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Random Forest for Multitemporal and Multiscale Classification of Remote Sensing Satellite Imagery

A. Chitradevi[1*], S. Vijayalakshmi[2]

[1*,2]*Department of Computer science, Bharathiyar University, India*

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***Abstract*—** An increasing number of optical High-Resolution (HR) remote sensing satellite systems, offering multispectral images. However, acquiring multi temporal HR data may not always be economically viable, particularly for large areas. Data having medium resolution (i.e., a GSD of 30 m) do not offer as much detail, but cover a larger area and may often be preferable from an economical point of view. In this research work present a new method for the multi temporal and contextual classification of georeferenced optical remote sensing images acquired at different epochs with having different geometrical resolutions. The method is based on Conditional Random Fields (CRFs) for contextual classification. But in CRF, pool of features used in this work is rather limited, particularly for the medium-resolution images. To solve this problem proposed work is expanded to pool of features for the medium-resolution images to improve the classification results. The Gaussian model used in the CRF is should be replaced by more sophisticated Random Forests (RFs) classifiers. RF is an ensemble of many decision trees, which have been trained on randomly selected pool of features for the medium-resolution images subsets of the training data, in order to decorrelate the individual trees. Extend such a framework to multitemporal classification and change detection, taking into account interactions between images acquired at different epochs and considering the fact that these images may have different geometrical resolutions. Results are given for two different test sites in Germany, where Ikonos, RapidEye, and Landsat images are available. State-of-the-art multitemporal classification method and that it is feasible to detect changes in lower resolution images.

***Keywords*—**Remote sensing satellite;Multitemporal classification;Random forest classifier

I. INTRODUCTION

Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object and thus in contrast to on site observation. Remote sensing is a sub-field of geography. In modern usage, the term generally refers to the use of aerial sensor technologies to detect and classify objects on Earth (both on the surface, and in the atmosphere and oceans) by means of propagated signals (e.g. electromagnetic radiation). It may be split into active remote sensing (when a signal is first emitted from aircraft or satellites) [Schowengerdt , 2007] [Schott, 2007][Guo et al, 2014] or passive (e.g. sunlight) when information is merely recorded [Liu et al, 2009].

Passive sensors gather radiation that is emitted or reflected by the object or surrounding areas. Reflected sunlight is the most common source of radiation measured by passive sensors. Examples of passive remote sensors include film photography, infrared, charge-coupled devices, and radiometers. Active collection, on the other hand, emits energy in order to scan objects and areas whereupon a sensor then detects and measures the radiation that is reflected or backscattered from the target. RADAR and LiDAR are examples of active remote sensing where the time delay between emission and return is measured, establishing the location, speed and direction of an object.

Remote sensing makes it possible to collect data of dangerous or inaccessible areas. Remote sensing applications include monitoring deforestation in areas such as the Amazon Basin, glacial features in Arctic and Antarctic regions, and depth sounding of coastal and ocean depths. Military collection during the Cold War made use of stand-off collection of data about dangerous border areas. Remote sensing also replaces costly and slow data collection on the ground, ensuring in the process that areas or objects are not disturbed.

Orbital platforms collect and transmit data from different parts of the electromagnetic spectrum, which in conjunction with larger scale aerial or ground-based sensing and analysis, provides researchers with enough information to monitor trends such as El Niño and other natural long and short term phenomena. Other uses include different areas of the earth sciences such as natural resource management, agricultural fields such as land usage and conservation, and national security and overhead, ground-based and stand-off collection on border areas.

II. APPLICATION OF REMOTE SENSING DATA

Conventional radar is mostly associated with aerial traffic control, early warning, and certain large scale meteorological data. Doppler radar is used by local law enforcements' monitoring of speed limits and in enhanced meteorological collection such as wind speed and direction within weather systems in addition to precipitation location and intensity. Other types of active collection include plasmas in the ionosphere. Interferometric synthetic aperture radar is used to produce precise digital elevation models of large scale terrain (See RADARSAT, TerraSAR-X, and Magellan).

Laser and radar altimeters on satellites have provided a wide range of data. By measuring the bulges of water caused by gravity, they map features on the seafloor to a resolution of a mile or so. By measuring the height and wavelength of ocean waves, the altimeters measure wind speeds and direction, and surface ocean currents and directions.

Ultrasound (acoustic) and radar tide gauges measure sea level, tides and wave direction in coastal and offshore tide gauges.

Light detection and ranging (LIDAR) is well known in examples of weapon ranging, laser illuminated homing of projectiles. LIDAR is used to detect and measure the concentration of various chemicals in the atmosphere, while airborne LIDAR can be used to measure heights of objects and features on the ground more accurately than with radar technology. Vegetation remote sensing is a principal application of LIDAR.

Radiometers and photometers are the most common instrument in use, collecting reflected and emitted radiation in a wide range of frequencies. The most common are visible and infrared sensors, followed by microwave, gamma ray and rarely, ultraviolet. They may also be used to detect the emission spectra of various chemicals, providing data on chemical concentrations in the atmosphere.

Stereographic pairs of aerial photographs have often been used to make topographic maps by imagery and terrain analysts in trafficability and highway departments for potential routes, in addition to modelling terrestrial habitat features [Mills et al,1999][Twiss et al,2001][Stewart et al, 2014]

Simultaneous multi-spectral platforms such as Landsat have been in use since the 70's. These thematic mappers take images in multiple wavelengths of electro-magnetic radiation (multi-spectral) and are usually found on Earth observation satellites, including (for example) the Landsat program or the IKONOS satellite. Maps of land cover and land use from thematic mapping can be used to prospect for minerals, detect or monitor land usage, deforestation, and examine the health of indigenous plants and crops, including entire farming regions or forests. Landsat images are used by regulatory agencies such as KYDOW to indicate water quality parameters including Secchi depth, chlorophyll a density and total phosphorus content. Weather satellites are used in meteorology and climatology.

Hyperspectral imaging produces an image where each pixel has full spectral information with imaging narrow spectral bands over a contiguous spectral range. Hyperspectral imagers are used in various applications including mineralogy, biology, defence, and environmental measurements.

Within the scope of the combat against desertification, remote sensing allows to follow-up and monitor risk areas in the long term, to determine desertification factors, to support decision-makers in defining relevant measures of environmental management, and to assess their impacts [Begni et al,2009].

III. MOTIVATION OF MULTITEMPORAL AND MULTISCALE CLASSIFICATION

An Increasing number of optical High-Resolution (HR) remote sensing satellite systems, offering multispectral images at a Ground Sampling Distance (GSD) of 5 m or below, have become available, e.g., Ikonos, Quickbird, WorldView-1, and WorldView-2, to name just a few.

As a consequence of the higher availability of data and the higher quality of these images, it should be possible to improve the classification accuracy and to analyze land-cover changes at a higher frequency than this is currently done based on a multitemporal analysis.

IV. PROBLEM SPECIFICATION

However, acquiring multitemporal HR data may not always be economically viable, particularly for large areas.

Data having medium resolution (i.e., a GSD of 30 m) do not offer as much detail, but cover a larger area and may often be preferable from an economical point of view.

It would be desirable to have a method capable of combining HR images with data of lower resolution and acquired at different epochs of arbitrary order for classification and for detecting land-cover changes.

Recent work on image classification has emphasized the importance of considering local context [Kumar and Hebert, 2006], [Schindler, 2012], but only in a monotemporal setting.

But in CRF, pool of features used in this work is rather limited, particularly for the medium-resolution images, so it reduces the classification accuracy of multi temporal image samples.

V. OBJECTIVE OF THE RESEARCH

The proposed system is able to deal with data of different resolution; the class structure at different epochs may vary with the resolution.

The goal of the multitemporal classification is an improved classification performance at all individual epochs, but also the detection of land-cover changes, possibly using lower resolution data.

Pool of features used in this work is rather extended by using random forest which increases the accuracy of classification in multitemporal dataset samples.

VI. RANDOM FOREST

As usual, the feature vector values of an image site with k channels are viewed as samples of a nonparametric function $I : R^2 \rightarrow R^k$. The number of feature pixels is denoted by n, and individual pixel locations are referred to by 2-D vectors, denoted with lowercase bold letters x. The aim of classification is to assign each image pixel feature vectors one of l possible class labels c_i, with epoch t to obtain a new single-channel image, the thematic map $C : R^2 \rightarrow \{c_1 \dots c_L\}$. Finding the thematic map with the highest probability amounts to searching the labeling which maximizes the probability $P(C|I) \sim P(I|C)P(C)$, respectively, minimizes its negative log-likelihood or "energy".

$$-\log P(C|I) = -\log P(I|C) - \log P(C) + const$$

$$E(I,C) = E_{data}(I,C) + E_{smooth}(I,C)$$

A. Random forest with temporal

The aim of classification is to assign each image pixel feature vectors one of l possible class labels c_i, with epoch t to obtain a new single-channel image, the thematic map $C : R^2 \rightarrow \{c_1^t \dots c_l^t\}$. Finding the thematic map with the highest probability amounts to searching the labeling which maximizes the probability $P(C^t|I^t) \sim P(I^t|C^t)P(C^t)$, respectively, minimizes its negative log-likelihood or "energy".

$$\log P(C^t|I^t) = \quad \log P(I^t|C^t) \quad \log P(C^t) \mid const$$

$$E(I^t,C^t) = E_{data}(I^t,C^t) + E_{smooth}(I^t,C^t)$$

Both Random forest and Randon forest temporal energy consists of two parts: a "data term" which describes how likely a certain label is at each feature vector given the observed site data and decreases as the labeling fits the observed site data better; and a "smoothness term" which describes the likelihood of a certain label configuration and decreases as the labeling gets smoother

B. Advantages of Random forest with temporal

- The pool of features used in this work is rather extended particularly for the medium-resolution images to increase the classification accuracy of multiple images.
- Could help to further improve the classification results.
- The multitemporal setting with random forest improved the classification accuracy for all images
- Majority of the changes could be detected in the medium-resolution images

C. Multitemporal and Multiscale classification in CRF and RF

The method is based on Conditional Random Fields (CRFs) and Random Forest (RF) for contextual classification. The CRF and RF model is expanded by temporal interaction terms that link neighboring epochs via transition probabilities between different classes. In order to be able to deal with data of different resolution, the class structure at different epochs may vary with the resolution. The goal of the multitemporal classification is an improved classification performance at all individual epochs, but also the detection of land-cover changes, possibly using lower resolution data.

A comparsion of the performance of different models for the interaction potentials. Results are given for two different test sites in germany, where Ikonos, RapidEye, and Landsat images are available. Our results show that the multitemporal classification does indeed increase the overall accuracy of all epochs compared to a monotemporal classification and to a state –of-the-are multitemporal classification, method, and that it is feasible to detect changes in lower resolution images.

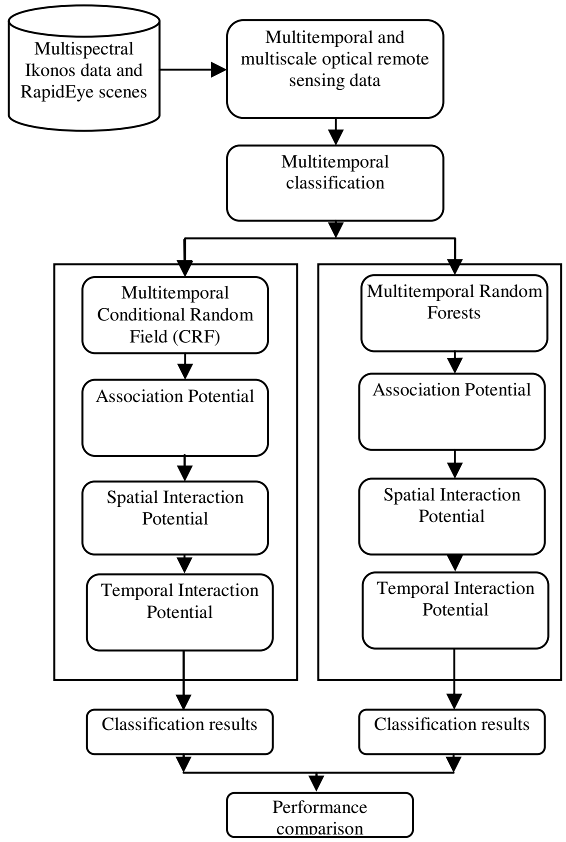

Fig. 1 Overall framework for Multitemporal and Multiscale Classification of Remote sensing Satellite Imagery

VII. RESULTS & DISCUSSION

Here, present the results of a quantitative evaluation of random forest and conditional random field methodology. Start with a comparison of the different models of the spatial interaction potentials in monotemporal classification. These results, in particular those achieved, also serve as a baseline for assessing the impact of our multitemporal model on the classification accuracy. The multitemporal model is evaluated for the case of using images of the same resolution and for images having different resolutions, assess the potential of using multiscale data for detecting changes. Finally, a comparison to a state-of the- art multitemporal classification technique is presented.

A. Test and training Dataset

In this work used two test areas for the evaluation of random forest and conditional random field methodology. The first test area is situated near Herne, Germany, and covers an area of 8.6 × 5.9 km2 (see Figure. 6.1). Used multispectral Ikonos data with 4-m GSD acquired in 2005 and 2007, a multispectral RapidEye image acquired in 2009 with an original GSD of 5 m, and Landsat data of 30-m GSD acquired in 2010. All images were recorded in summer.

Produced orthophotos with 4-m GSD from the Ikonos and RapidEye images and with 30-m GSD from the Landsat images. The classes to be distinguished with Ikonos and RapidEye imagery are residentialareas (res), industrial areas (ind), forests (for), and cropland (crp). Since there is no clear distinction of the classes res and ind in the Landsat imagery, they are fused to a new class builtup areas (bui) in that resolution. Reference data were obtained by manually labeling the images at pixel level in the Ikonos scene from 2005. The reference for res contained roads inside settlements, gardens attached to buildings, but also roads having a width larger than 8 m outside settlements. The percentage of the area covered by the four classes was 30% (res), 5%(ind), 22% (for), and 43% (crp), respectively.

Fig.2 Training samples area in Herne

The set of classes was identical to the one distinguished in Herne, but the reference was based on the German Authoritative Topographic Cartographic Information System (ATKIS). The percentage of the area covered by the four classes was 10% (res), 1.5% (ind), 8.5% (for), and 80% (crp), respectively. Both test sites are flat, and the agricultural areas show a characteristic pattern for Central Europe with rather small fields of heterogeneous appearance. The main difference between the test sites is that, in Herne, there is a more homogeneous distribution of the individual classes than in Husum, where the most dominant class (*crp*) accounts for 80% of the area. Tested multitemporal classification method using only images of the same resolution.

Fig. 3 Test area in Husum (RapidEye, 7/2009)

B. Performance comparison between CRF and RF

The results of a quantitative evaluation of random forest and conditional random field methodology. Start with a comparison of the different models of the spatial interaction potentials in monotemporal classification. These results, in particular those achieved, also serve as a baseline for assessing the impact of our multitemporal model on the classification accuracy.

Table.1 Performance metrics results comparison for methods

Metrics	Methods	
	CRF	RF
Precision (%)	45.21	60.4521
Sensitivity(%)	80.12	90.23
F measure(%)	72.72	82.53
Accuracy(%)	81.24	91.45

C. Color variation results of the input samples

For each data set, the classification was carried out two times, varying color varitiaon results are shown in the Fig. 4 under spatial interaction potentials.

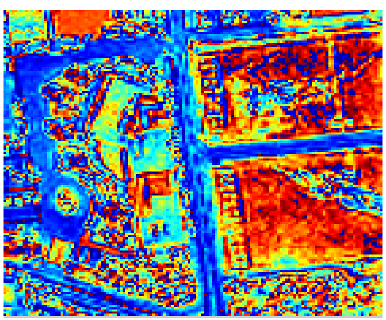

Fig. 4 Color variation results of the input samples

VIII. CONTRIBUTION OF THE RESEARCH

In this way, it should be possible to benefit from the higher information content of HR imagery, while performing change detection in data of lower resolution.

In order to achieve the general goals described earlier, in this research work extend such a framework to multitemporal classification and change detection, taking into account interactions between images acquired at different epochs and considering the fact that these images may have different geometrical resolutions.

In the proposed work is expanded feature pool could help to further improve the classification results.

The Gaussian model used for the association potentials of the CRF is rather simplistic and should be replaced by more sophisticated ones classifiers such as Random Forests (RFs).

RF is an ensemble of many decision trees, which have been trained on randomly selected pool of features subsets of the training data and/or with some randomization in the choice of decision functions for the individual nodes, in order to decorrelate the individual trees.

IX. CONCLUSION AND FUTURE WORK

The motivation for the present work has been twofold: first, attempt a systematic overview of classification methods which model Multitemporal and Multiscale Classification of the labels in Optical Satellite Imagery, and which are potentially relevant for remote sensing imagery. Second, perform an experimental comparison of these methods for the problem of classifying images of high spatial and resolution, and as far as possible—extract guidelines when and how to use them.

In this research work have presented a random forest supervised method for multitemporal and multiscale classification of remote sensing images that also considers local spatial context. It is an extension of the concept of RF by multitemporal terms, with the latter being modeled by transition matrices related to the probabilities of certain changes between the classes. In a multiscale setting, the method can deal with different class structures for images having different spatial resolutions. The data terms of the RF were determined by training, whereas the parameters of the (spatial and temporal) interaction terms were found empirically.

The global random forest methods, which image processing researchers have developed over the past decade, to expand pool features could help to further improve the classification results. The Gaussian model used for the association potentials of the CRF is rather simplistic and should be replaced by more sophisticated ones, e.g., by state-of-the-art discriminative classifiers such as random forests in this research work.

The interaction terms selected for proposed work are also relatively simple, depending only on the Euclidean distance of the feature vectors at neighboring sites. In the context of airborne laser scanning, more complex interaction terms have been shown to improve the classification accuracy for classes that do not occur very frequently [41]; this observation is still to be verified in the context of satellite imagery. The present work also neglected the possibility of data-dependent temporal interaction potentials, although proposed framework is suited to such an extension in principle. Finally, the incorporation of a geospatial database into the model, which would be related to the problem of change detection in the context of map updating more directly, but could also provide a strong prior for all subsequent epochs, still remains to be investigated.

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