A FAST METHOD FOR OBJECTS DETECTION AND RECOGNITION ON HIGH RESOLUTION IMAGERY BASED ON GEOSTATISTICAL AND LOCAL CLUSTER ANALYSIS

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ABSTRACT:

This paper describes a new methodology to detect and recognize Object on high resolution multi-spectral images, which involves successively: (1) Resampling the image according to the size of the object to reduce the data involved in the computation greatly. (2) Geostatistic method and a local indicator of spatial autocorrelation is used to detect and , more importantly, to locate all the local clusters with high or low reflectance values which are probably the interesting target objects. In this step, by leveraging both spectral and spatial information, the algorithm requires little or no input from user, and hence can be readily automated. (3) Finally, identify objects by extracting the spectral and geometry features in small image block of the original images. The approach is implemented and tested on 1m resolution aerial digital images collected in the east sea of China, and the ships sailing or anchoring on the sea surface are properly extracted.

1. INTRODUCTION

Object detection has always been one of the most popular researches in remote sensing science. From an application point of view, the object detection is usually defined as carrying on localization and recognition process on remote sensing data for interesting target. Object detection can be divided into two different stages, namely target searching and localization (dynamic question) and recognition and confirmation (static question) . In the static question, targets are located, needing further recognition and confirmation about attributes of the targets. In this stage, efficiency is not very important because of the accuracy request. However, in the dynamic question, target position is unknown; therefore, searching time is one of the most important evaluation criterions.

In recent years, high-resolution satellite and aerial imagery has recently become a new data source for extraction of small-scale objects such as vehicles, roads, ship and so on...This paper concern locating and extracting ships from the high resolution aerial image. At present, most of the ship detection studies are based on the Synthetic Aperture Radar (SAR) images and only a small number of the ship extraction researches uses panchromatic band images of high-resolution satellites. Therefore, the usual ship extraction algorithms are actually detection of light-target on dark-background. There are three notable aspects of limitation. Firstly, band limitation will cause a waste of spectral information. Secondly, current algorithms only concern a small block of data, which indeed includes the target object, but ignore developing method of searching potential targets on large imagery. Thirdly, a common and also very important difficulty in remote location and target recognition is the low efficiency and long calculation time when massive data is used. Since existing algorithms can hardly meet the fast increasing demand for real-time information management, we try to development a novel algorithm which is a kind of multi-scale strategy of information extraction based on geostatical and local cluster analysis.

An increase of use of spatial statistics in the analysis of remotely sensed data has occurred in the last decade. In particular; geostatistics offers a broad range of techniques that allow not only the characterization of multivariate spatial correlation, but also the spatial decomposition or filtering of signal values [Goovaerts, 2002]. The approach known as factorial kriging relies on semivariogram to detect multiple scales of spatial variability, followed by the decomposition of spectral values into the corresponding spatial components. This technique was first used in geochemical exploration to distinguish large isolated values from group wise anomalies that consisted of two or more neighbouring values just above the chemical detection limit.

The LISA (local indicator of spatial autocorrelation) statistic allows the comparison of an observation (i.e., a single pixel or small group of pixels) with the surrounding ones, followed by a test procedure to assess whether this difference is significant or not. This approach has been used recently to detect spatial outliers in soil samples [McGrath, Zhang, 2003], while the LISA has been introduced to quantify the degree of spatial homogeneity in remotely sensed imagery. The novelty of the proposed approach lies in the geostatistical filtering of the image regional background prior to testing the significance of LISA values through randomization, and the development of two new statistics to combine test results across multiple spectral bands.

2. SHIP DETECTION BASED ON GEOSTATISTICAL AND LOCAL CLUSTER ANALYSIS

The method put forward in this paper is an automatic target detection process, which capitalizes on both spatial and spectral bands correlation and does not require any a priori information on the target spectral signature. The technique does not allow discrimination between types of anomalies.

This approach combines geostatistical filtering for suppression of image background with local indicators of spatial autocorrelation (LISA), which are used routinely in health sciences for the detection of clusters and outliers in cancer mortality rates.

2.1 Data Pre-Processing

Taking some urgent applications into account, we have to traverse some considerably large images and extract interesting objects with a time limitation. Our way to resolve this problem is to resample the original image to a much lower spatial resolution with a kind of quad tree-like resampling method to reduce the number of pixels involved in the calculation. In this step, we need some priori knowledge about how many pixels a ship usually take in the image or width and height of the smallest block on the original image that includes one ship. Then the resample scale (the resample block size) can be confirmed. In the resampling processing, new gray value of each block will be calculated only using pixels in four directions (the two diagonals, horizontal midline and vertical midline), also for the purpose of saving computing time. In the output images, no more than 15 pixels can cover one ship which usually needs more than 1500 pixels in the original image, and the spectral characteristics of the original image was well preserved. As the result of this step, the ships to be detected in the image have been indicated by the cluster of pixels which has a remarkable spectral contrast with the background.

2.2 Anomaly Detection

The anomalies extraction is based on the geostatistical noise filtering and local indicator of spatial autocorrelation (LISA value) analysis.

2.2.1 Geostatistical filtering

This step involves removing from each spectral band of the original image the low-frequency component or regional variability. For the k_{th} band, the low-frequency component, denoted m_k, is estimated at each location u as a linear combination of the n surrounding pixel values:

$$m_k(u) = \sum_{i=1}^{n} \lambda_{ik} \times z_k(u_i) \tag{1}$$

Where λ_{ik} is quantified using the semivariogram, which is estimated as

$$\hat{\gamma}_k(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} \left[z_k(u_\alpha + h) - zk(u_\alpha) \right]^2 \tag{2}$$

Then the following system of linear equations is solved to compute the weights:

$$\begin{cases} \sum_{j=1}^{n} \lambda_{jk} \gamma_k(u_i - u_j) + \mu_k(u) = 0(i = 1, ..., n) \\ \sum_{j=1}^{n} \lambda_{jk} = 1 \end{cases} \tag{3}$$

2.2.2 Detection of anomalies using the local Moran's I

Depending on the different size of the anomalies, a detection kernel, whose size corresponds to the expected size of the anomalies, is defined and the pixels around the kernel consist of the kernel neighbour. The detection of local cluster is based on local Moran's I, which is the most commonly used LISA statics. Moran's I is calculated for each pixel u in each band z_k:

$$LISA_k(u) = \bar{r}_k(u) \left[\frac{1}{J} \sum_{j=1}^{J} r_k(u_j) \right] \tag{4}$$

Where $r_k(u) = z_k(u) - m_k(u)$, $\bar{r}_k(u)$ is the average value of the residuals,over the detection kernel centred on pixel u, and J is the number of pixels in the LISA neighbourhood(e.g. = 12 for a 2×2 kernel and J=16 for a 3×3 kernel).Cluster of low or high values, which respond to the presence of positive local autocorrelation, will lead to positive values of the LISA statistic. In addition to the sign of the LISA statistic, its magnitude informs on the extent to which kernel and neighbourhood values differ. To test whether this difference is significant or not, a Monte Carlo simulation is conducted, which consists of sampling randomly and without replacement from the whole image area and computing the corresponding simulated neighbourhood averages.

$$Sim\_LISA_k(u)_n = \bar{r}_k(u) g \overline{N}_{sim} \tag{5}$$

This operation repeats many times and these simulated values are multiplied by the detection kennel average to produce a set of values of the LISA statistic at the current pixel. This set represents a numerical approximation of the probability distribution of the LISA statistic, under the assumption of spatial independence. Lager probability value indicate large negative LISA statistic, corresponding to small values surrounded by high values or the reverse. Conversely, small probability value corresponds to large positive LISA statistics, which indicate cluster of high or low values.

Then we combine the probability values of the set of every band, an S statistics are conducted to summarize for each node the information provided by the three bands and to detect target pixels.

$$S = \frac{1}{K'} \sum_{k=1}^{K} i(u;k) p_k(u); \qquad K' = \sum_{k=1}^{K} i(u;k) \tag{6}$$

The static holds two important factors, one is the difference between the gray value of current detection kernel and its local neighbour pixels, and another is the difference between the current detection kernel and the image background. Using the two factors, we can detect the so called “anomalies”, whose gray values are obviously lower or higher than the image background.

When all the local clusters of anomalies are located, we find all the positions of potential targets. According to the image coordinate relationship between original images and resample images, we can unprotect the detected clusters on the resample images to the original images to locate some small image blocks, in which one (or maybe a few) potential target should be contained each.

2.3 Recognition

The output of Location step is a series of small located blocks in original image containing one (maybe more than one when two or three ships anchor together) potential target each. This paper studies on two issues: is there ship in the block and what type the ship is. Because there is not a universal automatic algorithm for detecting unknown object, the effect of the recognition result depends on the given prior knowledge. Unsupervised classification (clustering) is a traditional method to filter unexpected objects out in multi-spectral data, but it’s not perfect for our detection task because sometimes other objects show similar spectral characteristic. So a improved regional segmentation algorithm based both on the geometry features and spectral characteristic of ship objects is conducted[Xu Da-qi,2006].In order to recognize the target fast, knowledge about the shape and size of ship is required. The segmentation algorithm is an iteration of well-known Otsu segmentation, with an improvement in enhancing contrast of gray value of the image.

3. EXPERIMENTS

To validate this method proposed in this paper, an aerial image, with 1m spatial resolution and RGB three spectral bands, which is shot by digital frame camera in Yantai, Shangdong is used. The original image size is 2616(width) by 3214(height). On the sea surface there are 14 ships, four are navigating, the others are anchoring and three ships are anchoring together like one ship. The distribution of these ships is as following:

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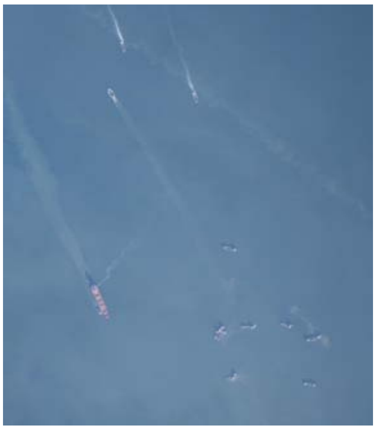

Figure 1. The original image.

In searching step, a 3×3 kernel is used and the threshold of the S value is set to 0.9.The searching results demonstrate the efficiency of this method. By using the LISA analysis searching method, all the anomalies are detected on the sampled image, which performance as red spot in Figure 2.The whole searching process on sampled image takes 0.133 second.

Figure 2.Searching results on the sampled image, whose size is 130(width) by 160(height).

A mathematical morphology dilation operation is processed on the searching result to make anomalies that belong to the same ship to connect to each other. Then each connected anomaly is unprojected to the original image and located use red block, which is a little larger than the anomalies area, shown in Figure 3. To avoid false alarm, a constrain is added to the detection method that each ship block should have more than 3 anomaly spots. So three blocks with only one spot in it are dropped. The figure 4 shows the final detection result. All 14 ships are detected, but in two blocks, ships anchoring together are considered to be one ship by this method.

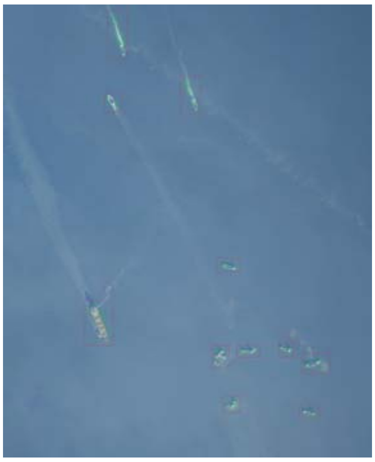

Figure 3. The located ships on original image

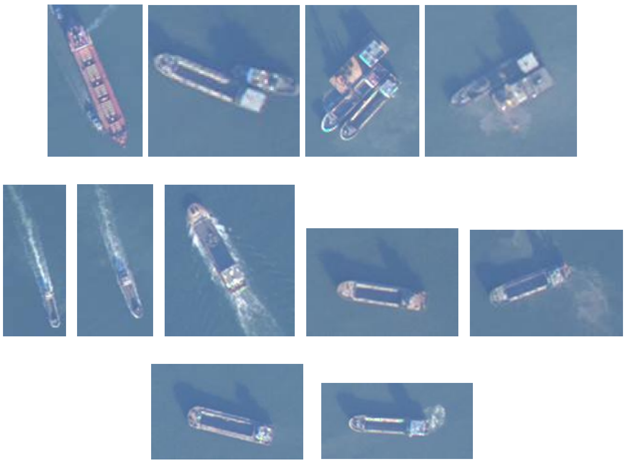

Figure 4.The final detection results

4. CONCLUTION AND FUTURE WORK

This paper proposes a fast method to detect object on large remote sensing image based on geostatical and local cluster analysis, and mainly focuses on ship detecting task on aerial image, which can be applied in many fast object detection fields such as harbor runtime management. The original data is sampled to a relatively smaller image and a LISA static is calculated for each kernel which centers on each pixel of each band of the sampled image. A novel static S is conducted to evaluate the extent how a kernel differs from the image back ground by combining LISA value of the kernel on three image bands and a threshold of S is set to extract the most different kernels we call anomalies which suggest the location of ships. A simple recognition process proceeds based on the location results. At last an image shot by airborne digital frame camera on East-See is experimented and all the 14 ships are properly detected. This algorithm is proved effective and timesaving. The future work will focus on how to extract objects on complex background images. Besides, the recognition method need researched more.

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