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**VISUAL SEARCH ALGORITHM FOR HIGH RESOLUTION
SATELLITE IMAGERY**

Abstract. In this paper we propose an image visual search algorithm for high resolution satellite imagery. An image description method which is based on the distribution of image object classes is developed. Different categories of image features for the description of satellite imagery are considered. Appropriate geometrical, statistical, texture, spatial and spectral features are selected for an accurate interpretation of objects at images. A satellite imagery classification algorithm is developed.

Key words: classification, satellite imagery, image similarity, distance metrics, image features, image description.

Problem formulation

Nowadays digital image processing is a topical problem in information technologies, medicine, and remote sensing. In our work we deal with satellite images. Remote sensing data are very important in different fields of human activity such as crop prediction, military surveillance, monitoring of disasters, urban planning, and control of nature resources utilization [1]. Every day satellites deliver to the Earth a huge amount of data. For instance, the WorldView-3 satellite has an average revisit time of less than one day and is capable of collecting up to 680,000 square kilometers per day, and the WorldView-2 has an average revisit time of 1.1 days and is capable of collecting up to 1 million square kilometers of 8-band imagery per day. Existing geoinformation systems collect and store remote sensing data for subsequent analysis and extraction of useful information. Geoinformation systems provide a variety of applications for dealing with data. There is a big variety of computer vision methods which allow to recognize and to classify the objects at digital images. One of the tasks of satellite image processing is to find areas of the Earth surface that contain similar geographic objects and types of land cover. For this purpose, large-size satellite images from data storage are cut into small parts called tiles, then the

tiles could be compared one to another. In other words, this is the task of image similarity estimation. Image similarity is used in visual search algorithms [2]. The visual search is a useful procedure for work with a large amount of data, where automatic processing is necessary. The problem of visual search is closely related to image description. To make a conclusion about image similarity, the features that describe images must be calculated first.

Analysis of publications on the topic research

A large number of previous studies have focused on searching for the image features most suitable for image description and analysis. Features are the qualitative and quantitative characteristics of image. Features are selected according to the problem under consideration. One image could be described by a number of features, and certain features could describe a number of different features [3].

Earlier, visual search algorithms for real-world images were developed. These algorithms realize a search for images similar to the user's input images from some data set. G. Chechik et al. presented an Online Algorithm for Scalable Image Similarity (OASIS) that learns a bi-linear similarity measure over sparse representations of images [4]. The experiments were performed on web data sets. Edge and color histograms were used as image features. The features were extracted by dividing each image into overlapping square blocks, and each block was then described with edge and color histograms.

Content based image retrieval (CBIR) systems that work by retrieving images related to the input image from huge databases were proposed in [5]. The real word scenes database was used. For image description, extensive robust features such as color signature, shape and color texture were determined. The similarity between the features of the input image and the features of the database images was evaluated using a meta-heuristic algorithm.

Work [6] was concerned with studying whether a negative selection algorithm for images comparing is valid for tackling the image visual search problem. Image distance measure was used for comparison of two images, typically an input image and an image from the database. In that work, color was used as the only feature to define distances between images.

Wang et al. proposed fine-grained image similarity with a deep ranking model, which characterizes the fine-grained image similarity relationship with a set of triplets. A triplet contains a query image, a positive image, and a negative image, where the positive image is more similar to the query image than the negative image. The similarity of two images from triplet was determined according to their squared Euclidean distance in the image space. The image similarity relationship is characterized by relative similarity ordering in the triplets [7].

Aim of the work

The selection of features for image description is a particularly important problem. The accuracy of image similarity estimation depends on the degree of correctness of image description. The brittness and color of images of the same objects may often be different. So the image features must present contextual information about objects on the image, not only visual characteristics. The aim of this work is to find out what image features will be the most appropriate for description of high resolution satellite imagery. After calculation of the image features the most similar images can be found.

Main material

Satellite data used in the work

The images were received from the WorldView-2 and the WorldView-3 satellites. These images have 8 multispectral channels received in the 400 nm – 1040 nm spectral range and one panchromatic channel received in the 0,5 μm - 1,1 μm spectral range. The resolution of these data is up to 0,31 meter per pixel. This is the highest satellite image resolution available today.

The primary data resolution was enhanced by the pan-sharpening procedure. High-resolution panchromatic channel and lower resolution multispectral channels was merged to create high-resolution color channels. We used satellite an image resolution enhancement technology based on HSV-, HCT-conversion and wavelet transform, which allows one to improve the spatial resolution of the primary digital image and to avoid spectral distortions in local areas [8].

Visual search algorithm

To perform a procedure of visual search on high resolution satellite images, we have to perform a few consecutive tasks. First, large satellite images are cut into a small samples, thus we obtain an image

dataset. One of the samples of the dataset is shown at Figure 1 (a). The visual search procedure retrieves images that are similar to the input image. Usually, an image from the dataset is chosen as the input image. For each image in the dataset, some features for their description are computed. After inputting the image, its features are computed and then compared with the stored features of every sample image in the dataset. The image description is an important stage of the visual search procedure. The accuracy of image retrieve depends on the proper choice of an image description model. In contrast to terrestrial scenes, which can include a wide variety of objects according to their specificity, satellite images usually include determined types of objects and land covers. We propose a special approach to satellite image description based on the image classification and image class histogram construction. The image classification must be performed first. Our classification algorithm is based on an object-oriented approach.

Image segmentation

The key step of the object-oriented image classification is segmentation. In our work the mean-shift algorithm for image segmentation was applied [9]. The mean-shift algorithm relates to unsupervised clustering algorithms. The main idea of the algorithm is to estimate the kernel density of pixel distribution in the RGBXY feature space. The local maxima of the distribution correspond to the centers of clusters. From the local extremum condition the shift vector $m(p)$ of a point $p \in RGBXY$ of the feature space is determined. After applying the shift operation to the point p , a sequence of points that converges to the center of nearest cluster is obtained.

After the image segmentation, objects (segments) for analysis were obtained [Fig. 1(c)]. A procedure of segmentation result refinement was also applied in order to delete small segments. Small segments could appear due to noises, and they significantly complicate the interpretation of image objects. The segments which had a size smaller than a given minimum were merged with the adjacent segments with the nearest mean value. The result of segmentation refinement is shown at Figure 1(d).

Image features calculation

We distinguished several basic classes which are typical for satellite scenes: buildings, trees, grass, bare ground, roads, shadows, and water. The features of each image object must be computed. In our work

the following categories [3] of features were used: geometric, spatial, spectral, statistical, and texture ones.

As geometric features, the area of each image object (segment), the border length, and border length/area ratio were calculated. For the correct identification of buildings, the rectangular fit function was used. Rectangular fit shows how much the object form corresponds to rectangular.

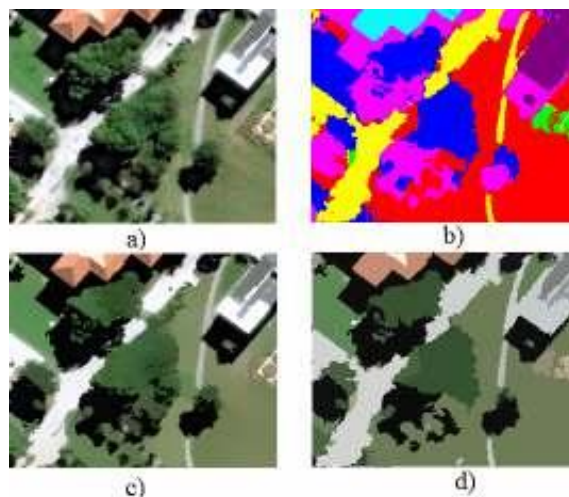


Figure 1 - a) – image sample obtained after cutting a large satellite image into tiles; b) - image objects after classification; c) – result of mean-shift clustering; d) – segmented image

The spatial features show the position of image objects relative to one another. The presence of a common border and its length were used as spatial features.

As spectral features, the spectral indices, brightness, saturation, and hue of objects were used. Such types of objects as trees and grass are easily identified due to the presence of near-infrared channels in satellite data. For the identification of trees and grass, the *NDVI* (Normalized Difference Vegetation Index) spectral index was used [10].

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

where *NIR* is the reflection in the near-infrared spectral region, and *RED* is the reflection in the red spectral region.

The *NDVI* index is based on the most stable regions of the green vegetation spectral signature. The maximum of radiation absorption by chlorophyll falls to the red spectral region while the maximum of radiation reflectance falls to the near-infrared region. So the ratio of reflectance's in these spectral regions allows one to distinguish vegetation

from other surface objects. The *NDVI* range is changed on the interval from -1 to 1. Generally the *NDVI* value of 0.7 corresponds to dense vegetation, the value of 0.5 – to sparse vegetation, the value of 0.025 – to bare ground, and the value of -0.25 – to water.

Another class that is easily distinguished by spectral feature is shadow. To identify shadows in an image, the shadow detection index *NSVDI* (normalized saturation-intensity difference index) was used.

$$NSVDI = \frac{S - V}{S + V} \quad (2)$$

where *S* is the saturation image component, and *V* is the value component. To obtain the *S* and *V* components, the object pixels are transformed from the *RGB* color model to *HSV* the color model. The decision on an object belonging to the shadow class is made after the *NSVDI* thresholding [11].

Sutich statistic features as the mean value and the standard deviation of pixels in an object were used.

The image edges were used as the texture feature. The edges on the image object border were analyzed. Image objects with high contrast have a higher gradient value on the borders. The image edges were extracted using the gradient Sobel filter.

Image classification

The rule set was used for assigning a class to objects. After assigning classes to all objects of the segmented sample image the map of objects classes was obtained [Fig. 1(b)]. We propose to describe each sample image by its histogram of class distribution. The pixels number of each class was calculated. Procedure of assigning classes and histogram building was repeat for all sample images from tested dataset.

Image similarity estimation

For finding of similar image samples at dataset we have to choose a method for images comparing. Our test dataset contains about 500 image samples. Each image is represented by its class distribution histogram. Histogram represents a contextual description of image. Classes represent the real world objects, which are semantically distinguished for user.

Since our image description model is represented by histogram we selected histogram distance metric for imagecomparing. We investigated a several methods of histogram similarity definition.

1. Histogram intersection. The distance between histograms is defined as

$$d(H_1, H_2) = \sum_i \min(H_1(i), H_2(i)) \quad (3)$$

the return value $d \in [0, 1]$. The similarity of histograms increases with d .

2. Chi-square metric. The distance between histograms is defined as

$$d(H_1, H_2) = \sum_i \frac{(H_1(i) - H_2(i))^2}{H_1(i)} \quad (4)$$

the return value $d \in [0, \infty)$. The similarity of histograms decreases with d .

3. Bhattachariya distance. The distance between histograms is defined as

$$d(H_1, H_2) = \sqrt{1 - \frac{\sum_i \sqrt{H_1(i) \cdot H_2(i)}}{\sqrt{\sum_j H_1(j) \cdot \sum_k H_2(k)}}} \quad (5)$$

the return value $d \in [0, 1]$. The similarity of histograms decreases with d .

To test our method a few random images from dataset were chosen as input images. The distance between each input image histogram and all sample images histograms was calculated. The input samples and the images from dataset which are the most similar to them are shown at Figure 2. Such similarity is computed on the basis of the above-mentioned distances.



Figure 2 - Result of image retrieval after histogram distance computation. Images at left column are input samples, the rest ones are the most similar samples from tested dataset

Conclusions and recommendations for further research

In this work we consider different categories of image features for the description of satellite imagery. The main advantage of our method is that we take into account such features of an image as geometrical, spectral, spatial, texture, and statistical features, which have not been taken into account before. A special classification approach was implemented to recognize each type of objects. As result the class distribution histogram for each image from tested dataset was built. Histogram represents a contextual description of image.

Proposed image description model was tested on dataset of 500 samples. Experimental result has shown a significant visual similarity of sample and retrieved images. The future research will be devoted to implementation of new features for more qualitative image description and enhancement of image comparison algorithm.

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