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HMM Based Super Resolution of Geospatial Images For Flora Classification

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ABSTRACT
Identification of tree crowns from remote sensing requires detailed spectral information and sub meter spatial resolution imagery. Traditional pixel-based classification techniques do not fully exploit the spatial and spectral characteristics of remote sensing datasets. We propose a contextual and probabilistic method for detection of tree crowns in urban areas using a wavelet based super resolution and classification of the tree area. First the image is converted to super resolution image by using DWT, then we segment the image based on spectral information with green markers on the vegetation area. Segmentation with thresholding is considered as direct marker for the forest area.

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I. INTRODUCTION

1.1 Statement of the problem

Satellite and VHR/ Multispectral images differ from normal images in the sense that these images are essentially multi band images with each band representing a particular geographic property. On the other hand normal images are not band limited and represent the objects with colors. Therefore extracting the features and the properties of such images and marking particular object of interest are difficult. Beside normal resolution of such images cannot be used to properly identify the objects. Therefore in this work we utilize the super resolution concept and enhance the resolution of the image and further classify the cluster of pixels based on their properties.

1.2 Objective of the study

The objective of the work is to mark and segment the vegetation or the forest area in super resolution multispectral satellite images. First the work maps the given map image into different resolution and bands. It asks the user to mark the area of interest. Features from the area of interest are extracted. The original given image's resolution is increased and the image is segmented. The segmented pixels are classified for the object of interest and finally we obtain the high resolution mapped with marking on the areas where object of interest like forest lies.

1.3 Scope of the Project

The work can be used to automatically mark and classify the objects in the maps and analysis of geospectral data. The work can be further used for map element marking and classification which are two of the important aspects of geospatial data analysis. The work can find its usage in zooming the geospectral data. As satellite images and map data are entirely different from normal images, special technique is required to identify the bands and zooming such images.

II. IMPLEMENTATION

We consider the classification of a multispectral image y that consists of K spectral bands with spatial resolution R and pixel locations bi belongs B, where B is a M1 X M2 pixel matrix. In addition we assume a panchromatic image z with finer spatial resolution r < R. The super-resolution map (SR map) c is defined on the set of pixel locations A and covers the same extent on the ground as y and z with spatial resolution r. The scale factor S = R/r is an integer for common VHR images. Hence each pixel bi corresponds to the area on the ground covered by S2 finer resolution pixels
M1=256
M2=256
B is the pixel values of original Image.

A panchromatic image z is temporary image (we assume) in which r (resolution of y) <R (resolution of z)
S (scale) =R/r; means S is how much time we want y to be zoomed.We assume the existence of a multispectral image x defined on the set of pixels A with K spectral bands and fine spatial resolution r.Means x is the super resolution image with not all the colors of y but only those bands that are significant.Image x is not observed directly while images y and z are considered as spatial and spectral degraded observations of x respectively. That means if X is the super resolution image (we still don't have it) then y and z are smaller images to x and therefore are called degraded images.

Furthermore, we assume that each pixel in x can be assigned to a unique class: c (a)
Where a=1, 2, 3, 4…..

Class means spectral band or Image

$$y_k(b_i) = \frac{1}{S^2}\sum_{j=1}^{S^2} x_k(a_{j|i}),\ \ k = 1,\dots,K$$

Each pixel in y is derived from the degraded color model of X

$$z(a_{j|i}) = \frac{1}{K}\sum_{k}^{K} x_k(a_{j|i})$$

So y to be matched to z and z to be matched to x.

We therefore do not intend to estimate image x; instead we aim to find the SR map c that corresponds to the maximum a Posteriori probability (MAP) solution P(c/y,z) for c given observed data y and z.Note that this setup does not constrain the SR map c to the estimated class fractions of a soft-classification method, but it rather optimizes the c map regarding the spatial distribution of class labeled pixels and the spectral properties of y and z images.[don't calculate direct mapping from low resolution to high resolution: First find distinct classes, find intermediate image, map from low to intermediate]

Thus, according to Bayes' theorem, P (c|y, z) is computed from prior probability P(c) and conditional probabilities P(y/c) and P (z/c) as
$$P(c|y,z) \propto P(c)P(y|c)P(z|c)$$

So super resolution means Find those classes or colors that can be inter related in y and z

$$P(c) = \frac{1}{A_1}\exp\left(-\frac{U(c)}{T}\right)$$

$$P(y|c) = \frac{1}{A_2}\exp\left(-\frac{U(y|c)}{T}\right)$$

$$P(z|c) = \frac{1}{A_3}\exp\left(-\frac{U(z|c)}{T}\right)$$

$$P(c|y,z) = \frac{1}{A_4}\exp\left(-\frac{U(c|y,z)}{T}\right)$$

U© is the prior energy of pixels (Training Energy of the pixels which is known to the system) so we are finding the probability of a color that color in y that color in z and that color in y and z both. Called posterior probability
$$U(c|y,z) = \lambda U_c(c) + (1-\lambda)\big(\lambda_p U(z|c) + (1-\lambda_p)U(y|c)\big)$$

MRF is a mathematical tool that allows modeling the global spatial context in the image through local interactions of class labels in a neighborhood system. A comprehensive introduction to MRF is given in Li (2009).

First make set of classes in the image from colors. Then using neighborhood system, search for these classes as equation above.

2.2 MRF Algorithm

The core of the algorithm is based on [1, 2]. We collect pairs of low-res and high-res image patches from a set of images as training. An input low-res image is decomposed to overlapping patches on a grid, and the inference problem is to find the high-res patches from the training database for each low-res patch.

We use the kd-tree algorithm, which has been used for real-time texture synthesis [3], to retrieve a set of high-res, k-nearest neighbors for each low-res patch. Lastly, we run a max-product belief propagation (BP) algorithm to minimize an objective function that balances both local compatibility and spatial smoothness.

Image->L, H

Find values or patches so that they can be applied on L to obtain H Patch means the value to convert from Low to HIGH also called weight w in following equation

$$U(c) = \sum_{i,j} U\big(c(a_{j|i})\big) = \sum_{i,j} \sum_{l \in N(a_{j|i})} w(a_l) I\big(c(a_{j|i}), c(a_l)\big)$$

$$w(a_l) \propto \frac{1}{d(a_{j|i}, a_l)}$$

Weight depends upon distance between the colors of low resolution version and the high resolution one. We model spectral values x of a class a with the Gaussian distribution. (Multiply pixel values with Gaussian kernel to get new values)

2.3 Conditional energy function

$$U(y|c) = \sum_i \frac{1}{2} \left[M(y(b_i), \mu_i, C_i) + \frac{1}{2} \ln |\det C_i| \right],$$

Where M(y (bi), li, Ci) is the Mahalanobis distance between the feature vector y (bi) and the mean vector li with the covariance matrix Ci. The values li and Ci are modeled as linear mixtures of mean vectors and covariance matrices based on area proportions of respective land cover classes c (a/i) inside the pixel bi.

$$U(z|c) = \sum_{i,j} \frac{1}{2} \left[\frac{\big(z(a_{j|i}) - v_\alpha\big)^2}{\sigma_\alpha^2} + \ln \sigma_\alpha^2 \right]$$

III. CONCLUSIONS

The MRF-based SR imaging of Geospatial images proposed in this project considered energy Function in terms of the spatial smoothness prior and conditional probability of multispectral and panchromatic bands of QB images. The method provided acceptable results for tree detection in a residential area and was found to be operational over real and large data. This method performs considerably well and accurately. Inclusion of the panchromatic band led to an improvement of tree crown detection as compared to a model ignoring the panchromatic information. We estimated optimal parameter values for energy minimization in tuning subsets which are in agreement with previous experiences. We conclude that the method introduced in this study reduces the impact of insufficient spatial resolution as well as the large within-class spectral variance of VHR images, and can thus be recommended for urban tree inventories. Further the system can be improved by incorporating more distinct bands of energy for example VH,H,M,L,VL bands and by inferring a mapping probability amongst all bands. That should not only increase the accuracy of SR image classification, it should also produce better quality SR.

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