Spatio-Temporal Modeling for Knowledge Discovery in Satellite Image Databases

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RÉSUMÉ. *L'extraction automatique des connaissances à partir des images satellitaires dans un contexte spatio-temporel est un défit majeur pour le domaine de la télédétection. Dans ce contexte, nous présentons une approche haut-niveau pour la modélisation des connaissances spatio-temporelles à partir des images satellitaires. Nous proposons, aussi, d'utiliser une segmentation multi-approche comportant plusieurs méthodes de segmentation pour améliorer la modélisation et l'interprétation des images. Les expérimentations montrent que les résultats de la segmentation issues de l'approche proposée sont meilleurs que celles des méthodes classiques.*

ABSTRACT. *Knowledge discovery from satellite images in spatio-temporal context remains one of the major challenges in the remote sensing field. It is, always, difficult for a user to manually extract useful information especially when processing a large collection of satellite images. Thus, we need to use automatic knowledge discovery in order to develop intelligent image interpretation systems. In this paper, we present a high-level approach for modeling spatio-temporal knowledge from satellite images. We also propose to use a multi-approach segmentation involving several segmentation methods which help improving images modeling and interpretation. The experiments, made on LANDSAT scenes, show that our approach outperforms classical methods in image segmentation and are able to predict spatio-temporal changes of satellite images.*

MOTS-CLÉS : *Modélisation spatio-temporelle, extraction connaissances, segmentation.*

KEYWORDS: *Spatio-temporal modeling, knowledge discovery, segmentation, remote sensing.*

1. Introduction

Advances in satellite image acquisition and storage technology have led to a vast amount of data. This data, when analyzed, can reveal to useful information in several fields such as the land cover detection, land cover change, deforestation, desertification, etc. Using these information in a spatio-temporal context is a highly desired goal for efficient interpretation of changes in dynamic phenomena (Barnes *et al.,* 2007) (Tang *et al.,* 2007) (Umamaheshwaran *et al.,* 2007). The spatio-temporal concept denotes the combination of the spatial and temporal concepts and this by recording the spatial view in time. However, the complexity of data remains a challenging problem when we attempt to discover knowledge from satellite images. This involves several operations (e.g. segmentation, features computing, etc.) in order to be able to interpret automatically images. Moreover, geographic objects in remotely sensed images, have always, spatio-temporal relations which can be metric (i.e. distance), non metric (i.e. direction) or temporal (i.e. before and after). These relations must be considered when analyzing this type of images. The third problem is the emergence of the very high-resolution sensors (i.e. spatial, spectral, and temporal resolution). So, the manual interpretation of images captured by these sensors become a very hard task. In order to resolve these problems, several researches consider using automatic systems for knowledge discovery from satellites images (Barnes *et al.,* 2007) (Tang *et al.,* 2007). However, this requires converting images data to data understandable by these systems. Much work has been invested in modeling image data. (Ettabaa *et al.,* 2008) presents a metadata based approach for mining and interpreting spatio-temporal knowledge. Authors suggested using only one algorithm to segment satellite images. This assumes that this algorithm is reliable and well adapted to all images ; which is not always the case. (Huang *et al.,* 2008) proposed a two-steps method for knowledge discovery from satellite images. Authors start by segmenting images, then computing features of extracted objects. This approach allows retrieving objects according to their features and spatial relations. However, this approach allows, only, processing spatial features of images. The spatial/temporal evolution is not treated. In (Forestier *et al.,* 2008), authors recommended a collaborative segmentation approach for data mining in satellite images. They presented a framework allowing unifying segmentation results in order to generate an ontology describing a given image. However, the temporal aspect in the approach presented in (Forestier *et al.,* 2008) is also not treated. The study on the State-of-the-Art of several knowledge discovery systems from satellite images depicts the benefices of using a model describing images. This model allows for a better processing, analyzing, and interpretation of images. But, the obvious observation for most works related to this field shows that spatio-temporal features of images has not been thoroughly studied. Moreover, segmentation (key process in knowledge discovery from images) is not well investigated.

In this paper, we propose to automate the generation of models describing satellite images. The generated models take into account spatial/temporal features. Besides, we follow a multi-approach segmentation involving several segmentation methods which help improving images modeling and interpretation.

The remainder of the paper is structured as follows : in Section 2 we review images segmentation. We detail our proposed approach for spatio-temporal model generation from satellite images in Section 3. Section 4 is devoted to validation. In this section, we highlight the role of the generated models in predicting spatio-temporal changes of satellite images. This paper closes with concluding remarks and future work.

2. A Review of Image Segmentation

Segmentation refers to the process of partitioning a satellite image into homogeneous regions of interest (also known as segments, clusters, objects) (Gançarski *et al.,* 2007). In this paper, we choose the "objects" term as results of the image segmentation. An extracted object from a satellite image can be a "lake", a "vegetation", an "urban site", a "forest", etc.

Several works have investigated this challenging domain (Umamaheshwaran *et al.,* 2007). The main objective of these works is to provide a segmentation of a satellite image which is close enough to the reality (Boubou, 2006) (Forestier *et al.,* 2008) (Gançarski *et al.,* 2007). We distinguish five methods of segmentation : hierarchical methods, partition-based methods, grid-based methods, density-based methods, and model-based methods (Boubou, 2006).

The hierarchical segmentation builds the hierarchy by establishing which two pixels are the closest together, then combining these into a single node and repeating until the tree is completed and image is segmented. Hierarchical algorithms are based on two concepts : grouping similar objects (done by the **D**escending **H**ierarchical **C**lustering (DHC) algorithm) and dividing dissimilar objects (done by **A**scending **H**ierarchical **C**lustering (AHC) algorithm) (Boubou, 2006).

Partition-based algorithms determine a partition of the patterns into K groups or objects such that the patterns in an object are more similar to each other than patterns in different objects (Boubou, 2006) (Nuzillard *et al.,* 2007).

Density-based methods rely on neighborhood notion to determine objects (Boubou, 2006). These methods deal with objects as regions of dense pixels which are separated by less dense regions. Here, the density is represented by the number of pixels in the whole image. The purpose of the density-based algorithms is to detect anomalies and to identify individuals which constitute "outliers".

The grid segmentation is based on a concept of multi-level granularity (Boubou, 2006). The key idea is to divide data space into a finite number of cells and to group neighboring cells in terms of distance. The grid-based segmentation algorithms allow a spatial classification of data using statistic information of pixels.

The last method of segmentation is the model-based method which affects to each object a model then it verifies each model to select the best one (Boubou, 2006). Model-based algorithms allow discovering understandable objects rather than defining similarity measures to minimize distances intra-objects and to maximize distances inter-objects.

3. The Proposed Approach

In (Boulila *et al.,* 2009b), the issue of spatiotemporal knowledge discovery from satellite images is discussed. This allows building decision, prevision and postdiction models useful in Satellite Image Time Series interpretation. Whereas, in (Boulila *et al.,* 2009a), the issue of taking into account imperfections related to discovering changes made throughout time is addressed. Different KDD methods are used to discover spatiotemporal changes. Each method presents a partial point of view of the evolution of a query model. In order to combine these points of view, the evidence fusion theory is used. This provides global decisions about changes which are more accurate and complete.
In this paper, we present a high-level approach for modeling spatio-temporal knowledge from satellite images. The proposed approach is a key step which prepares data for the knowledge discovery process. This study emphasizes the spatio-temporal model generation based on multi-approach segmentation. The proposed approach is presented as a process which is divided in two steps : spatio-temporal model generation and spatio-temporal model query steps.

3.1. *The Spatio-temporal Model Generation*

The model generation step ensures learning of the proposed approach through the preparation of spatio-temporal models representing satellite images. These models are stored in a model base. The model generation step is based on a multi-approach segmentation allowing the identification of objects, features processing allowing describing extracted objects and model building allowing the construction of spatio-temporal models. Figure 1 describes the spatio-temporal model generation.

3.1.1. *The Multi-approach Segmentation*

The key step in our approach is the multi-approach images segmentation. As seen previously, there are five methods of segmentation in the literature. However, one major problem of these methods is their inabilities to generate objects which are close enough to the reality. The main problem of the segmentation is the loss of information when we attempt to model satellite image. In order to reduce this loss of information, we apply, simultaneously, the five segmentation methods detailed in section 2. Each applied method has its own algorithm which can be more appropriate to segment certain images. Also, applying several methods of segmentation helps discover new knowledge not discovered when applying only one method.
Our approach uses the five segmentation methods : hierarchical, partition-based, grid-based, density-based, and model-based methods. We use the k-means algorithm (Hartigan, 1979) as a hierarchical segmentation method. We choose the **B**alanced **I**terative **R**educing and **C**lustering (BIRCH) algorithm (Zhang *et al.,* 1996) as a partition-based method. We use **ST**atistical **IN**formation **G**rid (STING) algorithm as a grid-based segmentation method (Wang *et al.,* 1997). We apply **D**ensity **B**ased **S**patial **C**lustering of **A**pplications with **N**oise (DBSCAN) algorithm (Ankerst *et al.,* 1999) for the density-

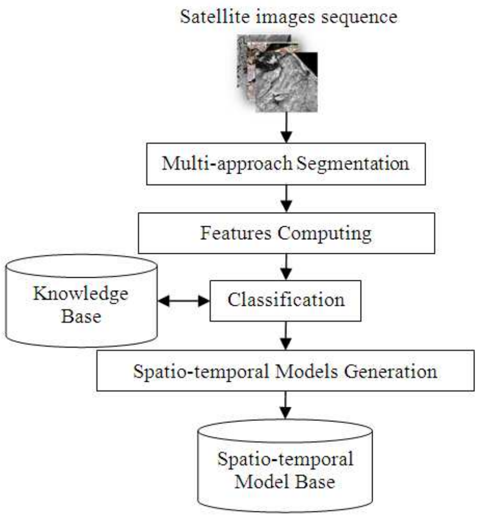

Figure 1. *The spatio-temporal model generation.*

based segmentation method. Finally, as a model-based segmentation method, we use **E**xpectation-**M**aximization (EM) (Dempster *et al.,* 1977).
The multi-approach segmentation provides segmented images which are different. To obtain a final segmented image, we process objects unification and combination. Objects unification allows detecting and resolving conflicts between objects. Objects unification allows detecting and resolving conflicts between objects. Objects unification assists objects combination by either a separation of a class of objects into several subclasses, a fusion of subclasses into a new class or a reclassification (a class is shifted and its objects are reclassified among the remaining classes) (Forestier *et al.,* 2008). We start by evaluating the dissimilarities between couples of segmented images. Once conflicts are detected, their resolutions are started. This process is iterated until all conflicts are resolved. The objects combination provides a final segmented image that takes into account the five segmentation algorithms. We use a vote majority algorithm which is well adapted for combining decisions (Gançarski *et al.,* 2007). The vote algorithm starts by examining all objects in the k-means segmented image. For each object, the vote algorithm searches for corresponding objects in the all others four segmented images. Then, it compares the class types relative to each object in all images. Finally, the new class type of a given object is the maximum of the class types for this object.
The last step in segmentation is the extraction of objects. This step aims to determine meaningful objects from segmented images. We choose two criteria for objects extraction : minimum threshold and connectivity. Minimum threshold defines the minimum number of pixels that an object encloses. Connectivity describes the number of pixels surrounding a given pixel.

Algorithm 1 depicts the process of objects extraction. For each type of object class (the type of object class involves all objects having the same nature ; the same label), we start by separating all objects. Then, objects having a pixel number less than the minimum threshold (*ExtractionThresh*) and a connectivity less than the connectivity threshold (*ConnectivityThresh*) are disregarded. Achieved objects belonging to the same type of object class are registered in a separate object structure (*StructObjs*).

Algorithm 1 Objects Extraction Algorithm

Require: *ImageSegmente,* ExtractionThresh*,* ConnectivityThresh
Ensure: *StructObjs*

```
for all Objects classes in an image I do
    Separate each objects class
    Eliminate regions having a less number of pixels than ExtractionThresh
    Only keep pixels having a connectivity greater than ConnectivityThresh
    Divide each object into a separate image
    Register objects belonging to the same class in a separate structure StructObjs
end for
```

3.1.2. *Features Processing*

Geographic objects, usually, evolve according to three axes : spatial, temporal, and thematic. To follow object evolution according to these axes, we represent each object by five features : radiometry, geometry, texture, spatial localization, and acquisition context (Aksoy *et al.,* 2005) (Boulila *et al.,* 2009a) (Chitrakala *et al.,* 2009) (Ettabaa *et al.,* 2008).

1) Radiometric Features

The radiometry of an object depends on its spectral composition. Among the features we use in our work : the mean radiometric, the standard deviation, the swekness, and the kurtosis (Chitrakala *et al.,* 2009).
Let us suppose a satellite image *I* having a size of $N_p * N_q$ pixels. *I*=$\{I_{pq}|$ *p*=1, . . ., N_p ; *q*=1, . . ., $N_q\}$, $I_{pq}\in\{0,\ldots, L\text{-}1\}$ where *L* represent the number of gray level.
The mean radiometric X_1 is defined as

$$X_1 = \frac{1}{N_p N_q} \sum_{p=1}^{N_p} \sum_{q=1}^{N_q} I_{pq} \qquad [1]$$

The standard X_2 deviation is defined as

$$X_2 = \sqrt{\frac{1}{N_p N_q} \sum_{p=1}^{N_p} \sum_{q=1}^{N_q} (I_{pq} - X_1)^2} \qquad [2]$$

The swekness X_3 is defined as

$$X_3 = \frac{1}{N_p N_q X_2^3} \sum_{p=1}^{N_p} \sum_{q=1}^{N_q} (I_{pq} - X_1)^3 \qquad [3]$$

The kurtosis X_4 is defined as

$$X_4 = \frac{1}{N_p N_q X_2^4} \sum_{p=1}^{N_p} \sum_{q=1}^{N_q} (I_{pq} - X_1)^4 \quad [4]$$

2) Geometric Features

Geometric features describe the shape of a geographic object independently of sensors and points of observation. Among these features, we list length, width, perimeter, and area. For the length and width, we use the **M**inimum **B**ounding **R**ectangle (MBR).

3) Textural Features

Textual features are related to the contrast of processed images. The textural features can be used to differentiate between objects having the same color. Among these features, we used the Haralick and Gabor features (Manjunath *et al.,* 1996). Haralick features are computed based on co-occurrence matrix. We use five attributes from these features which are : energy, entropy, correlation, homogeneity, and contrast. The Gabor filters represent a visual perception model of texture. Gabor features are the mean and variance of the filtered image.

4) Spatial Features

The spatial description highlights neighborhood relations between objects extracted from satellite image. The spatial features concern the arrangement, spatial relation, and position of the objects to be detected. In our study, we work with two types of spatial relations : directional and metric relations (Aksoy *et al.,* 2005).

Directional relations describe the spatial position of an object with regard to another object. These relations give information about the organization of objects independently from their size, shape or distance. Directional relations can be formulated with numerical values specifying where an object is located inside the reference object. Here the angle between two considered objects is computed while referring to their respective centroids.

Metric relations depict the distances between objects in satellite images. In the proposed approach, the distance between two objects *obj1* and *obj2* corresponds to the distance between their respective centroids (Bedel *et al.,* 2008).

5) Acquisition Context Features

The acquisition context features encloses a set of characteristics describing the circumstances, conditions, and environmental features of the acquisition context. Among these features, we list : image description (e.g. resolution, name, information, etc.), sensor description (e.g. type, spectral interval, degree of certainty, etc.), and atmospheric condition (e.g. temperature, pressure, moisture, etc.).

3.1.3. *Spatio-temporal Model Building*

For each object extracted of a satellite image, we compute the five features describing a given object : radiometric, geometric, textural, spatial, and acquisition context features. The feature attributes are calculated for each image-acquisition date and then translated into an XML file. Let us suppose that we have an object *obj* extracted from a satellite image ; this object can be a lake, vegetation, urban, etc.

For each date, *obj* is identified through a set of attributes value (A_1, ..., A_N) describing the five features. At a given date, the set of attribute values define the state of *obj*. In the proposed approach a model M_p is a set of object states relative to a particular object. The equation (5) presents the form of a model M_p.

$$M_p = \begin{pmatrix} t_1 \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} \\ \vdots \\ t_n \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} \end{pmatrix} \quad [5]$$

3.2. *The Spatio-temporal Model Query*

The model query step ensures prediction of changes throughout time for a query model (Boulila *et al.,* 2009a) (Boulila *et al.,* 2009b). It tracks the same process (as the model generation step) in order to obtain the spatio-temporal models. In this step, the most similar models to the query one are retrieved. The proposed approach process takes advantages of the application of several knowledge mining methods to provide local decisions about the change made throughout time for a given object. The multi-approach model mining is based on four steps : fuzzy clustering, similarity measure, fuzzy classification and spatio-temporal change tree building. The fuzzy clustering is used to decompose the whole model base into several sub-bases having each one models with similar behavior and close attributes. The second sub-step is the similarity measure. This step has as objective to rank models in the considered sub-bases according to their resemblance to a query model. Thus, we obtain a set of similar models at different dates. The fuzzy classification sub-step provides confidence degrees representing the fitting of a state to the different land cover types. The last step, the spatio-temporal change tree building, provides the possible changes of a query model M_p to these land-cover types. It also provides the percentage of these changes and the confidence degree in these changes.
Figure 2 depicts the spatio-temporal model query process.

The similarity measure is ensured by the normalized cosine distance. Cosine similarity is used for calculating the resemblance between two spatio-temporal models. It is often used to limit the dimensionality of the problem. Cosine similarity is more practical for potential applications and online processing unlike other approaches like Euclidean distance-based algorithm, where data need to be normalized first (Dong *et al.,* 2006).

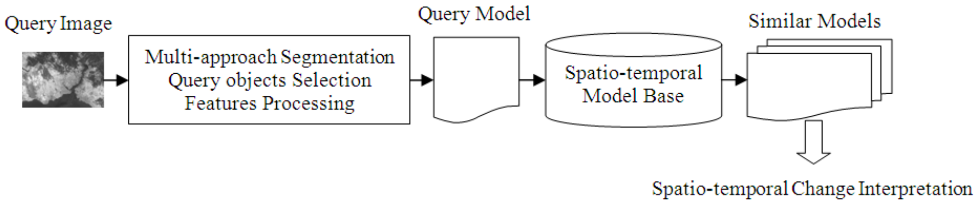

Figure 2. *The spatio-temporal model query.*

Let us suppose that we have two spatio-temporal models M_p and M_q taken at two different dates as follow :

$$M_p = \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix}, M_q = \begin{pmatrix} A'_1 \\ A'_2 \\ \vdots \\ A'_N \end{pmatrix} \quad [6]$$

where A_k and A'_k are respectively the attributes of M_p and M_q.
The similarity between M_p and M_q is computed as follow :

$$Similarity(M_p, M_q) = cos(M_p, M_q) = \frac{\sum_{k=1}^{N} A_k * A'_k}{\sqrt{\sum_{k=1}^{N} A_k^2} * \sqrt{\sum_{k=1}^{N} A'^2_k}} \quad [7]$$

The score for the similarity between two spatio-temporal models ranges from 1 (identical) to 0 (not similar).
As mentioned previously, object extracted from satellite images are identified by five features : radiometry, geometry, texture, spatial localization, and acquisition context. Here, the radiometry, texture and geometry features describe the object attributes without considering the other objects in the image. However, the acquisition context and the spatial localization describe the image in its totality ; the dependence of objects as well as the way of acquiring images. Then, each of the five features influences the matching between the query and the retrieved models in the equation 7.
Finally, only models having a similarity measure higher than a given threshold are considered. All possible states of the retrieved models are inspected (these states constitute the different attributes of the retrieved models considered at several dates such as in the equation 5 ; a state represents a model attributes taken at a given date). Then, we determine the fitting of each state to the different land cover types. The proposed approach provides the percentage of these changes and the confidence degree in these changes.

4. Validation

The validation section is devoted to highlight the goal of metadata generation process in interpreting spatio-temporal change in satellite images. We conduct a series of experiments on two LANDSAT thematic mapper images of the city of Tunis, Tunisia. The first one (Figure 3 at left) is acquired on 1984 whereas the second (Figure 3 at right) is acquired on 2004. We have performed the multi-approach segmentation for the satellite image acquired on 1984 as shown in Figure 4.

Figure 3. *Satellite image acquired on 1984 (at left) and on 2004 (at right).*

After combining segmentation results, we obtain a final segmentation image illustrated by Figure 5.
In order to evaluate the segmentation accuracy of the proposed approach, we conducted series of test using 50 satellite images. The figure 6 depicts an excerpt of the comparison between the proposed approach and the five segmentation methods (k-means, Birch, EM, DBSCAN and Sting) made on twenty images. The comparison shows that the proposed method outperforms the five other methods in the most of cases (30 cases). The global accuracy is 84.31% for the proposed approach, 73.10% for the k-means method, 71.63% for the Birch method, 71.41% for the EM method, 66.63% for the DBSCAN method and 70.78 for the Sting method. Figure 7 shows the percentage of number of times having the best segmentation accuracy for each method. We have 60% for the proposed approach, 8% for Birch, K-means, and DBSCAN, 6% for EM and 10% for Sting.

The major contribution of our approach is to support users in remote sensing filed to discover relevant knowledge. For the purpose of this paper, we choose to predict spatio-temporal changes for the urban site in Figure 5 (this object will represent the query object).
Next, attributes of the five features mentioned above (radiometric, geometric, texture, spatial and acquisition context) are computed for the urban site. Then, the relative spatio-temporal model is built based on these attributes. The main challenge is to retrieve the most similar models to the query one. For that, we start by normalizing the model attributes according to the following formula :

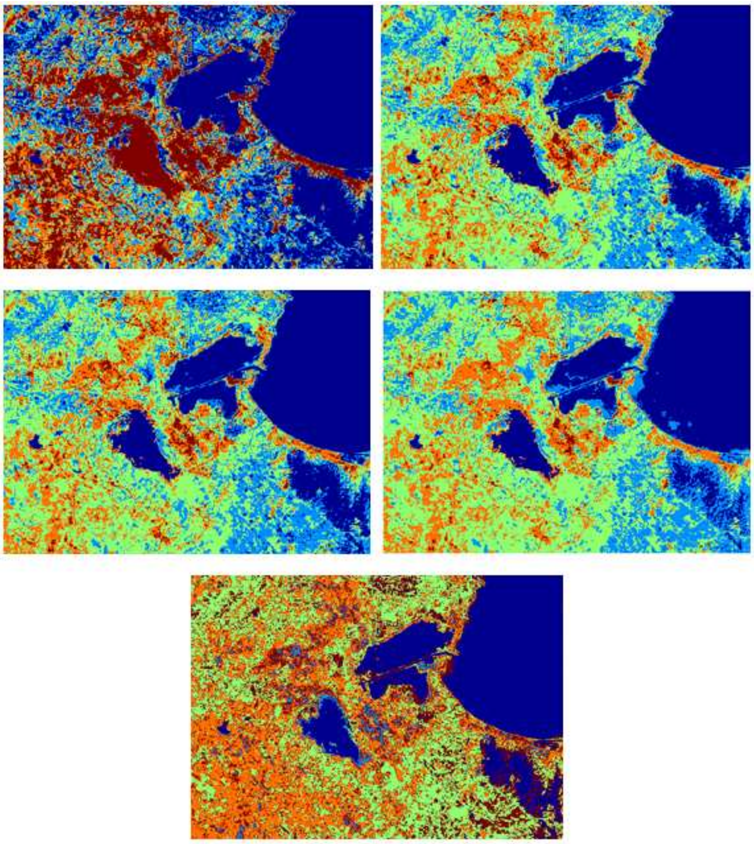

Figure 4. *Respectively from left to right : Birch, k-means, DBSCAN, EM and Sting segmentation for image acquired on 1984.*

$$A_i = \frac{A_i - A_{min}}{A_{max} - A_{min}} \quad [8]$$

where A_{max}=$max_{1\leq i\leq N}\ A_i$; A_{min}=$min_{1\leq i\leq N}\ A_i$.

Our goal is to predict changes for the urban site at the date 2004 for which we have a ground truth image (Figure 3 at right). The retrieved models must have a common characteristic which is the presence of change state after twenty years. This is essential in order to be able to predict the change for the query model for the date 2004. The prediction of change throughout the time can be done for all the attributes of the features already mentioned.

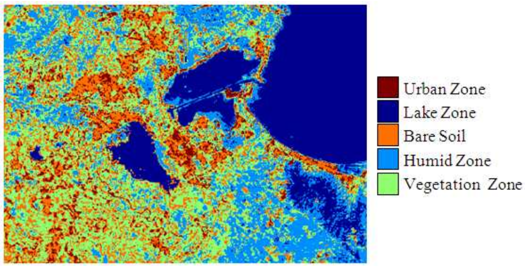

Figure 5. *Final segmentation for the satellite image acquired on 1984.*

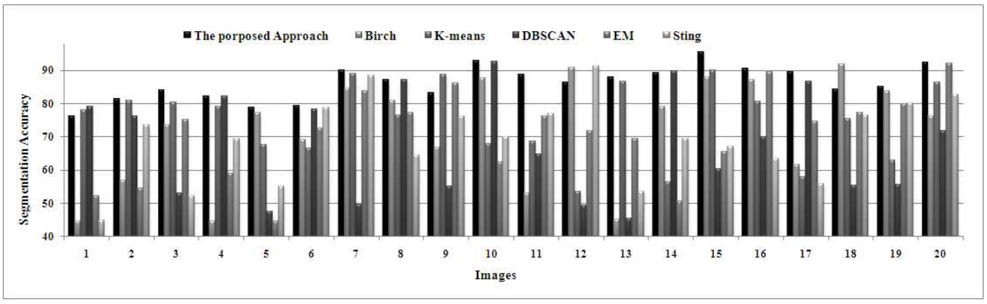

Figure 6. *Segmentation accuracy for the Birch, k-means, DBSCAN, EM, Sting and the proposed approach for 50 image test.*

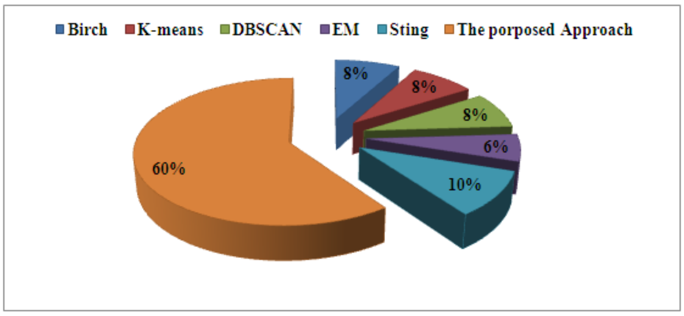

Figure 7. *The percentage of number of times having the best segmentation accuracy for each method.*

For example, we can evaluate the change of the radiometric, geometric, textural and spatial features between 1984 and 2004. This is done using the difference between attributes of the query and the retrieved models.
We can also predict the evolution rate of the query object (urban zone) to the five land cover types (urban, lake, vegetation, bare soil and humid zones). Table 1 depicts the evolution of the query object between 1984 and 2004.

	Urban	Lake	Vegetation	Bare soil	Humid
(1)	187.47	-21.15	-49.12	-4.63	-12.57
(2)	184.15	-20.76	-50.20	-4.30	-8.89

Tableau 1. *Comparison between the proposed (1) and the real (2) changes for the urban site between 1984-2004.*

Table 1 highlights the urbanization and the expansion that the city has undergone during the course of the twenty years. Indeed, the urban area is raised of 87.47% from 1984 to 2004. This growth has especially affected the vegetation and lake zones which lost respectively 49.12 % and 21.15 % of their surfaces.
The growth of urbanization can be explained by the explosion of the modern town of Tunis (capital of Tunisia). According to Tunisia's National Statistical Institute, Tunisia's urban population grew from 4.86 million on 1990 to 6.20 million in 2002, an increase of around 28 %.
Figure 8 depicts the segmentation of the satellite image of the city of Tunis acquired on 2004.
In order to measure the prediction accuracy of the proposed system, the real change

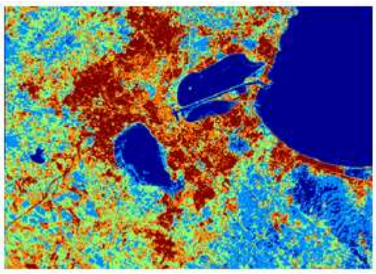

Figure 8. *Final segmentation for the satellite image acquired on 2004.*

made between 1984 and 2004 is computed (Tab. 1). Table 1 indicates a cumulative error between the real change and the change predicted by the proposed approach equal to 8.8%.

5. Conclusion

In this paper, we presented our approach for spatio-temporal modeling of satellite images.
Our contribution resides in : (i) automating the process of spatio-temporal modeling of satellite images, (ii) taking into account the spatial/temporal features of objects extracted from images, (iii) improving the identification of objects by following a multi-approach segmentation. The proposed approach takes advantages of the redundancies and complementarities of segmentation methods in order to decrease imperfections related to images and therefore improving the prediction of changes for objects in satellite images.
The proposed approach is evaluated by two LANDSAT images representing the city of Tunis, Tunisia. Experiments show different applications of spatio-temporal models generated by our approach.
As future works, we consider testing our approach on several images of different domains such as medical one. In addition, we plan to improve the accuracy of the objects identification by finding good features describing these objects.

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