ANARCHIC URBAN EXPANSION DETECTION AND MONITORING WITH INTEGRATION OF EXPERT KNOWLEDGE

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ABSTRACT

With the advent of very high spatial, spectral, and temporal resolution satellites, Satellite Image Time Series (SITS) analysis and interpretation become even more challenging than before. Besides, several conventional techniques for controlling and monitoring anarchic urban expansion have been initiated but they remain not sufficient to overcome this issue.

This paper proposes an automatic method of detection and monitoring of anarchic urban expansions starting from multi-sources and multi-temporal data (VHR satellite images and geographic information data). First, the illegal urban areas are extracted using an original SVM based technique integrating expert knowledge and auxiliary data by means of ontology construction. This leads to the formalization of the expert semantic information and the urban construction rules (often in sentences form) and their confrontation with the classification results.

Secondly, the SITS classified images are modeled using Spatial-Object Temporal Adjacency Graphs (SOTAG) constructed for each region of the first image. These graphs are then classified using a Marginalized Graph Kernel (MGK) SVM based classification in order to extract regions with similar temporal evolution. We are focusing mainly on monitoring legal and illegal urban expansions. The resulted spatio-temporal map describes urban areas types and their changes over time.

Index Terms— VHR images, SITIS monitoring, SVM classification, ontology, concepts, SOTAG, MGK, etc.

1. INTRODUCTION

These last years, African urban sprawl becomes very significant in comparison with the demographic development. A considerable urban expansion next to surrounding rural regions has led to a non-control of urban space sprawl and a significant loss of farmland, natural, ecological and environmental areas.

Besides, the large number of new earth observation satellites enhances the capacity to acquire data with improved spatial, spectral and temporal resolutions and allows land cover classification and monitoring. Especially, VHR satellite images can be used to provide indicators that could help policy makers to take appropriate measures to control urbanization and rationalize consumption of land heritage.

Several researches have been undertaken in the area of urban expansion detection and monitoring in order to control anarchic construction especially by mean of change detection techniques. These studies remain insufficient either because they use low resolution images [1] or because they only rely on remote sensing images [2]. The need for expert knowledge and auxiliary data integration become more required and arouse the interest of some researchers. In [3] they proposed a simple integration of the municipal property database to detect building changes between two panchromatic images. Forestier et al. studied the semantics of urban areas to build ontology for topographic mapping using Quickbird images [4]. Recently, to solve illegal building expansions, a semi-automatic method of urban boundary extraction was proposed in [5] in order to generate a series of standardized rules for urban extraction. We proposed in previous works [6,7] the integration of expert knowledge in automatic Satellite Image Time Series (SITS) analysis to improve results reliability and precision for land cover monitoring.

In this paper, an automated method of extraction and monitoring of illegal urban expansion is proposed. First, thanks to VHR Pleiades images, we start identifying urban regions by applying SVM based classification. Several spatial, spectral and textural features are used to discriminate between urban regions and other cartographic areas. The obtained classification results are combined with other formalized multi-sources data (urban landscape judgment, urban boundary outline drawing, rivers and coastlines maps, agricultural map, etc.) by building an adapted ontology. Three regions are highlighted: legal urban, illegal urban and non-urban areas.

Secondly, for each region of the first SITS classified image, a graph characterizing its temporal evolution is built using discriminative signatures for vertices and edges labelling. Then, a MGK SVM based algorithm is used to analyse and classify the obtained graphs. The resulted temporal map discerns between the three urban classes behaviours (stable, expanded, etc.).

This paper is organized as follows. The second section presents the main steps of the knowledge-based anarchic constructions extraction approach. Then, the graph based temporal classification is detailed in the third section. Finally, data description and experimental results are highlighted and discussed in the fourth section.

2. URBAN EXPANSION DETECTION

The proposed urban expansion detection technique consists in extracting the anarchic constructions in order to support urban expert diagnostic. It is organized in two steps as illustrated by the figure1.

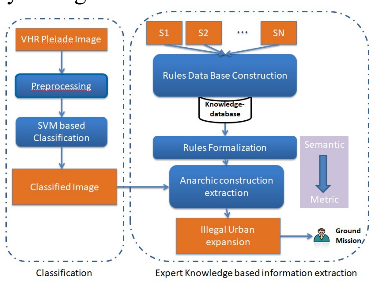


Figure1. The workflow of the proposed knowledge based urban expansion extraction approach.

We first need to identify urban regions by applying pre-processing techniques for geometric and radiometric correction followed by an SVM classification step. The classified image is then used in a second step to decide if the detected urban constructions are anarchic. The main contribution of this work is the automatization of this step by introducing and formalizing multi-sources information's such as other thematic data and expert knowledge to avoid manual and visual interpretation. Several rules are collected from government documents, boundary maps, expert's judgments, etc. to form a knowledge database. These rules are formalized then digitized to be used in the decision process. The semantic information is thus transformed to metric information helping the user to delimit the anarchic constructions perimeter and optimize the exploration missions.

2.1. Features used for SVM based classification

For SVM Classification, we compute various features in order to build a feature vector for every pixel.

For spectral signature, we use obviously radiometric values and specified indices such as: the Normalized Difference Vegetation Index (NDVI) which is used to discriminate vegetation regions; The Soil Brightness Index (SBI) which is used to characterize bare soil; The Difference Water Index (NDWI) and the Index Surfaces Built (ISU) which are intended respectively for water and urban areas.

For textural signature, the mean, the standard deviation, the entropy, the energy and Gabor wavelet decomposition features are used to identify texture variation.

After the feature selection step which involved spectral and texture information, image samples, derived from a supervised segmentation procedure were used to train the RBF kernel SVM based algorithm. Then the classifier was supplied with all image feature vectors to derive the final classification map.

2.2. Ontology construction

Expert knowledge formalization has been addressed within earth observation scope especially when dealing with image classification and interpretation.

This work proposes a new automatic detection of anarchic constructions by rules formalization instead of manual extraction which is complex and time consuming. Those rules are set using basic government urbanization documents and available land-use data as an input for the knowledge base (cf. Figure 1). Formalization is done by means of an adapted ontology construction (cf. Figure 2). This last refers to the way of representing knowledge. Experts have to translate their semantic interpretation and rules into concepts to build the scene ontology (the concepts correspond to ontology leaves). The relationship between two levels in the ontology may represent a membership relation "is a", an obligation "obey to", a verification "verify", etc. The aim of the ontology is to transform the semantic information into spatial and/or radiometry information to be able to apply automatically the decision process.

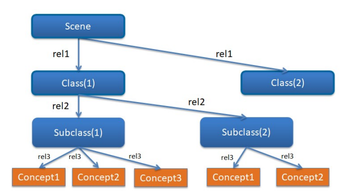


Figure 2. Remote Sensing scene ontology. (rel_i) refers to relation i which can be "is a"; "obey to"; "verify"; etc.

The decision process is made by combining the formalized rules as follows:

$$ACD \equiv \bigcap_{i=1}^{N} C_i \quad (1)$$

Where ACD refers to Anarchic Constructions Decision, C_i is the i^{th} concept and N is the number of concepts.

2.3. Concepts formalization

After concepts identification, we need to translate those abstract linguistic terms into identifiable objects in images. In this step, we make the correspondence between qualitative definition of a concept (textual definition) and its quantitative description (image representation). These definitions allow to describe and to use inference (reasoning) on remote sensing domain. For concept formalization, the above notions are defined:

Definition 1. (Concept) Consider Θ the set of concepts in the ontology. A concept C_i, $i=1..N$, is a rule extracted from the knowledge base. It corresponds to a leave of the ontology.

Definition 2. (Image) Let C_i, $i=1..N$ be the concepts. We define I_i as the resulted image containing a quantitative representation of the concept. This image is a binary mask translating spatial rules.

Formalizing the semantic information consists then in defining the ontology, the concepts set Θ, the N corresponding binary images and then to apply the ontology decision.

3. URBAN EXPANSION MONITORING

This section presents an overview of the proposed multi-temporal based SITS classification principle detailed in [6] (cf. Figure1). We need first to identify the spatio-temporal regions included in the SITS by applying classification on each image (cf. last section). SITS images are supposed to be pretreated (pansharpening and co-registration) before applying classification.

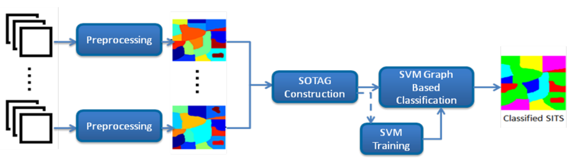


Figure 3. Urban expansion monitoring using temporal graphs classification.

Spatially homogenous regions are temporally analyzed through graph construction. Indeed, a SOTAG is constructed for each region of the first image. Here, we use chronological order to arrange SITS images.

The SOTAG begins by a region of the first image and it grows up involving following SITS images. In those graphs, a node represents a region and an edge represents the temporal relationship between regions.

The nodes are labelled using the discriminative signatures presented in section 2.1. However, the edges are labelled according to area intersection (neighborhood overlap) between temporal regions as images are co-registered.

After SOTAGs construction, they are all classified using a graph kernel SVM based algorithm (cf. Figure1). This step is done in order to extract regions with similar temporal evolutions. In this paper, we use a particular graph-based kernel called Marginalized Graph Kernel, introduced by Kashima et al. [6]. It uses the concept of random walk which is a sequence of labels and vertices selected on a graph along a random path. The adapted expression and all the mathematical framework of this MGK is detailed in [6]. It allows the spatio-temporal classification of the SITS basing on graph forms.

4. RESULTS AND DISCUSSION

The study region is located in the north east of Tunisia (A town called Kelibia covering 1100Ha) and is characterized by several anarchic urban expansions around rivers, agricultural regions and along the sea. The available data for this area is: One Arial image 2010; Two Pleiades images acquired in 2012 and 2016; Urban Development Plans; the agricultural map; the coastal lines, a digitalized rivers map, government urbanization documents, etc. These data have been collected and generated with a strong help and assistance from urban experts.

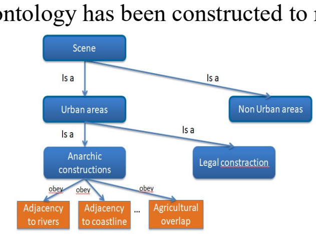
4.1. Mono-date classification results

As mentioned before, supervised SVM algorithm is chosen owing to its flexibility with adaptive feature vectors and kernel trick. For each pixel, a feature vector composed of different discriminating features (indicated in section 2) is generated.

Figure 4 illustrates the obtained classification results. The proposed SVM based classification achieves 88% of OA and 0.72 of Kappa index which is a very sufficient result comparing to other tested methods.

Figure 4 . Urban areas extraction.

For the extraction of illegal urban expansions, the above ontology has been constructed to model the identified rules.



- Concept1: The adjacency to rivers rule can be expressed by measuring the distance of each pixel of the image to rivers (digitalized rivers map) and mask those which distance is less than 20m. The resulted binary image indicates the forbidding areas according to this rule.
- Concept 2: The adjacency to coastline rule is defined by measuring the distance of each pixel of the image to coastline (digitalized coastline map) and masks those which distance is less than 25m. A binary image is thus obtained.
- Concept3: The adjacency to roads rule is defined as concepts 1 and 2.
- Concept4: The adjacency to public areas rule is defined as concepts 1, 2 and 3.
- Concept5: The agricultural overlap rule exploits the Urban Development Plan and the agricultural map which are combined to generate the spatial natural regions to be preserved from illegal constructions (binary images).

Figure 5. Ontology model and concepts definitions.

Based on the available knowledge of Kelibia region, five concepts have been identified and used in this work (additional concepts/rules can be added according to available data). These concepts are listed in Figure 5.

The ontology decision is applied by intersecting all the binary images and confronting them to the obtained urban classified image. Figure 6 illustrate some anarchic construction detection near rivers and along the coastlines. The main interest of the proposed work is that these regions are automatically identified according to several rules combined after their formalization to metric information (binary images).

Figure 6. Localization of anarchic constructions after ontology decision.

4.2. Multi-temporal classification results

Figure 7 shows the temporal evolution of the three identified regions. The non-urban areas are non-colored to emphasize urban boundaries. As we can notice, legal urban regions have globally a stable evolution. However, a new construction has been added and has been classified as an illegal building because of its distance to the river. Another legal building has been also identified. The illustrated graphs describe these temporal evolutions. The resulted temporal map highlights the evolution of the three regions and can greatly help the urban experts to control urban anarchic expansion.

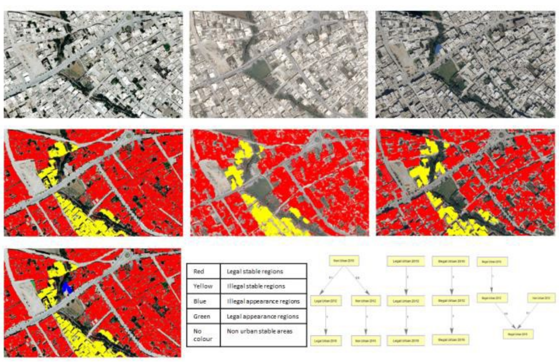


Figure 7. Results of temporal classification of urban (legal and illegal)/non urban areas.

5. CONCLUSION

In this work, illegal urban expansion monitoring issue is In this work, illegal urban expansion monitoring issue is considered by combining classified VHR images and formalized semantic rules. The originality of this work consists in the formalization of the expert knowledge overcoming thus the semantic gap between human image interpretation and developed algorithms. The proposed approach has mainly two steps: anarchic urban expansions detection and monitoring. The knowledge-based approach allows identifying illegal buildings by using a specified ontology intended for combining semantic rules translated to concepts. These buildings are then monitored using graphs allowing the recognition of their spatio-temporal evolution.

The proposed technique performs sufficient results in the context of Kelibia project. It allows the assistance of experts and helps them to find the location of suspicious anarchic constructions by avoiding time and effort waste in checking large areas. We propose as a future work the integration.

6. ACKNOWLEDGEMENTS

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