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Post-classification and spatial reasoning: new approach to change detection for updating GIS database

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Abstract— Demand for up-to-date geographic data is increasing due to the fast growth of Geographic Information System (GIS). The process of updating GIS database can be subdivided into three steps. In the first step, changes of the landscape must be detected. In the second step, different data sources must be used to add further attributes. In the last step, the changes with all additional information have to be stored into a GIS database. In this paper, a new approach of change detection for updating GIS database by using remote sensing image is presented. This approach of change detection is based on post-classification comparison and spatial reasoning. Firstly, two different classification methods of satellite imagery, one of pixel-based classification and other of object-oriented classification, have been used. The already existing GIS data are used for deriving the training areas for the classification. The fusion of the results of classification methods yields a good comparison of classification to realizing the change detection between the remote sensing data and GIS data. Secondly, a qualitative approach using spatial reasoning system (Region Connection Calculus RCC8) to representing GIS data and satellite image content in addition to the quantitative information is performed. After a step of segmentation of the satellite image, the spatial reasoning system RCC8 is used to extract and identify the spatial relations (topological and orientation) between the GIS objects and the objects of the results of segmentation. The topological relation describes how the boundaries of two objects relate to each other, while the orientation relation describes where the objects are placed relative to one another. The fusion of the results of post-classification comparison and the spatial reasoning system can detect changes at the level of thematic data, geometric and spatial relations between objects in satellite image and the GIS data. Finally, the changes with all information are returned and stored into the GIS database. This approach is tested with Corine Land Cover (CLC) database and SPOT satellite images.

Keywords—component; Remote sensing, change detection, GIS updating, classification, spatial reasoning

I. INTRODUCTION

Demand for up-to-date geographic data is increasing, due to the fast changes in many regions, and as the result of the spreading of many GIS applications in everyday life. With the

arrival of high resolution sensors, space images are becoming a good source of information to gather knowledge, and to track changes. There are two approaches for updating geo-spatial databases. The first one is to gradually establish a new database that replaces the old one. This approach is slowly. It is suitable for new database building for new area. The second approach is only to detect, identify and update only the changes. It is quick and suitable for those existence databases.

Spatial relations are generally classified into three categories, i.e., topological, metric and order relations. In the GIS spatial analysis, e.g., detection of topological change and topological inconsistency, it often needs detailed topological relations. So, topological relations are very useful for spatial analysis, e.g., change detection, assessment of scene similarity, automatic detection of spatial inconsistency. Indeed, topological change indicates geometric modification of the involved spatial objects, but it is not true for vice versa. The practical usefulness of the hierarchical approach for the description and determination of the topological relations between spatial regions by a case study of change detection is illustrated in [1]. The theory of spatial reasoning RCC-8 is used in [2] for classifying satellite images and recognition objects.

The remainder of this paper is organized as follows. The section II described the change detection methods used in our study. Post-classification comparison and spatial reasoning change detection methods are studied. In section III, this approach is applied by using satellite images SPOT4 and CLC2000 database. Results of the change detection methods are presented. Section IV concludes this paper with further recommendations for our future research works.

II. CHANGE DETECTION

Change detection analysis can be defined as the identification and location of differences of two temporal datasets at times t_1 and t_2 . In [3], especially change detection involves the comparison of two datasets and consists of four processes: detection; recognition that is the thematic classification of the change; identification that is the description of the feature of the thematic change; and

quantification that is the measure of the magnitude of changes. For comparison tow datasets, vector data provides a classified abstract representation of the landscape, while imagery is an unclassified continuous but resolution-dependent generalized representation of the landscape. If comparing data of the same nature (i.e., two homogeneous satellite images) the change detection can be determined at the data level domain (comparison of pre-processed data), while when comparing heterogeneous datasets the change detection is performed at the decision level domain (comparison of analyzed data), as some data processing (e.g., image classification, vectorization of detected features) needs to be done prior to change detection [3]. Then at the decision level, changes of features occur, when either the spatial and/or the attribute characteristics of an existing feature have changed. A change can therefore be in the form of: spatial modification, when the changes in the geometry of an existing feature and its corresponding new feature exceed the accuracy buffer limits and/or when the topology changes; and attribute modification, when the thematic values of an existing feature change. Two ways of detecting changes between existing topographic data and satellite imagery was implemented in [3], based on the results of the extraction of homogeneous features: interactive and semi-automated change detection. Many change detection techniques have been developed.

The paper [4] summarizes and reviews these techniques. One category of these change detection methods is the classification category which includes post-classification comparison, spectral-temporal combined analysis, expectation-maximization algorithm (EM) change detection, unsupervised change detection, hybrid change detection, and ANN. These classification methods often require a large amount of training sample data for supervised or unsupervised classification of image data. Image transformation, vegetation indices, advanced classification methods, modeling, and integration of different data sources are often used to improve classification results. Post-classification comparison is a common approach used for change detection in practice, but the difficulty in classifying historical image data often seriously affects the change detection results. In the following section, we used post-classification technique.

II.1 Post-classification comparison change detection

A change detection approach based on an object-based classification of remote sensing data was introduced in [5]. This approach classifies not single pixels but groups of pixels that represent already existing objects in a GIS database. This approach is based on a supervised Maximum Likelihood Classification (MLC). The multispectral bands (Red R, Green G, Bleu B, Near-Infra Red NIR) grouped by objects and very different measures that can be derived from multispectral bands represent the n-dimensional feature space for the classification. The feature space for the classification is the mean grey value for (B, G, R, NIR) bands and vegetation index, the variance for (B, G, R, NIR) bands, vegetation index and texture, and the percentage class pixel (forest, green land, settlement and water). The training areas are derived automatically from the geographical information system (GIS) database. In our study, for post-classification comparison change detection, two

methods of classification are studied, the first is pixel-based classification and the second is an object-based classification.

Training and validation data: To train the classifier and to evaluate the classifications, we gathered training and validation samples across the study areas and the GIS database. Training data were obtained by visual sampling using the satellite images as support. These sample zones were verified on the GIS and CLC database where necessary.

Feature extraction: Vegetation indices are very often used in pixel-based classification as an input channel to improve the classification result. Vegetated portions of the image are detected using a threshold applied to the Normalized Difference Vegetation Index (NDVI). Both spectral and textural features were used for the classification. The spectral response in all three bands: NIR, R and G were expanded with some spectral indices: we chose to use the NDVI [6] and the Brightness Index (IB) which allow a better recognition of vegetation. Their expressions are given by:

$$NDVI = \frac{NIR - R}{NIR + R} \quad IB = \sqrt{NIR^2 + R^2}$$

Where NIR is the reflectance value of the near-infrared channel, and R is the reflectance value of the red channel. Vegetation has a high reflectance in the NIR channel and a low reflectance in the R channel. In order to obtain two class's vegetation and non-vegetation, consequently, vegetated areas with an NDVI higher than 0.3 were classified.

We also used another spectral index which characterizes urban fabrics. This index, noted ISU, is described in [7] as:

$$ISU = A - B \times \frac{R}{NIR}$$

With A = 100 and B = 25 for HRV SPOT images.

Usually water bodies [8] have a high reflectance in the G channel and a low reflectance in the R channel. Thus, we used:

$$\frac{G - R}{G + R}$$

In order to distinguish water bodies where values higher than 0.15 were extracted out.

Pixel-based classification: Two methods of pixel-based classification were tested, the first supervised Maximum Likelihood Classification (MLC) and the second is ISODATA non supervised classification.

Supervised Maximum Likelihood Classification: the remote sensing data is classified into different land use classes by a supervised maximum likelihood classification. The training areas are derived from the GIS database and visual sampling the satellite images.

ISODATA non supervised classification: this method mostly failed in assigning a resulted cluster to a specific land cover class. Generally, it could be said that the ISODATA results did not allow land cover class discrimination either because a class belonging was distributed among more than one clusters or because one cluster described well more than one classes.

Object-oriented classification: Usually spectral feature criteria: Fusion of the classified objects unites the spectral and spatial information of neighboring same classified objects and

a polygon topology leading to a land cover thematic map is created. The eCognition [9] classification method succeeded in most cases to achieve a high percentage of right land cover class assignment. The resulted land cover classes contained the spatial features and topology information for the objects that they consisted of. These enriched the spectral features in the accompanying attribute table. Using the eCognition capabilities the land cover thematic map and the NDVI image layer provided the spectral and spatial rule sequence to classify non homogeneous sites inside a plot according to the vegetative status, while respecting the land cover class boundaries.

Post-classification comparison change detection: this method of change detection examines changes over time between suites of independently characterized thematic categories. It is very advantageous when using data from different sensors with different spatial and spectral resolutions. Post-classification change detection is one of the most common methods used for change detection. Finally the post-classification change detection is the longest and heaviest method, but also the most precise method concerning the information about types of changes that have occurred. Visually, the thematic map obtained has a better precision. But it is important to note that this method depends on the results of the classification of both images and data stored in GIS database. The quality of the change detection depends on the aspects related to the quality of image interpretation. Accuracy assessment is an important aspect of land cover change mapping. And also the most important thing to consider in change detection is actually the number of false alarms.

II.2 Spatial Reasoning for change detection

Spatial relations are generally classified into three categories, i.e., topological, metric and order relations. Topological relations describe a kind of qualitative spatial information among spatial objects. These three relations act as spatial constraints in different perspectives for the GIS spatial query and analysis in order to detect spatial inconsistency in spatial dataset. However, topological relations are most important and fundamental among these three relations. For example, topological relations are required to automatically detect and remove the spatial inconsistency between rivers and roads, buildings and rivers which may have been created during the map updating process, or in the multiple representations. The key issue of spatial reasoning is the qualitative shape representation. Humans can easily visualize and reason about objects without precise knowledge about their dimensions. The same is true for spatial scenes. This enables humans also to compare different scale scene representations (i.e. images and maps). Such a qualitative approach clearly has its advantages and is therefore useful for the automatic comparison between map (i.e. GIS data) and satellite image. Regions and objects are derived directly as the segmented images by using segmentation methods. Two sorts are declared: pixels and regions as aggregates of pixels.

In a two-dimensional space (IR²), most existing topological models can distinguish the eight basic topological relations between two spatial regions. For region–region topological relations, the most representative models are the 4-intersection, the 9-intersection. In the 4-intersection model, a region is

defined by its interior and boundary, and four intersection sets are included. This model can differentiate eight kinds of the topological relations for two regions. We rely on the RCC-8 theory in this study. The representation of topological relations in the form of lattice inside an Object-based Representation System (ObKR), in order to perform the calculation of these relations on raster images and achieve type deductive reasoning on the relations calculated is tested in the work [10]. Two lattice topological relations are studied with their properties: the lattice portions of RCC-8 and the Galois lattice. This system for representing topological relations that: defines primitives for computing relations on raster images: to compute or to check a relation R between two objects x and y means to test if R(x, y) holds; integrates all the relations used in the landscape models; allows one to store new information; allows reasoning on relations: to reason on relations means to deduce new relations from already computed ones. R(x, y) and R(y, z) known then R(x, z) is estimated. The conjunctions of eight conditions are equivalent to the eight base relations of RCC-8 [11]. Then, computing a relation on the image is the same operation as verifying a set of conditions.

A set of hierarchically topological invariants is defined in [1] based upon the boundary–boundary intersection set (BBIS) of two involved regions. Five types of topological information are focused, which can be defined from a spatial set, including: separation number of a spatial set; dimension of a spatial set; dimension of each element; neighborhoods of each element and holistic sequence of a spatial set.

Several relational-based Qualitative Spatial Reasoning (QSR) theories, each supporting a Conceptual Neighborhoods Diagram (CND), are used to determine the identity of tracked regions over time [12]. In Qualitative Spatial Reasoning (QSR), the nodes of CNDs are typically populated by individual relations defined on regions or intervals, and the edges connecting adjacent nodes as continuous transformations between them. CNDs have been used to measure the similarity between relations and their relation. This matrix of similarity is diagonal. Typically, the set of relations used to populate the nodes of CNDs are defined to be Jointly Exhaustive and Pair wise Disjoint (JEPD). The composition table topological relationships basic theory RCC-8 and the CNDs are presented in the Table I, where the relationship EQ(x, y) is not represented because it is neutral element to the composition. The composition table is used to reason about spatial relations between regions.

The method used in our study is based on the strategy presented in [1] for the extension of the intersection and difference model where the BBIS is a spatial set. Therefore, topological invariants including separation number of the BBIS, dimension of the BBIS, dimension of spatial elements in the BBIS, neighborhoods of spatial elements in the BBIS, and sequence of the BBIS, are utilized for the description and determination of topological relations, and these five invariants can be divided into three levels to obtain: firstly, at the set level: the separation number and dimension model, secondly, at the element level: the element type and number model and finally, at the integrated level: the holistic sequence model (for more details see [1]).

III. TESTS AND RESULTS

Data description: The work is done with CORINE Land Cover data of a French district and the corresponding SPOT images. These SPOT scenes with 20m resolution and three channels (Near-Infra Red, Red and Green) are geo-referenced and radiometrically corrected. CORINE Land Cover (CLC) maps are generated using satellite images and many ancillary data such as aerial photographs. The information provided by the maps is derived manually by GIS-aided visual image interpretation with huge financial and human effort. In [13], the study addresses: the methodology of LC change detection in the context of I&CLC2000 project and; presents results obtained in the Netherlands and the Slovak Republic; and the applications of CLC methodology and data. The CLC90/2000-changes data layer is generated by the overlay of the CLC90 and CLC2000 data layers with the change area of minimum 5 ha. Thematic accuracy of derived data layers is $\geq 85\%$ and the geometric accuracy is better than 100m. CLC classes are very heterogeneous regarding their spectral characteristics. Objects that fall under one class can be fairly different (e.g. artificial surfaces, urban greens, small water bodies, etc.) and such varied objects cannot be classified by computer approach into one class only on basis of spectral signature or texture. The CLC nomenclature is based mainly upon physiognomic attributes (shape, size, color, texture and pattern) of landscape objects (natural, modified-cultivated and artificial) and spatial relationships of the landscape objects. These attributes are crucial for identification of LC classes on satellite images. Artificial surfaces and agricultural areas are also discerned by functional (user) attributes and are related to land use (LU). Please note the principal differences between LC and LU. A LC change is interpreted as a categorical change, when one LC class or its part(s) is replaced by another LC classes. An example of conversion is the change of a broad-leaved forest area into a mineral extraction site area, or a pasture area into a discontinuous urban fabric area. The basic condition for identification of LC changes by application of satellite images is the existence of changes in spectral reflectance. Such changes are manifest on images due to changes of characteristics of interpretation elements (shape, color, texture, pattern etc.). From the methodological point of view it means that images acquired in two or more time horizons are used in identification of LC changes. Three basic approaches are known, by which information on LC changes can be obtained from images: visual and computer aided visual interpretation; digital methods of change identification; and finally use of a combination of these two methods is frequent. To make more efficient the CORINE Land Cover generation by the use of satellite images, in [14], they studied how much information they provide to the CORINE Land Cover map. The use of spectral and textural features, Maximum a Posteriori classification method and Markov Random Field into a hierarchical per pixel classification, and assesses them for the generation of CORINE Land Cover classification is studied. When comparing the classified image with the map, the results show that the hierarchical classification improves the accuracy of some classes, and thus makes it possible to extract many more CORINE Land Cover classes than the single Maximum a Posteriori classification method. Few CLC classes could be extracted with a good accuracy rate. It means that much

exogenous data are needed to identify the other classes which cannot be isolated.

Firstly, the post-classification change detection, in the Figure 2(a), the method of supervised maximum likelihood classification is tested with image SPOT 4 for the region of CENTRE (department Loir-et-Cher) in France. The satellite image is classified into different land use classes of the nomenclature CLC. The training areas are derived from the CLC database and visual sampling the satellite images. The results of classification thematic are compared with the class thematic of the data stocked in the base of CLC2000. In the Figure 2(b), the method ISODATA is applied on the image SPOT 4 for the same region. We observed that this method failed in assigning a resulted cluster to a specific land cover class. For example, the class Water Bodies CLC522 is misclassified with this method.

Secondly, for spatial reasoning change detection and to explain this method of change detection, we used a satellite image classified and a data from the base CLC with their class thematic Figure 2(c). We exploited the approach presented in the section II and [1]. A zone is made of image regions, i.e., connected sets of pixels with the same label, the label representing the land-use category. Δ denotes the set of the regions of an image that are regular, with no hole, closed, and not necessarily connected. A region $A \in \Delta$ is made of two sets, Where A° is the interior of A and ∂A is the boundary. At the coarse level, we tested *the Intersection and Difference model (ID)*:

$$\begin{aligned} ID(A, B) &= [A^\circ \cap B^\circ, A - B, B - A, \partial A \cap \partial B] \\ ID(A, B) &= \begin{bmatrix} \emptyset & \neg \emptyset \\ \neg \emptyset & \neg \emptyset \end{bmatrix} \equiv Meet(A, B) \\ ID(A, C) &= \begin{bmatrix} \emptyset & \neg \emptyset \\ \neg \emptyset & \neg \emptyset \end{bmatrix} \equiv Meet(A, C) \\ ID(A', C') &= \begin{bmatrix} \emptyset & \neg \emptyset \\ \neg \emptyset & \neg \emptyset \end{bmatrix} \equiv Meet(A', C') \end{aligned}$$

We observed that there are no changes but visually this is incorrect. To correct this error, we used at the detailed level according to: the separation number and dimension model; the element type and number model; the holistic sequence model for a complete description of the topological relations between these two regions. *The Separation number and Dimension model (SD)*:

$$SD(A, B) = [A^\circ \cap B^\circ, A - B, B - A, \chi(\partial A \cap \partial B), \dim(\partial A \cap \partial B)]$$

The concept of spatial set for a spatial object; it is treated as a set in the GIS spatial operation and analysis. Therefore, a spatial set can represent an individual spatial object, or a sort of spatial objects (e.g., road networks), even or a mixture of them. The separation number of a spatial set is regarded as:

$$\begin{aligned} S1 &= \partial A \cap \partial B = \{s1, s2, s3, s4, s5\} \\ S2 &= \partial A \cap \partial C = \{s6, s7\} \\ S3 &= \partial A' \cap \partial C' = \{k1, k2, k3, k4, k5, k6, k7, k8\} \end{aligned}$$

TABLE I. CND AND THE COMPOSITION TABLE TOPOLOGICAL RELATIONSHIPS BASIC THEORY RCC-8

$R_1(x, y)$	$R_2(y, z)$						
	<i>NTPP</i>	<i>TPP</i>	$NTPP^{-1}$	TPP^{-1}	<i>PO</i>	<i>EC</i>	<i>DC</i>
NTPP	NTTP	NTTP	8	DC EC PO TPP NTTP	DC EC PO TPP NTTP	DC	DC
TPP	NTTP	TPP NTTP	DC EC PO TPP^{-1} $NTPP^{-1}$	DC EC PO TPP TPP^{-1} EQ	DC EC PO TPP NTTP	DC EC	DC
$NTPP^{-1}$	PO TPP NTTP TPP^{-1} $NTPP^{-1}$ EQ	PO TPP^{-1} $NTPP^{-1}$	$NTPP^{-1}$	$NTPP^{-1}$	PO TPP^{-1} $NTPP^{-1}$	PO TPP^{-1} $NTPP^{-1}$	DC EC PO TPP^{-1} $NTPP^{-1}$
TPP^{-1}	PO TPP NTTP	PO TPP TPP^{-1} EQ	$NTPP^{-1}$	TPP^{-1} $NTPP^{-1}$	PO TPP^{-1} $NTPP^{-1}$	EC PO TPP^{-1} $NTPP^{-1}$	DC EC PO TPP^{-1} $NTPP^{-1}$
PO	PO TPP NTTP	PO TPP NTTP	DC EC PO TPP^{-1} $NTPP^{-1}$	DC EC PO TPP^{-1} $NTPP^{-1}$	8	DC EC PO TPP^{-1} $NTPP^{-1}$	DC EC PO TPP^{-1} $NTPP^{-1}$
EC	PO TPP NTTP	EC PO TPP NTTP	DC	DC EC	DC EC PO TPP NTTP	DC EC PO TP TPP^{-1} EQ	DC EC PO TPP^{-1} $NTPP^{-1}$
DC	DC EC PO TPP NTTP	DC EC PO TPP NTTP	DC	DC	DC EC PO TPP NTTP	DC EC PO TPP NTP	8

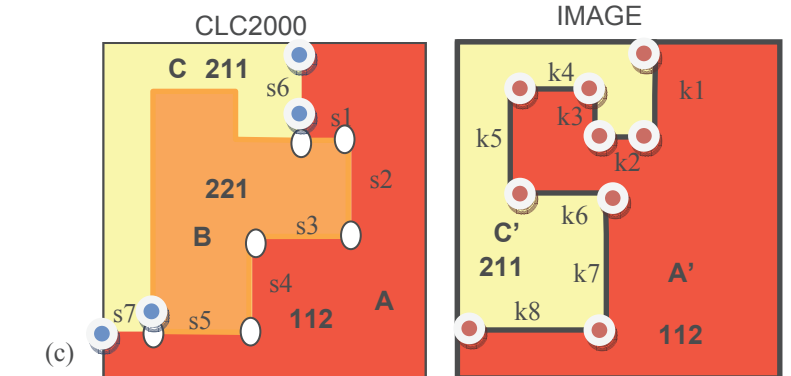
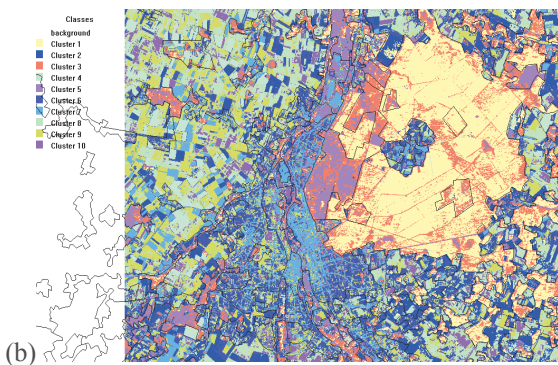
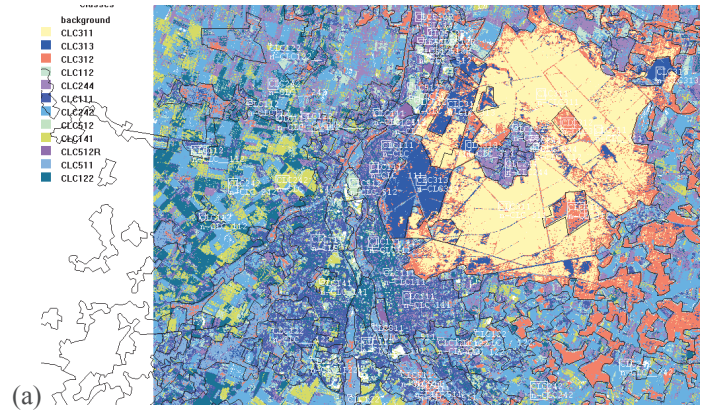
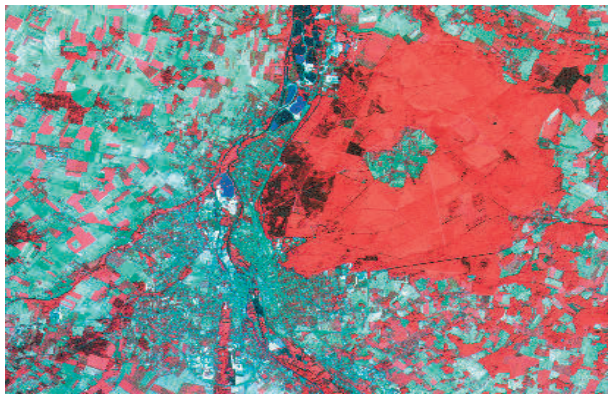


Figure 1. maximum likelihood classification (a) and ISODATA classification (b)

(c) CLC2000 data and Image classified with segment lines

The separation number of spatial sets $r = \chi(\partial A \cap \partial B)$ to : S1 is equal to five line segments for A and B; S2 is equal to two line segments for A and C; S3 is equal to eight line segments for A' and C'. Then, the dimension of a spatial set, denoted by $\dim(S)$, may be defined as the maximal dimension of its spatial elements:

$$\dim(S) = \max_i \{ \dim(s_1), \dim(s_2), \dots, \dim(s_n) \}$$

We take the spatial sets S1, S2 and S3 for compute the dimension:

$$\begin{aligned} \dim(S1) &= \dim(\partial A \cap \partial B) \\ &= \max_5 \{ \dim(s_1), \dim(s_2), \dim(s_3), \dim(s_4), \dim(s_5) \} \\ &= 1 \\ \dim(S2) &= \dim(\partial A \cap \partial C) \\ &= \max_2 \{ \dim(s_6), \dim(s_7) \} = 1 \end{aligned}$$

Spatial Element	Dimension of a Spatial Element
Point (P)	$\dim(P) = 0$
Line (L)	$\dim(L) = 1$
Area (A)	$\dim(A) = 2$
Empty	$\dim(\text{Empty}) = -1$

$$\dim(S3) = \dim(\partial A' \cap \partial C')$$

$$= \max_8 \left\{ \begin{array}{l} \dim(k_1), \dim(k_2), \dim(k_3), \dim(k_4), \\ \dim(k_5), \dim(k_6), \dim(k_7), \dim(k_8) \end{array} \right\}$$

$$\dim(S3) = 1$$

The Separation number and Dimension model (SD):

$$SD(A, B) = [\emptyset, \neg\emptyset, \neg\emptyset, 5, 1]$$

$$SD(A, C) = [\emptyset, \neg\emptyset, \neg\emptyset, 2, 1]$$

$$SD(A', C') = [\emptyset, \neg\emptyset, \neg\emptyset, 8, 1]$$

We can detect that there are a change occurred but we can't defined completely how the relation between A and C are occurred. For more information, we take *the element Type and Number model (TN)*:

$$TN(A, B) = \left[A^\circ \cap B^\circ, A - B, B - A, N_I(.) \right]$$

With:

$$N_I(.) = N_0(P0), \dots, N_9(P0), N_{10}(L10), \dots, N_{25}(L25)$$

Where: $N_I(.) (0 \leq i \leq 25)$ represents number of the *ith* type of spatial elements. Point (P) elements in the BBIS between two spatial regions can be differentiated into ten categories and Line (L) elements into 16 categories. For line elements, we have extended the table of categories of line elements in the BBIS [*] is extended to take in account the case "Meet" in all observations. We applied the element type and number model: for A and B, we have three of five segment lines L22 and one L24 and one L25, and for A and C, we have two segment lines L11 and L23. We obtain:

$$TN(A, B) = [\emptyset, \neg\emptyset, \neg\emptyset, 3(L22), 1(L24), 1(L25)]$$

$$TN(A, C) = [\emptyset, \neg\emptyset, \neg\emptyset, 1(L11), 1(L23)]$$

For A' and C', we have eight segment lines, six L22, one L24 and one L25:

$$TN(A', C') = [\emptyset, \neg\emptyset, \neg\emptyset, 6(L22), 1(L24), 1(L25)]$$

We can observe the change occurred and who the change could be effect the relation between two regions. But we can't determine the order and the position of the change. In order to capture more information about the order we take *the holistic Sequence model (SC)* based on the complete order of the spatial elements in the BBIS, which is formed as:

$$SC(A, B) = \left[A^\circ \cap B^\circ, A - B, B - A, Oc(.) \right]$$

$$\text{With: } Oc(A, B) = \langle c_0(t_0), c_1(t_1), \dots, c_{r-1}(t_{r-1}) \rangle$$

Where: $t_i (1 \leq i \leq r - 1)$ is the type of spatial elements and $c_i (1 \leq i \leq r - 1)$ is the numeric label of t_i . $Oc(A, B)$ is also a topological invariant, and contains more topological details than both types and numbers of spatial elements. In our case, we have:

$$Oc(A, B) = \langle 1(L24), 2(L22), 3(L22), 4(L22), 5(L25) \rangle$$

$$SC(A, B) = [\emptyset, \neg\emptyset, \neg\emptyset, 1(L10), 2(L22), 3(L22), 4(L22), 5(L10)]$$

This describe there are no region between A and B and the two regions are connected or Tangential Proper Part (TPP) completely.

$$Oc(A, C) = \langle 1(L24), 2(L23) \rangle$$

$$SC(A, C) = [\emptyset, \neg\emptyset, \neg\emptyset, 1(L11), 2(L23)]$$

This describe that there are a region between A and C the two regions are partially connected or Tangential Proper Part (TPP) but not completely.

$$Oc(A', C') = \left\langle \begin{array}{l} 1(L24), 2(L22), 3(L22), 4(L22), \\ 5(L22), 6(L22), 7(L22), 8(L25) \end{array} \right\rangle$$

$$SC(A', C') = [\emptyset, \neg\emptyset, \neg\emptyset, Oc(A', C')]$$

This describe there are no region between A' and C' and the two regions are connected or Tangential Proper Part (TPP) completely. The changes are occurred and one region or object is disappeared. In the case inverse, when a new object is appeared. How can we detect this new object? We used also *the holistic sequence model (SC)*.

IV. CONCLUSION

In this paper, new approach of change detection based on post-classification comparison and spatial reasoning is studied. For post-classification comparison, two different classification methods of satellite imagery, one of pixel-based classification and other of object-oriented classification, are tested to realizing the change detection between the remote sensing data and CLC2000 data. The Normalized Differentiated Vegetation Index (NDVI), the Brightness Index (IB), the spectral index that characterizes urban fabrics (ISU) and water index are used in the process of classification. A qualitative approach using spatial reasoning system (Region Connection Calculus RCC8) to representing GIS data and satellite image is performed. The spatial reasoning system is used to extract and identify the

spatial relations topological between the GIS classes at the coarse and detailed level. For spatial reasoning change detection, we are used satellite images (SPOT 4) classified and a data from the base CLC with their classes thematic. This approach can be detecting changes where objects, regions or classes appear or disappear when we take the bounding box of objects.

In our future research works, we envisaged use the composition table and the CND combined with the Galois lattice to optimize the calculus of topological relations between regions.

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