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PSO Based SVM for Optimizing Classification in Remotely Sensed Images

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***Abstract*— This paper includes a prospective approach of developing an efficient algorithm for classification of remotely sensed images. Image classification is the first and foremost step in remote sensing applications. Classification using SVM is a efficient technique which when optimized with the particle swarm intelligence will yield better classification accuracy. The main focus will be on the boundary pixels that are misclassified by standard SVM and other conventional methods.**

***Index Terms*— Image classification, Remotely sensed images, SVM, Fuzzy, PSO etc.**

1. INTRODUCTION

Dealing With The Background Of Prospective Approach

Remote sensing image classification is a prerequisite for remote sensing applications. Image Classification uses the spectral information represented by the digital numbers in one or more spectral bands, and tries to find each individual pixel based on this spectral knowledge

The objective is to allocate every pixel in the image to particular classes or themes. The ensuing classified figure is comprised of a mosaic of pixels, every of which fit in to a fuzzy theme, and is fundamentally a thematic "map" of the original image.

An outline of the main stages in an end to end classification of land cover using remotely sensed data is given. The success of the consequential types depends on making the Correct decisions in relation to substantial lots of choices. The vital use of the land coat products should be the over-riding factor in making all these decisions.

In the case when the number of training data is small, SVMs outperform traditional classifiers .in other hand when we increase margins performance of traditional classifiers can be easily improved.

Image Classification: uses the spectral information represented by the digital numbers in one or more spectral bands, and tries to find each individual pixel based on this spectral knowledge. The objective is to allocate every pixel in the image to particular classes or themes (e.g. water, coniferous forest, deciduous forest, corn, wheat, etc.).

The ensuing classified figure is comprised of a mosaic of pixels, every of which fit in to a fussy theme, and is fundamentally a thematic "map" of the original image.

A Selection of Images: usually, the victory of a land cover classification can lie in the astute selection of imagery with respect to season and date. So the apparently ordinary process of searching image archives for suitable data assumes vital significance stemming from the need to answer questions such as: What season will provide the optimum contrasts between classes to be mapped?

Classification*:* Classification is one of the most widely used analysis techniques in RS (it is easy to collect class data relative to many continuous data). Good classification often relies on a good understanding of the RT state variables present and how they affect a class. If two classes have identical RT state variables, they cannot be distinguished Using RS data alone (this doesn't stop citizens from annoying, though!).

Procedures of Classification:

(a)*Supervised*
- *User-controlled process*
- *depends on knowledge and skills of analyst for accurate results.*

(b) *Unsupervised*
- *Primarily a computer process*
- *Minimal user input*

Unsupervised Image Classification

It can be defined as identification of normal groups, or structures inside multispectral data. Image pixels are examined and aggregated into a number of spectral classes based on natural clustering in multi-dimensional space and UC is the explanation, classification, labeling and mapping of natural spectral classes.

Assumption: A natural spectral groupings exist within a scene (inherently uniform in respect to brightness in several spectral channels; Spectral classes within a given cover class should "cluster" close together whereas data in different classes should be well separated.

(a)Supervised: define information categories and then examine their spectral severability.

(b)Unsupervised: determine spectrally separable classes and then define their informational usefulness.

Stages to Unsupervised Classification

There are various stages like Definition of minimum and maximum number of categories to be generated by the particular classification algorithm (based on an analyst's knowledge or user requirements), Random selection of pixels to form cluster centers, Algorithm then finds distances between pixels and forms initial estimates of cluster centers as permitted by user defined criteria, As pixels are added to the preliminary estimates, new class means are considered. This is an iterative method until the mean does not change significantly from one iteration to the next.

2. RELEVANT ANALYSYS

In the last few years, attention has been drawn to the support vector machine (SVM) for remotely sensed data classification. SVM are promising technique in remotely sensed image classification because they yield better results in the minimum available samples.

PSO

- PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms.
- PSO applies the concept of social interaction to problem solving.
- It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.
- Each particle is treated as a point in a N-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles.

3. PROSPECTIVE WORK

1. Take an input image.
2. Select the region of interest.
3. Apply SVM to train the model.
4. Apply Particle Swarm Optimization technique to optimize the SVM training.
5. Calculate Posterior Probability of each pixel.
6. Calculate Optimal threshold value of each pixel.
7. Compare the values of Posterior Probability with the threshold value.
8. If Posterior Probability <= threshold value
9. Classify each of the pixels and use connected components to combine the boundary regions.
10. Else
11. Classification of the interior pixels.

TABLE : RELEVANT PREVIOUS WORK

S. No.	Authors	Specific name	Description
1		Multispectral land use classification using neural networks and support vector machines: One or the other, or both?	In this paper, authors applied the SVM classification to the Landsat Thematic Mapper (TM) image classification and compared the results with the maximum likelihood classifier (MLC), the neural network classifier, and the decision tree classifier. The results show that the SVM achieved higher classification accuracy than those of the other classifiers [1]
2	Giorgos Mountrakis, Jungho Im	"Support vector machines in remote sensing: A Review""	Studied a wide range of methods for analysis of airborne- and satellite-derived imagery continues to be proposed and assessed [2]
3	Foody	"A Relative evaluation of multiclass image classification by support vector machines,"	The author applied the SVM algorithm to classify the airborne image, and the results indicated that the SVM often achieved a higher accuracy than those of other classification methods [3]
4	Chiang and Hao	Support vector learning mechanism for fuzzy rule-based modeling: A new approach,"	The author proposed an SVM-based fuzzy inference system which provides reliable performance in the cases of classification and prediction. [4]
5	Farid Melgani, Lorenzo Bruzzone	"Classification of Hyperspectral Remote Sensing Images With Support Vector Machines",	They considered the problem of the classification of hyper spectral remote sensing images by support vector machines (SVMs). [5]
6	Hua Zhang, Wenzhong Shi, and Kimfung Liu	"Fuzzy-Topology-Integrated Support Vector Machine for Remotely Sensed Image Classification",	The main idea of this was to obtain the significant boundary and the interior parts of the classification in the fuzzy topology space.The proposed approach was tested through two differentexperiments. The results demonstrated that the FTSVM approach can achieve higher classification accuracy than those of the standard SVM and other classification methods [6]

Particle Swarm Optimization to Optimize SVM

```
1.  Initialize max-iterations and number of particle and dimensions.
2.  for i= 1:no_of_particles
3.      for j= 1:dimensions
4.   particle_position(i,j) = rand*10;
5.   particle_velocity(i,j) = rand*1000;
6.   p_best(i,j) = particle_position(i,j);
7.      end
8.  end
9.  for count = 1:no_of_particles
10. p_best_fitness(count) = -1000;
11. end
12. for count = 1:max_iterations
13.     for count_x = 1:no_of_particles
14.         x = particle_position(count_x,1);
15.         y = particle_position(count_x,2);
16.         ker = '@linearKernel';
17.         global p1 ;
18.         p1 = x;
19.         C = y;
20.         trnX=X;
21.         trnY=Y;
22.         tstX=X';
23.         tstY=Y';
24.         [nsv,alpha,bias] = svmTrain(trnX,trnY,C);
25.         actfunc = 0;
26.         predictedY =
    svcoutput(trnX,trnY,tstX,ker,alpha,bias,actfunc);
27.         Result = ~abs(predictedY)
28.         Percent = sum(Result)/length(Result)
29.         soln = 1-Percent
30.                 if soln~=0
31.             current_fitness(count_x) =
    1/abs(soln)+0.0001;
32.         else
33.             current_fitness(count_x) =1000;
34.         end
35.     end
```

4. SIMULATION WORKFLOW

We will be implementing the proposed work on MATLAB for various remotely sensed Thematic mapper images and the work will be compared with previous FTSVM (Fuzzy topology Integrated support vector machine) and performances will be evaluated based on various parameters like kappa, confusion matrix etc.

5. CONCLUSION AND FUTURE WORK

The paper focuses on classification of satellite images using an optimization technique. The algorithm focuses on The SVM for optimization using PSO and hence improves the accuracy of classification as compared to the existing technique. Hence, the prospective algorithm goals in achieving better, efficient results of various performance parameters of SVM, simultaneously providing more classification accuracy as compared to previous SVM based methods.

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