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# Improving Spatiotemporal Change Detection: A High Level Fusion Approach for Discovering Uncertain Knowledge from Satellite Image Databases

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*Abstract*—This paper investigates the problem of tracking spatiotemporal changes of a satellite image through the use of Knowledge Discovery in Database (KDD). The purpose of this study is to help a given user effectively discover interesting knowledge and then build prediction and decision models. Unfortunately, the KDD process for spatiotemporal data is always marked by several types of imperfections. In our paper, we take these imperfections into consideration in order to provide more accurate decisions. To achieve this objective, different KDD methods are used to discover knowledge in satellite image databases. Each method presents a different point of view of spatiotemporal evolution of a query model (which represents an extracted object from a satellite image). In order to combine these methods, we use the evidence fusion theory which considerably improves the spatiotemporal knowledge discovery process and increases our belief in the spatiotemporal model change. Experimental results of satellite images representing the region of Auckland in New Zealand depict the improvement in the overall change detection as compared to using classical methods.

*Keywords*—Knowledge discovery in satellite databases, knowledge fusion, data imperfection, data mining, spatiotemporal change detection.

## I. Introduction

REMOTELY sensed imagery in spatiotemporal context is an invaluable tool for scientists, governments and the military. It has several applications to include land change detection, land use monitoring and management, fire protection, and so on. However, the amount of information received from satellites is constantly increasing. Therefore, automatic knowledge discovery and content-based retrieval is becoming very valuable as they help develop intelligent interpretation systems based on remote sensing image databases. Indeed, knowledge discovery in satellite image databases denotes the association of data mining and satellite image processing technology help analyze, discover and interpret data in an image-rich domain. It is a disciplinary endeavor that draws upon expertise in image processing and retrieval, data mining, machine learning, database, and artificial intelligence. Knowledge Discovery in Databases (KDD) has been defined as the non-trivial process of discovering valid, original, potentially useful and ultimately understandable patterns of data [8]. In this context, a pattern is a model which describes a satellite image, the objects contained in that image and their spatiotemporal evolution. Besides data complexity (spatiotemporal context), the KDD process is facing a major problem which can lead to erroneous discovered knowledge. This problem is the imperfections associated with satellite images [7] [6]. Thus, in order to produce conclusions and predictions useful to the image interpretation field, KDD systems should be able to analyze such information. Much work has investigated problems related to KDD, particularly the issue of spatiotemporal image modeling and knowledge discovery [10] [12] [14] [15] [16]. However, most works focus on the KDD process and neglect handling imperfections related to processed data or to the KDD process itself. Indeed, few works have explored the problem of imperfections in KDD. We can refer to Kriegel and Pfeifle in [11] where they describe a density-based clustering algorithm founded on vague and uncertain information. The proposed method integrates a fuzzy distance concept to perform clustering and assign a probability for each possible distance value. The resulting algorithm FDBSCAN helps the user get an overview over a large set of fuzzy objects. In [3], Chau et al. propose a UKmeans algorithm, which aims to improve the accuracy of clustering by considering uncertainty associated with data. Authors describe how uncertainty can be incorporated in data mining by using data clustering (k-means algorithm) as a motivating example. In [9], authors propose centroid-linkage-based agglomerative hierarchical algorithm (named U-AHC) for clustering uncertain objects. They introduce a notion of uncertain prototype according to univariate and multivariate uncertainty models. These prototypes are represented as mixture densities that summarize the pdfs (probability density function) of all the uncertain objects in the clusters.

As we can notice, the minority of KDD systems that addresses the issue of uncertain spatiotemporal data, only takes into consideration very restricted parameters of processed data and models for the mining process. In this paper, we study the problem of knowledge discovery from satellite image databases while considering imperfections related to KDD and images. We focuse our efforts on using several KDD methods to extract spatiotemporal knowledge and then combine them to provide a new and more relevant knowledge. In this paper, we start by proposing our approach in Section 2, then we present the experimental results in Section 3 and we end by

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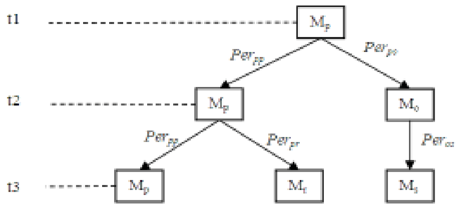


Fig. 1. Transition for an $M_p$ spatiotemporal model.

illustrating our conclusions in section 4.

## II. The proposed Approach

### A. Prototype System Design

This section describes in more details the framework that we propose for uncertain knowledge discovery from satellite image databases. This framework uses a multi-approach knowledge discovery component to improve the reliability of discovered spatiotemporal patterns. Indeed, each KDD approach presents a given point of view about the evolution of an object extracted from a satellite image which may differ from others KDD approaches; combining these methods enhances the image interpretation process. Let us suppose that we have a query model $M_p$ (which represents an object in a satellite image such as "vegetation", "urban", "road" or "lake"). Each KDD method provides a set of spatiotemporal models which are similar to this query model. Let $M_p$ be a retrieved model which is similar to $M_q$. Figure 1 presents the evolution of the $M_p$ model between two dates $t_1$ and $t_3$. For example, the $M_p$ evolves at date *t2* to $M_p$ model with a percentage of change $Per_{pp}$ and to $M_o$ model with a percentage of change $Per_{po}$.

Let us consider two models $M_q$ as a query model and $M_p$ as a retrieved model.

$$M_q = \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix}, M_p = \begin{pmatrix} A'_1 \\ A'_2 \\ \vdots \\ A'_N \end{pmatrix} \tag{1}$$

where $A_1$, ..., $A_N$ and $A'_1$, ..., $A'_N$ are the attributes of $M_q$ and $M_p$.

Let, also, consider two functions:
1) *similar($M_q$,$M_p$,$w_{qp}$)* which provides an $M_p$ model similar to a query model $M_r$ with a degree of similarity $w_{qp}$ and 2) *change($M_q$,$M_p$,t,$Per_{qp}$)* which depicts the evolution of the $M_q$ model to an $M_p$ model at instant *t*. $Per_{qp}$ denotes the percentage of evolution from an $M_q$ to $M_p$ models.
The similarity degree $w_{qp}$ is computed as follow:

$$w_{qp} = 1 - d(M_q, M_p) \tag{2}$$

Where *d()* is the normalized cosine distance as shown in equation 3.

$$d(M_q, M_p) = cos(M_q, M_p) = \frac{\sum_{k=1}^{N} A_k \times A'_k}{\sqrt{\sum_{k=1}^{N} A_k^2} \times \sqrt{\sum_{k=1}^{N} A'^2_k}} \tag{3}$$

The percentage of change $Per_{qp}$ is found using equation 4 which computs the difference between all attributes of the $M_q$ and $M_p$ models.

$$Per_{qp} = \frac{\sum_{i=1}^{N} |A_i - A'_i|}{N} \tag{4}$$

Once we obtain an $M_p$ model similar to the query model $M_q$, we conclude that the $M_q$ model has the same evolution compared to the $M_p$ model with a given degree of confidence for this change. After applying the multi-approach KDD method, we obtain a set of rules having the following structure:
**R1: If** *similar($M_q$,$M_p$,$w_{qp}$)* **then** *change($M_q$,$M_p$,$t_2$,$Per_{qp}$)* **and** *change($M_q$,$M_o$,$t_2$,$Per_{qo}$)* **and** *change($M_q$,$M_p$,$t_3$,$Per_{qp}$)* **and** *change($M_q$,$M_r$,$t_3$, $Per_{qr}$)* **and** *change($M_q$,$M_s$,$t_3$,$Per_{qs}$) (conf)*.
Where *"conf"* indicates the confidence that the expert grants for the rule R1.

Rules obtained by the application of several KDD methods present, always, different situations of redundancy and contradiction. In order, to take advantage of these situations and give a more accurate evolution for a query model, we choose to follow a fusion approach.

### B. Fusion Process

As we stated earlier, the proposed framework is based on multi-approach knowledge discovery from satellite image databases. Each KDD approach is adapted to a specific type of imperfection. Additionally, each approach provides a distinct knowledge model. Combining these models will reduce imperfections related to KDD process and significantly improve image interpretation results. The goal behind fusion module is to increase our belief in a model change. By combining multiple changes (given by several KDD methods as rules) of the same model, we can build a more relevant model that is close to reality. To achieve this goal, we develop an evidence fusion method that allows combining knowledge obtained after the multi-approach KDD process. The fusion process is shown in Figure 2. Each KDD method provides a local decision about the spatiotemporal change. The fusion of these local decisions generates a global one which is more relevant and certain.

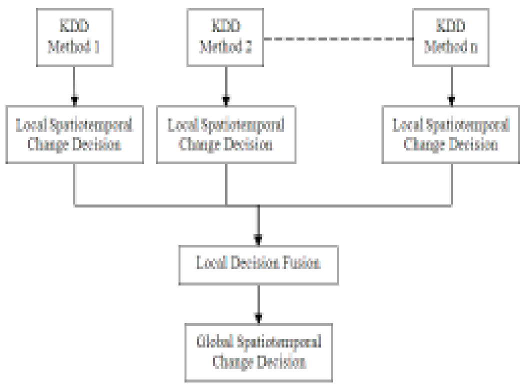


Fig. 2. The fusion process.

The fusion process has four main steps: 1) modeling; 2) estimation; 3) combination; and 4) decision.
Let $\Omega$=$\{d_1, d_2, ..., d_C\}$ be a frame of discernment; $d_k$ (1 $k$ C) are hypotheses in favor of which a decision can be taken. $d_k$ are the possible spatiotemporal models to which a query model can evolve. An example of these decisions for the R1 rule is $\Omega$=$\{M_p, M_o, M_r, M_s\}$.
Dempster−Shafer theory, or evidence theory, allows the representation of imprecision and uncertainty using the mass "*m*", belief "*bel*", and plausibility "*pl*" functions [7] which are then defined from $2^{\Omega}$ to [0, 1], such that [1]:

$$\sum_{A\subseteq\Omega} m(A) = 1 \tag{5}$$

$$A \quad \Omega, bel(A) = \sum_{\emptyset\neq B\subseteq A} m(B) \tag{6}$$

$$A \quad \Omega, pl(A) = \sum_{B\cap A\neq\emptyset} m(B) \tag{7}$$

In our approach, masses are estimated by computing the percentage of change of a query model to each model in the frame of discernment.
In order to improve the estimation of spatiotemporal model change, we assign a degree of reliability to each KDD method. This degree is computed according to the similarity of models mentioned in the section 2.1.
Let *w* be the degree of reliability of a KDD method. The mass of A (A Ω) can be computed as follows:

$$m^w = w \quad m(A) \tag{8}$$

$$m^w(\Omega) = (1 - w) + w \quad m(\Omega) \tag{9}$$

The third step in the fusion process is combination. We use the Dempster's orthogonal rule depicted by the equation 10.

$$m(A) = (m_1 \quad m_2 \quad ... \quad m_l)(A)$$

$$= \frac{\sum_{B_1\cap...\cap B_l} m_1(B_1)m_2(B_2)...m_l(B_l)}{1 - K} \tag{10}$$

where

$$K = \sum_{B_1\cap...\cap B_l=\emptyset} m_1(B_1)m_2(B_2)...m_l(B_l) \tag{11}$$

*K* represents the conflict degree between the *l* decisions.
Decisions in the evidence method are taken using one of several rules [1]:

- The maximum of plausibility is defined as

$$M_q \quad d_i if pl(d_i)(M_q) = max\{pl(d_k)(M_q), 1 \quad k \quad n\} \tag{12}$$

- The maximum of belief is defined as

$$M_q \quad d_i if bel(d_i)(M_q) = max\{bel(d_k)(M_q), 1 \quad k \quad n\} \tag{13}$$

The evidence fusion algorithm (Algorithm 1) operates on a set of spatiotemporal rules *R*. It has four steps. The first aims at determining the frame of discernment, the reliability of KDD methods and the possible evolution status of the query model. The second step computes mass, belief and plausibility functions based on the reliability of KDD methods and the change rate of retrieved models. The third step applies the Dempster's orthogonal rule for each query model's decision existing in $\Omega$. The last step is devoted to determining the right change rate for the query model. This step depends on the rule chosen to make decision in the evidence theory. The output of Algorithm 1 is a spatiotemporal tree representing the evolution of query model between two dates *t* and *t'*.

**Algorithm 1** The Fusion Algorithm Based on Evidence Theory

```
Require: R: set of spatiotemporal rules
Ensure: T: spatiotemporal evolution tree
   %% Modeling Step
   Determine Ω
   Determine reliability of KDD methods
   Determine the possible evolution of query model
   %% Estimation Step
   for all Possible status M_i for the query model in R do
      Compute m(M_i), bel(M_i) and pl(M_i)
   end for
   %% Combination Step
   for all M_i in Ω do
      Combine masses by the Dempster's orthogonal rule
   end for
   %% Decision Step
   Choose the decision rule for evidence theory
   Determine the change rate for query model
   Compute the evolution date for query model
   Construct the spatiotemporal evolution tree T for the query model
```

To better explain the fusion of spatiotemporal change models, let us consider that a query model $M_q$ (taken at *t* date) is similar to $M_1$ with 0.9 and to $M_2$ with 0.8. Here, $M_q$ represents a lake in Tunisia, $M_1$ is a lake in France and $M_2$ is a lake in Italy. If we suppose that $M_1$ and $M_2$ have the following spatiotemporal evolution trees:

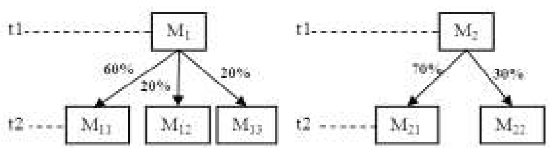


Fig. 3. Examples of spatiotemporal models change.

Where $M_{11}$ and $M_{21}$ represent lakes, $M_{12}$ and $M_{22}$ represent urban zones and $M_{13}$ represents a vegetation zone.
The two trees shown in Figure 3 can be translated into the following spatiotemporal rules:
IF similar($M_q$,$M_1$,0.9) THEN change($M_q$,$M_{11}$,*t'*,60) AND change($M_q$,$M_{12}$,*t'*,20) AND change($M_q$,$M_{13}$,*t'*,20)
IF similar($M_q$,$M_2$,0.8) THEN change($M_q$,$M_{21}$,*t'*,70) AND change($M_q$,$M_{22}$,*t'*,30).
The focus of this study is to determine the spatiotemporal tree

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which results from combining trees obtained by the application of several KDD methods. As a consequence, we obtain an estimation of the evolution of a query model which is more accurate and certain. Let us consider that the tree depicted in Figure 4 is the tree resulting from the fusion of the two trees in the Figure 3. The main challenge is to determine *Per1*, *Per2*, and *Per3* which represent respectively, the percentage of evolution of $M_q$ model to lake, urban and vegetation.
Figure 4 depicts the spatiotemporal evolution of the $M_q$ model between two dates $t$ and $t'$; where $t$ is the present date of the query model $M_q$ and $t' = t + (t_2 - t_1)$ .

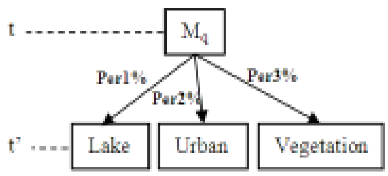


Fig. 4. The spatiotemporal evolution of the $M_q$ model after applying the evidence fusion method of $M_1$ and $M_2$.

We have:
$m_1(M_{11})$=0.6, $m_1(M_{12})$=0.2, $m_1(M_{13})$=0.2.
$m_2(M_{21})$=0.7, $m_2(M_{22})$=0.3.
Then, it is possible to include reliability into modeling belief for each source before fusion to compensate for their different reliability according to values granted to the two methods. We obtain:
$m_1(M_{11})$=0.6*0.9=0.54, $m_1(M_{12})$=0.2*0.9=0.18, $m_1(M_{13})$=0.2*0.9=0.18, $m_1(\Omega)$=1-0.9=0.1.
$m_2(M_{21})$=0.7*0.8=0.56, $m_2(M_{22})$=0.3*0.8=0.24, $m_2(\Omega)$=1-0.8=0.2.

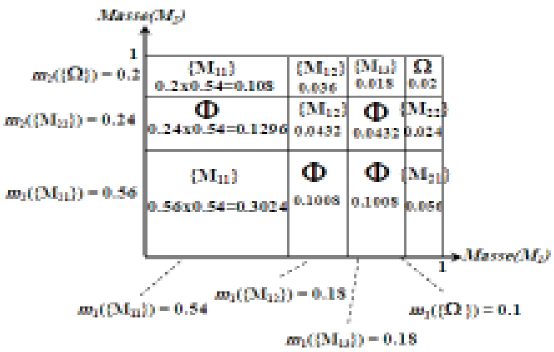


Fig. 5. The mutual mass's part between the two KDD methods.

Figure 5 depicts the mutual part between the two KDD methods. The contradictory mass between these methods is equal to 0.3744=(0.1296+0.1008+0.1008+0.0432). As we notice, the contradictory mass between the two KDD methods is big. The integration of the reliability degree lets appear a belief degree ($\Omega$) for each source.
Masses are, then, combined using the Dempster's orthogonal rule, we obtain the following values for *Per1*, *Per2* and *Per3*: 79.1, 17.5 and 3.4 respectively.

As we note, integrating reliability of the beliefs computed within our framework introduces a second uncertainty level (uncertainty of evaluation of uncertainty) and represents an adequacy measure for our system and the observed environment.

Additionally, We notice that following a fusion concept helps us resolve two types of situations: redundancy and complementarity rules. Redundancy rules involve fusing rules with the same model transition but with different percentages of change and different confidence degrees. Complementarity rules, however, involve fusing rules with different model transitions, different percentages of change and different confidence degrees.

## III. Experimental Evaluation

In the experimental evaluation section, we conduct a series of experiments to show the effectiveness of our system and to analyze the fusion process's contribution in improving change detection accuracy. Figure 6 (at left) represents a satellite image acquired in 1998 showing the region of Auckland in New Zealand[1]. This image covers a region of 20 x 20 km.

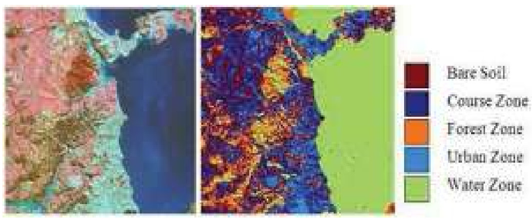


Fig. 6. Satellite and classified image for the 1998 date.

We start by performing a segmentation of the satellite image shwon in Figure 6 (at left). Then, a collaborative step is performed based on three segmentation methods, namely: FCM, Fuzzy IsoData and Cobweb [2]. Figure 6 (at right) presents the classified image after the collaborative segmentation. This image is composed of five land cover types which are: bare soil, course, forest, urban and water.

Fig. 7. The query object.

In this study, we intend to follow the evolution of the object shown in Figure 7 representing "the course zone". We start by generating metadata related to this object which represents the query model $M_q$ [2]. To follow the change of this model over time, we look for the most similar model to

[1]Source: http://www.landcareresearch.co.nz/

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$M_q$, and then we obtain with a certain degree of confidence the change made throughout time for the model $M_q$.

In order to determine the evolution of the query model in 1999, we construct a base enclosing models which have an evolution after one year. Indeed, the validation of our approach is dedicated to predict the change of the query model between 1998 and 1999 (after one year).

By applying three knowledge discovery methods (decision tree ”C4.5” [13], rule induction ”CN2” [4] and Nearest-Neighbor [5]), we obtain a set of rules expressing the change made by the model $M_q$ between 1998 and 1999.

The final step in our approach is fusion. As mentioned in section 4.3, we used the evidence fusion method in our approach. Thus, all generated rules by C4.5, CN2 and NN are fused to obtain more relevant ones. Table 1 describes the evolution of an $M_q$ model (which represents the query object in Figure 7) between 1998 and 1999. The change is performed according to four KDD methods: C4.5, CN2, NN and fusion of the latter methods.

TABLE I
CHANGE DETECT FOR $M_q$ MODEL AMONG THE FOUR METHODS

| $98-99$ | Meth | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| | (1) | 34.17 | 23.34 | 3.59 | 13.49 | 25.41 |
| $M_q$ | (2) | 33.12 | 22.18 | 4.89 | 11.16 | 28.65 |
| | (3) | 30.20 | 37.36 | 9.04 | 4.02 | 19.38 |
| | (4) | 38.15 | 28.9 | 9.34 | 6.34 | 17.27 |

Where
(1): C4.5, (2): CN2, (3): NN, (4): Fusion of C4.5, CN2 and NN.
1: Bare soil, 2: Course zone, 3: Forest zone, 4: Urban zone and 5: Water zone.

In order to evaluate the performance of KDD methods, we use an image acquired in 1999 representing the same region (Fig. 8). Then, we perform the same process to this image (the process previously described for the image at the date 1998) and we compute the change rates. Table 2 depicts the real change of the $M_q$ model between 1998 and 1999. It also describes the best method approaching the real result for each land cover type. We remark that the proposed method has the best change rate (compared with the real one) for the evolution of $M_q$ model into bare soil, course zone and urban zone. Whereas, the C4.5 has the best rates for the evolution of $M_q$ model into forest, and the best evolution into water zone is achieved by the NN method.

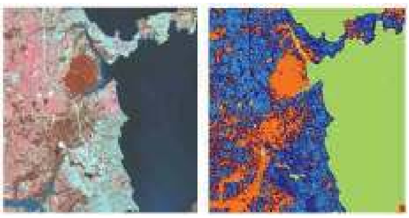

Fig. 8. Satellite and classified image for the 1999 date.

TABLE II
EVALUATION OF THE BEST CHANGE DETECT METHOD FOR EACH CLASS

| Change 98-99 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Real change | 36.42 | 32.27 | 01.93 | 08.18 | 21.20 |
| Best method | (4) | (4) | (1) | (4) | (3) |

The cumulative error for each method is listed in Table 3; we notice that the fusion of C4.5, CN2 and NN outperforms others methods even though it is not the best method approaching the real result for all land cover types.

TABLE III
CHANGE DETECT ACCURACY COMPARISON AMONG THE FOUR KDD METHODS

| KDD methods | Cumulative error |
|---|---|
| C4.5 | 22.36 |
| CN2 | 26.78 |
| NN | 24.4 |
| Fusion of C4.5, CN2 and NN | 18.28 |

## IV. CONCLUSION

In this paper, we presented our approach for intelligent spatiotemporal knowledge discovery from satellite image databases. Our method outperforms other spatiotemporal knowledge discovery methods in image interpretation field. Indeed, the majority of KDD systems focus their efforts to develop efficient techniques for discovering knowledge from satellite images and disregard the problem of managing imperfections related to the KDD process. The main contribution in our work is to propose a fusion scheme to combine knowledge extracted from different KDD methods. This scheme is based on evidence theory and aims to reduce imperfections related to KDD process in order to improve the image interpretation results, to increase our belief in a model change and to pick up relevant and hidden knowledge.

The developed system is evaluated by comparing the results obtained by applying several KDD methods and the fusion of these methods, to an image acquired on an upcoming date. Results show the effectiveness of the proposed approach. As a perspective for this paper, we might consider the integration of user interestingness in the KDD process, which allows for better control of output results.

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