artificial neural network (ANN) and filtering algorithms. This spectral resolution has opened the door to a series of city-dweller and armed forces applications is actually successfully employed in many other fields like; land use, cultivation assessment, natural and green monitoring, ground-cover classification, asphalt characterization, healthcare and pharmaceutical sectors, mineral exploitation, change detection, man-made materials identification and detection, target activities, and surveillance . The method provides excellent generalization as the derivation at test points never deviates more to that of exact one.

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