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Combining Spectral and Texture Information for Remote Sensing Image Segmentation

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Abstract: *Remote sensing image is taken as the input and converted into the gray scale image. Then the gray scale image is filtered by using Laplacian of Gaussian (LOG) filters. After that, the features are enhanced by using local spectral histogram. Then we are clustering the image using k-mean clustering. Moreover, the clustered image is segmented by using RGB colors. The SVD is calculated for error estimation and plot in the graph. The overall performance is good. Linear filters are used to provide enhanced spatial patterns. For each pixel location, we compute combined spectral and texture features using local spectral histograms, which concatenate local histograms of all input bands. We regard each feature as a linear combination of several representative features, each of which corresponds to a segment. Segmentation is given by estimating combination weights, which indicate segment ownership of pixels. We present segmentation solutions where representative features are either known or unknown. We also show that feature dimension scan be greatly reduced via subspace projection. The scale issue is investigated, and an algorithm is presented to automatically select proper scales, which does not require segmentation at multiple scale levels.*

1. Introduction

Image segmentation has been extensively studied. In remotesensing, a segmentation method should leverage the advancesmade in data acquisition, specifically the spectral and spatial resolution capability. Multispectral (MS) images, which are themain type acquired by remote sensing radiometers, provide much enhanced capabilities of characterizing ground objects. Meanwhile, high-resolution images contain rich texture information, which has been shown to improve segmentation results

Therefore, remote sensing segmentation methods areexpected to make use of both spectral and texture informationIn this paper, we use local spectral histogram representation which consists of histograms of filter responses in a localwindow. This representation provides an effective feature tocapture both spectral and texture information. However, asa form of texture descriptors, local spectral histograms alsosuffer from the problems of high dimensionality and boundarylocalization. To address these problems, we employ a recently proposed segmentation method, which formulates segmentationas multivariate linear regression. This method worksacross different bands in a computationally efficient way and accurately localizes boundaries. remote sensing images, segmentation is inextricablylinked to the scale issue. Conceptually, scale is a “window of perception”. It is well known that meaningful structuresand objects exist over a certain range of scales. In imageprocessing, a scale usually refers to the size of the operatorsor measurement probes used to extract information from imagedata. Improper scales can lead to oversegmentation, wheresegments correspond to portions of regions, or under segmentation, where one segment contains multiple land-cover classes.Due to the inherent multiscale nature of real-world objects,many multiscale segmentation algorithms have been proposed.

However, manual interpretation is typically neededin order to utilize the segmentation results at multiple levels, which inevitably involve subjectivity. Moreover, it has beenshown that, in specific cases, single-scale representation mightbe sufficient and more straightforward.

In this paper, wefocus on selecting a single scale: Based on our new formulation of the segmentation problem, we propose a scale selectionmethod to appropriately characterize spatial patterns and givea controlled smoothing effect.

2. EXISTING SYSTEM

Satellite images are automatically segmented which is useful for obtaining more timely and accurate information. Segmentation is realized by comparing similarities between different features of sub-regions. The image can be segmented into different regions that frequently correspond to different land-use or other objects. It can be potentially applied within a broad range of image segmentation. High spatial resolution satellite imagery has become an important source of information for geospatial applications. Automatic segmentation of high-resolution satellite imagery is useful for obtaining more timely and accurate information. In this paper, we develop a method and algorithmic framework for automatically segmenting imagery into different regions corresponding to various features of texture, intensity, and color. The central rationale of the method is that information from the three feature channels are adaptively estimated and integrated into a split-merge plus pixel-wise refinement framework. In the procedure for split-merge and refinement, segmentation is realized by comparing similarities between different features of sub-regions. The similarity measure is based on feature distributions. Without prior knowledge of image content, the image can be segmented into different regions that frequently correspond to different land-use or other objects. Experimental results indicate that the method performs much better in terms of correctness and adaptation than using single feature or multiple features, but with constant weight for each feature.

Disadvantages:

It does not make use of spatial information.

The number of clusters cannot usually be obtained directly and automatically. The feature extraction is difficult and the process is more complicated. There are two main problems associated with such texture descriptors framework.

First, applying multiple filters to spectral bands generates high-dimensional features.

As a result, not only is the computational cost high, but many clustering methods also fail to work for high-dimensional data.

The second problem stems from texture descriptors generated from the image windows crossing multiple regions, which cause difficulty in localizing region boundaries.

Morphological operations have limited forms and, thus, lack the ability to describe complex textures.

3. PROPOSED SYSTEM

Remote sensing image is used as an input image for segmenting the image. First, the input image is converted into the gray image and then filtered by Laplacian of gaussian (LOG) filters. Then the filtered image is enhanced by the histogram equalization's-mean clustering algorithm was used for clustering the image. After that the image is segmented by the RGB colors. The SVD is calculated for error estimation based on the size of the image. The overall performance is good.

In Order to develop the project, we compute combined spectral and texture Features using local spectral histograms, which concatenate local histograms of all input bands. We regard each feature as a linear combination of several representative features, each of which corresponds to a segment. Segmentation is given by estimating combination weights, which indicate segment ownership of pixels. We present segmentation solutions where representative features are either known or unknown.

Advantages:

- This method is effective and provides better accuracy.
- This process gives high resolution.
- It will save time and reduce a delay process.
- This representation provides an effective feature to capture both spectral and texture information.
- This method works across different bands in a computationally efficient way and accurately localizes boundaries.
- It has been shown that, in specific cases, single-scale representation might be sufficient and more straightforward and also computational cost low by using the proposed system.

4. Modules

- Input image
- Filtered image
- Enhanced image
- Clustered image
- Segmented image
- Performance

4.1. Input Image

Remote sensing images are taken as input to the system and save the images into the computer. After that, the input image is converted into the gray image. In order to improve the quality of the images we normally employ some filtering operations.

4.2. Filtered Image

Then the gray scale image is filtered by using Laplacian of gaussian (LOG) filters. To specify the histogram there are certain set of filters? But in this process we use Laplacian of gaussian (LOG) filters. It is used for the removal of noise.

4.3. Enhanced Image

The images are enhanced by using local spectral histogram. The histogram is taken for all input bands. It provide effective feature for both spectral and texture information for remote sensing images. Then the enhanced image is clustered.

4.4. Clustered Image

K-mean clustering algorithm was used for clustering the image. Simply speaking k-means clustering is an algorithm to classify or to group the objects based on attributes/features into K number of group. K is positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid.

4.5. Segmented Image

Image segmentation is typically used to locate objects and boundaries in images. The clustered image is then segmented based on the spectral and texture features. The images of segmented boundaries with RGB colors.

4.6. Performance

The SVD is calculated for error estimation based on the size of the image .The SVD is extensively used in image processing for plotting the graph. The overall performance is good.

Method	**Spectral features**	**Texture Features**	**Proposed method (Automatic Scaling,K-means clustring)**
Accuracy	65%	67%	75%

4.7. Local Spectral Histogram

Based on a local spatial/frequency representation, weemploy a spectral histogram as a feature statistic for texture classification. The spectral histogram consists of marginal distributions of responses of a bank of filters and encodes implicitly the local structure of images through the filtering stage and the global appearance through the histogram stage. The distance between two spectral histograms is measured using2-statistic. The spectral histogram with the associated distance measure exhibits several properties that are necessary for texture classification. A filter selection algorithm is proposed to maximize classification performance of a given dataset. Our classification experiments using natural texture images reveal that the spectral histogram representation provides a robust feature statistic for textures and generalizes well. Comparisons show that our method produces a marked improvement in classification performance. Finally we point out the Relationships between existing texture features and the spectral histogram, suggesting that the latter may provide a unified texture feature. A spectral histogram, defined as the marginal distribution of filter responses, as a quantitative definition for a text on pattern. By matching spectral histograms, an arbitrary image can be transformed to an image with similar textons to the observed. Local spectral Histograms are the basis for numerous spatial domain processing techniques.

The histogram manipulation can be used effectively for image enhancement. These Histograms can be used to provide useful image statistics. The Information derived from histograms are quite useful in other image processing applications, such as image compression and segmentation. Image histogram is a graphical representation of the intensity distribution of an image. It quantifies the number of pixels for each intensity value considered. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

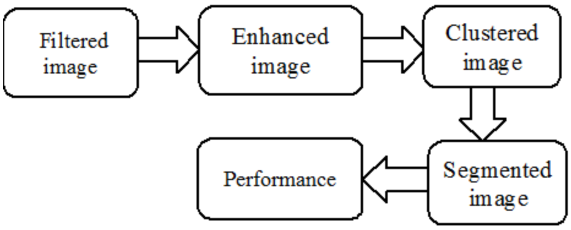
In scientific imaging where spatial correlation is more important than intensity of signal (such as separating DNA fragments of quantized length), the small signal to noise ratio usually hampers visual detection.

Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images that user would apply false-color to. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low color depth. For example, if applied to 8-bit image displayed with 8-bit gray-scale palette it will further reduce color depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher color depth than palette size, like continuous data or 16-bit gray-scale images.

4.8. K-Mean Clustering

In a general sense, k-means clustering works by assigning data points to a cluster centroid, and then moving those cluster centroids to better fit the clusters themselves. To run an iteration of k-means on our dataset, we first randomly initialize k number of points to serve as cluster centroids. A common method, employed in my implementation, is to pick k data points and affix the centroid in the same place as those points. Then we assign each data point to its nearest cluster centroid. Finally, we update the cluster centroid to be the mean value of the cluster. The assignment and updating step is repeated, minimizing fitting error until the algorithm converges to a local optimum. It's important to realize that the performance of k-means depends on the initialization of the cluster centers; a bad choice of initial seed, e.g. outliers or extremely close data points, can easily cause the algorithm to converge on less than globally optimal clusters. For this reason, it's usually a good idea to iterate k-means multiple times and choose the clustering that minimizes overall error. When looking at data for the purpose of classification, there are several ways to approach classifying the examples in a given set. For example, we have parametric approaches, semi-parametric approaches, and nonparametric approaches. The spherical k-means algorithm, i.e., the k-means algorithm with cosine similarity, is a popular method for clustering high-dimensional text data. In this algorithm, each document as well as each cluster mean is represented as a high-dimensional unit-length vector. However, it has been mainly used in batch mode. That is, each cluster mean vector is updated, only After all document vectors being assigned, as the (normalized) average of all the document vectors assigned to that cluster. This paper investigates an online version of the spherical k-means algorithm based on the well-known Winner-Take-All competitive learning. In this online algorithm, each cluster centroid is incrementally updated given a document. We demonstrate that the online spherical k-means algorithm can achieve significantly better clustering results than the batch version, especially when an annealing-type learning rate schedule is used. We also present heuristics to improve the speed, yet almost without loss of clustering quality.

4.9. System Architecture



5. EXPERIMENTAL RESULTS AND COMPARISONS

We first test our method on a set of GeoEye-1 images with a spatial resolution of 0.5 m. The images have three bands (red, green, and blue), and the red band is shown in the top row in Fig. 2. For each image, we use three filters: the intensity filter, LOG (s), and LOG (2s). Filter scale s and the integration scale are determined using the automatic method.. The only free parameter is the number of segments, which is set to 3, 2, and 3, respectively, for the three images. The results are presented in Fig. 2, where the top row shows the segment boundaries overlaid on the red-band images, and the bottom row shows region labeling.

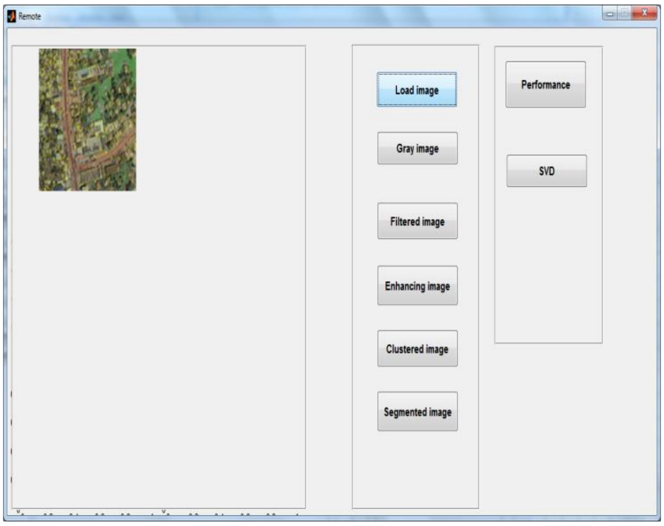


Fig. *Front Screen for the project*

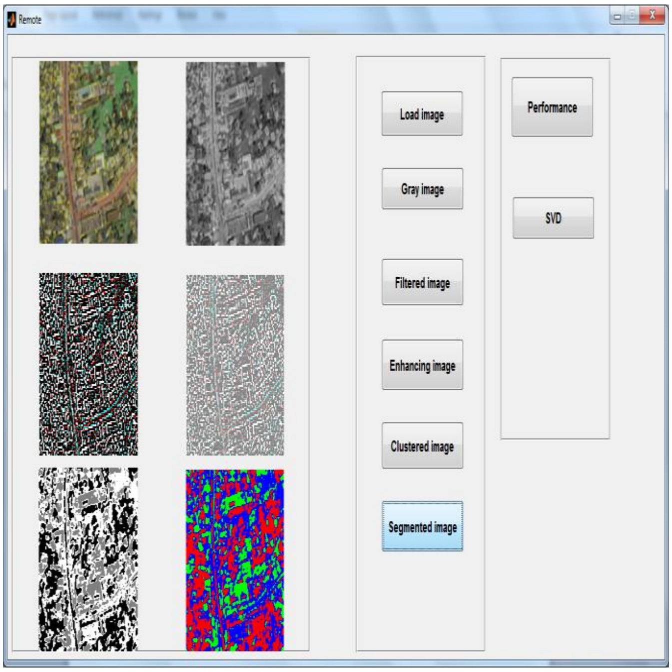


Fig. After Segmentation

6. Conclusion and Future Enhancement

The remote sensing image is segmented and it is useful in many of the processes. The remote sensing image is segmented based on RGB colors. The SVD is calculated for error estimation and plot the graph. The overall performance is good. In this project we have presented a new method for segmenting remote sensing images based on spectral and texture features. We use local spectral histograms to provide combined features. By regarding each feature as a linear combination of several representative features, we formulate the segmentation problem as a multivariate linear regression, which can be solved by least squares estimation. We have also proposed methods based on SVD to automatically estimate representative features and select proper scales. The process can be further developed by the segmentation of multi resolution remote-sensing images, which fits into the general split-and-merge paradigm. The whole process is based on a recently developed hierarchical model of the image, which accurately describes its textural properties. In order to reduce the computational burden and preserve contours at the highest spatial definition, the algorithm works on the high-resolution panchromatic data first, using low-resolution full spectral information only at a later stage to refine the segmentation. It is completely unsupervised, with just a few parameters set at the beginning, and its final product is not a single segmentation map but rather a sequence of nested maps which provide a hierarchical description of the image.

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