A Time-Travel Tool for Monitoring Environmental Phenomena by Remote Sensing Techniques

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ABSTRACT

Iin monitoring dynamic phenomena through remote sensing images it is often necessary to generate virtual images of the phenomenon representing its spatial reference at ideal times of observation, when no real image is available. In this contribution we propose a method based on fuzzy logic to generate virtual images on the basis of available images taken before and after the ideal date, and vague and incomplete knowledge of the phenomenon dynamics synthesised by fuzzy rules. The virtual image is generated as a non-linear coalescing of the real images based on the application of a fuzzy rule inference mechanism.

INTRODUCTION

Monitoring the variation of some environmental phenomena by remote sensing relies on images from non-programmed satellites that have been acquired in a reference period. For example, the estimation of glacier extension by measuring its covered area and some morphological parameters, such as the equilibrium line, is based on the analysis of Landsat images taken during the ideal period of observation that is approximately July-October. However, often the quality of the available images during the ideal period is low due to atmospheric perturbations that obscure or hide the glaciers themselves.

In this framework, it should be useful to have methods and tools to guess virtual images of the monitored phenomenon at a given date within the ideal period of observation. When the dynamic laws governing the phenomenon are precisely known applying modifications to an available image taken before the desired date can generate this virtual image. Unfortunately, the dynamics of natural phenomena is generally too complex to be described precisely. For this reason we have to exploit methods to cope with the incompleteness and vagueness characterising the knowledge of the phenomena. The most recent researches on the temporal properties of spatial data developed the concept of time-travel tool, allowing tracing the spatio-temporal evolution of dynamic phenomena (Parent et al., 1999).

In this contribution, we propose a heuristic method to guess a virtual image of a phenomenon taken at a desired date when no real image is available. Specifically, the method is based on fuzzy logic to model the knowledge of the phenomenon dynamic that is represented in the form of fuzzy rules (Zadeh, 1975). Both the available images acquired before and after the desired date, and the trends of some variables (described by fuzzy rules) affecting the phenomenon are considered. A fuzzy dual representation of spatio-temporal information is adopted to represent the uncertainty and imprecision affecting either the spatial or the temporal reference of the phenomenon (Bordogna et al., 2003). This way the validity of the available images is determined and represented at the ideal date of observation, and the virtual image is generated by a non-linear coalescing of the original images.

The method is exemplified by discussing the case study of glacier observation. In particular we are committed with the generation of a virtual image of the glacier spatial reference at an ideal date of observation when no real image is available. The fuzzy rules defined to encode the glacier dynamics assume that the temperature and the snowing events occurred during the period of observation mainly influence the spatial extent of the glacier. Starting with two real snapshots of the glacier acquired before and after the ideal date, by applying the set of fuzzy rules, the temporal validity of the available snapshots of the glacier is computed and the virtual image at the desired date is generated by a non-linear coalescing of the two real images.

A method to monitor uncertain dynamic spatial phenomena

The advantages of remote sensing in environmental applications are pretty well documented (National Research Council, 2001): remote sensing images behave homogeneously in space and time; the observations are synoptic, direct, non intrusive, and the cost/benefit ratio is good with respect to the alternative use of human observers or instrument networks which, moreover, produce accurate but local results.

In monitoring environmental phenomena changing through time it is often necessary to perform the observations at key dates or within specific time ranges, which constitute therefore constraints on data acquisition. One example is the best time of observation for monitoring the annual glacier extent: it is the so-called "end of the ablation season", a time range between the end of snow melting season (Summer) and the beginning of autumn snowfalls. These kinds of time constraints may be influenced by many climatic factors and then vary from year to year: it is quite impossible to precisely determine their limits. For the same reason, it is not so easy to program sensor acting in such a vague period of time. Moreover, the meteorological conditions of mountainous zones very often screen a good observations of the area of interest, ought to the frequency of cloudy cover.

For these reasons it is useful to define decision criteria helping both to better identify the best period of observation and to support the estimation of a virtual image when real images are not available at all or are not good enough in the specific period. This image could be generated on the basis of both the available images and the values of some variables, which are supposed to influence the phenomenon under observation. The proposed procedure consists in the following steps:

- The choice of two available images of the phenomenon as close as possible to the best period of observation; the phenomenon under study must be spatially identifiable in these images; thus we assume that the available images can be segmented so as to obtain binary images in which the pixels belonging to the spatial reference of the phenomenon have value 1. In the following we assume that the phenomenon spatial reference corresponds with a class (ex. ice in the glacier observation). We thus name these segmented binary images as classified images.
- The choice of the ideal date of observation of the phenomenon.
- A new, virtual, grey-level image is created starting from the two corresponding binary images of the previous step (which are associated with two real observations at subsequent dates); the grey level of each new pixel expresses the possibility that the pixel belongs to the spatial reference of the phenomenon of interest (ex. to the class ice) at the ideal date. This virtual image corresponds with an intermediate time instant within the two real observations.

The creation of the virtual image is based on a temporal coalescing process of the spatial information taking into account the uncertainty related to the temporal validity of the classifications in the chosen observation range. The fusion is founded on the representations of spatio-temporal information by a dual fuzzy model proposed in (Bordogna et al., 2003) which is briefly illustrated in the following section.

A dual model for uncertain dynamic spatial phenomena

Unified spatio-temporal models represents entities with a spatial and a temporal dimension that are dealt with as orthogonal dimensions (Worboys, 1994), (Parent et al., 1999). Such models usually do not manage the uncertainty that often affect spatio-temporal information due to several reasons among which the sparseness of the observations, the vagueness of the time when phenomena are observed, the continuously changing nature of the objects under examination. In (Bordogna, 2003) a unified Fuzzy model for uncertain spatio-temporal information has been defined. It is based on the idea that a dynamic phenomenon may be represented by a sequence of observations (snapshots), each one defining the state of the phenomenon in a time range. It is assumed that this time range identifies the temporal validity of the observations, i.e. the temporal validity of the snapshots. By assuming that the transition from one state to a successive one is gradual, the fuzzy representation models this gradual transition by associating to each snapshot a fuzzy validity range. The model is dual and it deals uncertainty relative to the two orthogonal dimensions of space and time. In this way, two different situations can be described. In the first one, a phenomenon can be represented by a precise spatial reference associated with an indeterminate or vague validity range (by example "The car is in Milan around 9 a.m."). The orthogonal situation is described by a vague or indeterminate spatial reference corresponding with a precise time range or instant ("The car is near Milan at 9 a.m."). A dynamic spatial object o_d is formally represented as a set of pairs (τ_i, o_i):

$$o_d := \{(\tau_1,o_1), (\tau_2, o_2), \ldots, (\tau_n, o_n)\} \qquad (1)$$

where each τ_i is the Fuzzy range of temporal validity associated with the spatial object o_i. That is to say, o_i is regarded as a valid spatial description of the dynamic object o_d during the time range τ_i. τ_i is defined as a Fuzzy subset of the temporal domain T. Figure 1 illustrates the semantics of τ_i. At a generic time instant t both o_2 and o_3 can be considered valid spatial references with different degrees of validity, $\nu_2(t)$ and $\nu_3(t)$ respectively.

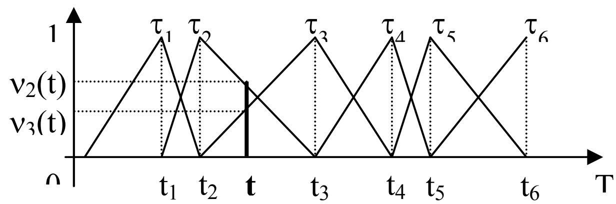

Figure 1: Fuzzy temporal validity intervals in the scenario (1)

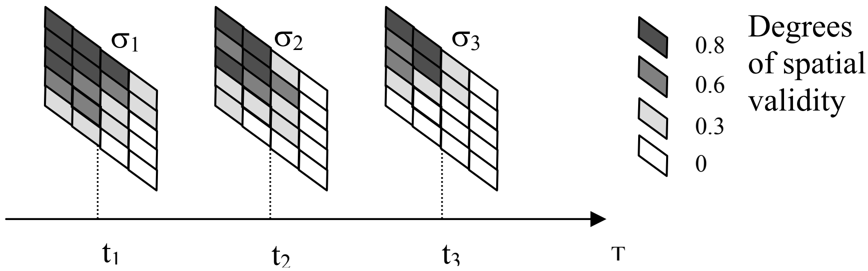

Figure 2: Fuzzy spatial validity in the scenario (2)

The dual representation of (1) is defined for the scenarios where the temporal observation is precise while the spatial reference is Fuzzy. It is again a set of pairs (t_i, σ_i):

$$\underline{o_d} := \{(t_1,\sigma_1), (t_2,\sigma_2), \ldots, (t_n,\sigma_n)\} \qquad (2)$$

where σ_i is the Fuzzy spatial validity of the phenomenon at the time instant t_i. σ_i is defined as a Fuzzy subset of the spatial domain X. Figure 2 illustrates its semantics in the case of a raster representation of the phenomenon; the legend shows the values of spatial validity of each element of the grid at the associated time instant.

Generation of a virtual image of an natural phenomenon at a given instant of time

A dynamic phenomenon represented on the basis of formula (1) is regarded as a sequence of snapshots each one characterised by a temporal validity that can be determined on the basis of our knowledge of the dynamic laws, which presumably govern its change through time. These laws, though uncertain, vague or incomplete, help us in figuring out the temporal trend of the validity of classified images derived from real observations which are taken outside the best period of observation, or with a worst temporal granularity than needed. In this way we can generate virtual images corresponding to generic time instants.

In many cases, the dynamic laws of natural or environmental phenomena are not known precisely since they are dependent on a huge number of variables, sometimes not all identified, and on complex interrelationships between such variables. Therefore we limit our expression of such laws to heuristic terms, through rules derived from the expert knowledge and codified as Fuzzy rules (Zadeh, 1975).

A single Fuzzy rule has the form "if A then B" where both A and B are Fuzzy predicates, like, for example, "if A=(*the snowfall is heavy*) then B=(*the extent of snow cover increases*)". We can exploit such kind of rules to determine the validity of the classified binary images at a given date: of course, its maximum validity degree is in correspondence with the time when the image was acquired. The list of fuzzy rules encoding the phenomenon dynamics are therefore of the type:

if $V_1(t)$ is *high* and $V_2(t)$ is *low* and $V_n(t)$ ... $\Rightarrow$ $\Delta\upsilon$ is *positive low*
if $V_1(t)$ is *low* and $V_2(t)$ is *low* and $V_n(t)$ ... $\Rightarrow$ $\Delta\upsilon$ is *positive medium*
.... ……………..
if $V_1(t)$ is *low* and $V_2(t)$ is *high* and $V_n(t)$ ... $\Rightarrow$ $\Delta\upsilon$ is *negative high*

where $V_i(t)$ for i= 1..n indicates the precisely known values of the variables V_i at time instant t, $\Delta\upsilon$ is a fuzzy increment (or decrement) of the validity degree occurring in a constant interval of time $\Delta t < \min([t_1, t_2])$ and can assume linguistic values such as *low, high, positive low, negative low, and etc.*. The semantics of these terms can be defined by triangular membership functions (such as those depicted in figure 1) on the numeric domain of the variable they qualify. The Fuzzy rules are used to modify the value of the output variable, i.e. the validity degrees υ_1 or υ_2 of two snapshots S_1 and S_2 (the classified binary images), by increasing or decreasing them of the defuzzified quantity $\Delta\upsilon$.

The degree of validity $\upsilon_1(t_i)$ of the snapshot S_1 (which is $\upsilon_1(t_1)=1$ at t_1) at a general time instant $t_i \in (t_1, t_2)$ defined in a temporal range T so that the difference between two subsequent observations is Δt, can be evaluated by the following algorithm:

Begin
  $t = t_1$
  $\upsilon_1(t_i) = \upsilon_1(t_1)$
  while $t < t_i$ in T
  do
    evaluates $\Delta\upsilon$ by applying the Fuzzy rules
    $\Delta\upsilon$ = defuzzifies($\Delta\upsilon$)
    $\upsilon_1(t_i) = \upsilon_1(t_i) + \Delta\upsilon$
    $t = t + \Delta t$
  enddo
end

in which function defuzzifies computes a numeric increment (decrement) $\Delta\upsilon$ given a fuzzy increment (decrement) $\boldsymbol{\Delta\upsilon}$. This is necessary in order to determine the numeric degrees of validity $\upsilon_1(t_i)$ e $\upsilon_2(t_i)$. The Fuzzy rules are applied by a Fuzzy inference engine, which evaluates the generalised Modus Ponens rule computing this way the Fuzzy increment (decrement) $\boldsymbol{\Delta\upsilon}$. The degree of validity of S_2, $\upsilon_2(t_i)$, is evaluated by the same algorithm letting the variable t_i decrease starting from t_2 to t_i.

AN EXPERIMENTAL EVALUATION

To exemplify the methodology, we made an experiment to evaluate the extension of Alpine glaciers by remote sensing in the ablation period (the period of the year in which ice finished melting and before Autumn snow falls). Roughly speaking the following variables are assumed to determine the trend of the phenomenon in the best time period for observation (July-October):

- The average daily temperature: “the validity decreases when the temperature increases above 0°C”
- The occurrence of heavy snow events: “ the validity decreases when snow events occur and becomes null when they are heavy”

Formally, we have defined the fuzzy rules in table 1 to encode the previous ones assuming the following input variables:

- The average daily temperature in the observation period, T_{dav};
- The snow events in the observation period, S_{day}.

The temporal granule (Δt) is the day.

Table 1: Fuzzy rules encoding the dynamics of the phenomenon; they compute the $\Delta\upsilon$ value

1.	if $T_{dav}(t)$ is *lower or equal than 0*, and S_{dav} (t) is *around 0* then $\Delta\upsilon$ is *equal to 0*
2.	if $T_{dav}(t)$ is *above 0*, and S_{dav} (t) is *around 0* then $\Delta\upsilon$ is *negative*
3.	if $T_{dav}(t)$ is *lower or equal than 0*, and $S_{day}(t)$ is *much more greater than 0* then $\Delta\upsilon$ is *negative*

The experiment is based on three remote sensing images of the *Lys* glacier, in *the Mount Rosa group* of the *Western Alps* between *Italy* and *Switzerland*. Since Summer 2001, this glacier is monitored by acquiring satellite images (from Landsat ETM with a time resolution of sixteen days). For the first time, in Summer 2003 we were able to collect a sequence of three satellite images not covered by clouds, so that a first evaluation of the proposed method could by performed. The dates of the images are July, 28th, August, 13th, and September, 13th . We use the two images of July and September as starting snapshots to apply the rules, while the image of August is used as a reference to evaluate the obtained results. Figures 3 a., b. and c. show the three satellite images as well as the glacier cover class from the classifications of the three images.

It’s worth remembering that Summer 2003 was an exceptionally dry and hot season, when also a great glacier like *Lys* suffered melting so that its tongue retreated about forty meters, existing rock holes became wider and many new ones opened. Moreover, the melting of ice and permafrost in the steep walls around the glacier borders caused the increase of debris accumulation, which further diminishes the ice surface perceived from the optical sensors on board of the Landsat satellite. In particular, from the end of July till the middle of August the threshold of 0°C was about 4000 mt. a.s.l. After the middle of August the temperature decreased and some snow events occurred.

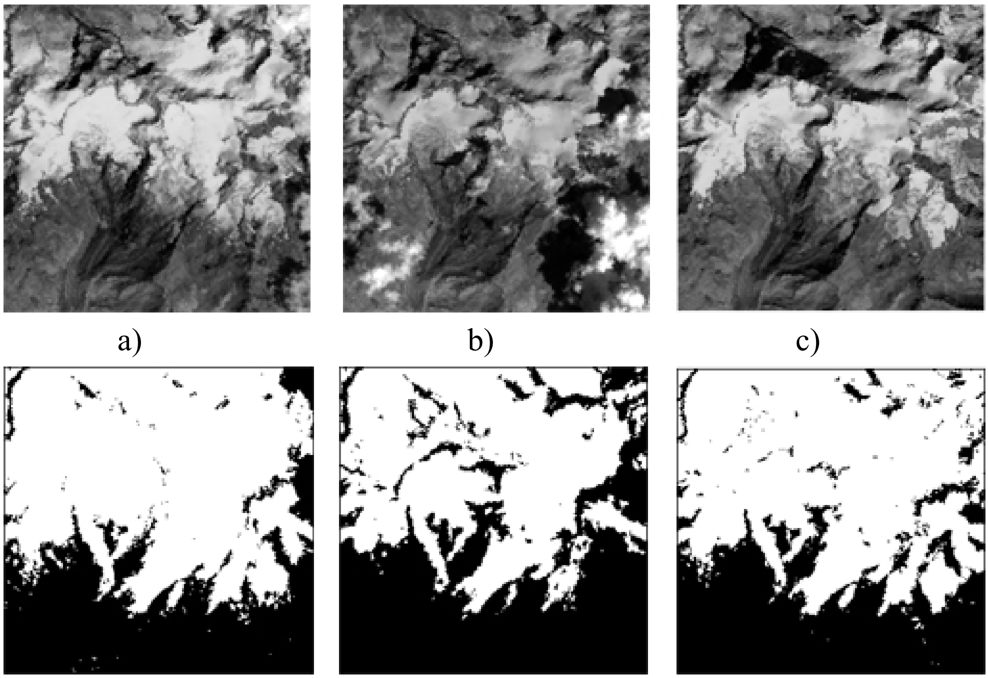

Figure 3: Three classifications of the ice cover class from remote sensing images of the Lys glacier (Western Alps); the respective timestamps are July, 28th (a), August 13th (b), and September, 13th (c)

We applied the rules in Table 1 to the two snapshots of July and September, thus obtaining the maps of their validity at August, 13th. It is worth noticing that since the available temperatures where taken at a monitoring point in the analysed region[52], we had to determine the daily temperatures at each pixel of the map by computing the variation of the available data depending on the altitude of the region at the pixel's position. Figure 4 is the map of the validity at August, 13th derived from the image of July, while figure 5 is the maps derived from the image of September. The white colour of the maps corresponds to the highest validity degree; the darker tones indicate the decreased values of validity. In fact, the possibility that a spatial location of the maps can be still classified as glacier decreases with time due to the occurrence of the meteorological events (in terms of temperature increase and snowfall).

For a given t_i in the range (t_1, t_2) the corresponding virtual image is generated on the basis of the degrees of validity of the two snapshots S_1 and S_2 at time t_i , i.e. on the basis of $\upsilon_1(t_i)$ and $\upsilon_2(t_i)$. Each spatial location in the virtual image is classified like in the snapshot S_1 if $\upsilon_1(t_i) > \upsilon_2(t_i)$, otherwise it is classified like in the snapshot S_2. The way in which the two snapshots are combined follows an 'optimistic' attitude, so that we select, for each spatial location, the classification value derived from the snapshot with the highest validity degree in that location. Figure 6 shows the virtual image generated by the above methodology corresponding to August, 13th. It represents a virtual extent of the glacier at the intermediate date.

[52] Meteorological data were collected at Gressoney D'Ejola (1850 mt. a.s.l.)

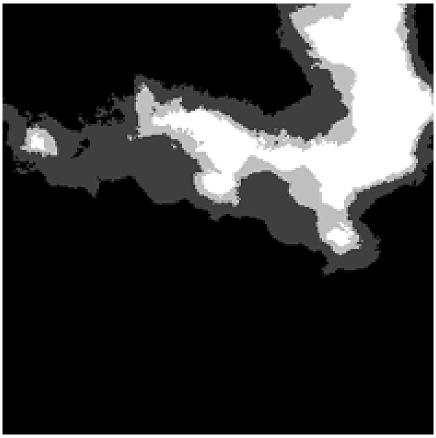

Figure 4: Validity map at August, 13th obtained applying the rules of Table 1 to the snapshot of July 28th

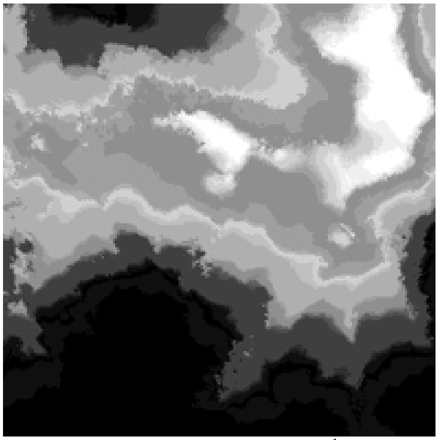

Figure 5: validity map at august, 13th obtained applying the rules of table 1 to the snapshot of september 13th

This result has been evaluated by comparison with the cover class *glacier* taken from classification of the real image acquired at August, 13th. 87% of the pixels in the two images belongs to the same class. The pixels with mismatching classifications are only 13%, and their values of validity are always below 248 (the maximum value is 255). Specifically, 71% of the pixels that mismatch the real classification has validity degrees below 241. It means that the validity of these pixels as a representation of the glacier cover class is very low at the date August, 13th. Moreover, these pixels are situated around the borders of the glacier, i.e. an area whose dynamic is not well described by the rules in Table 1., and some clouds screened the glacier in the image of August 13th (right-low corner on the central satellite image in Figure 3.b), thus preventing the whole classification of the image itself. This consideration, besides revealing encouraging results, shades some lights on the way the model could be further improved. For example, the available source for daily temperature was a measure station situated at a rather low elevation: we hope to add in the future more sources at different levels. Furthermore, other factors affecting the glacier evolution (and their corresponding Fuzzy rules) could be integrated into the dynamic model. Primarily the analysis of the pixel context could be taken into account so as to model the fact that the pixels' proximity to glacier's borders, where the thermal properties of rocks speed up the ice melting, makes their transition to another class more likely to occur. In the future, not only the whole class *glacier* will be taken into account but also its composing classes *snow* and *ice*.

CONCLUSIONS

The methodology we proposed in this work makes it possible to follow the evolution of a dynamic phenomenon through time (time travelling) also when real observations are missing or their quality is not suitable. It can also be adopted to simulate different scenarios corresponding with different alternative models of the dynamic evolution codified by distinct sets of fuzzy rules.

The method could also be set up to model not just the temporal validity of a given classification, but also to time-stamp the variation of classifications.

The glacier evolution through remote sensing images is an attractive benchmark, but presents many drawbacks due to the low time resolution and to the climate conditions on mountains, since clouds often screen the interesting scene. To better evaluate the method we plan to use other case study, with better time resolution and richer sequences of snapshots to allow comparison.

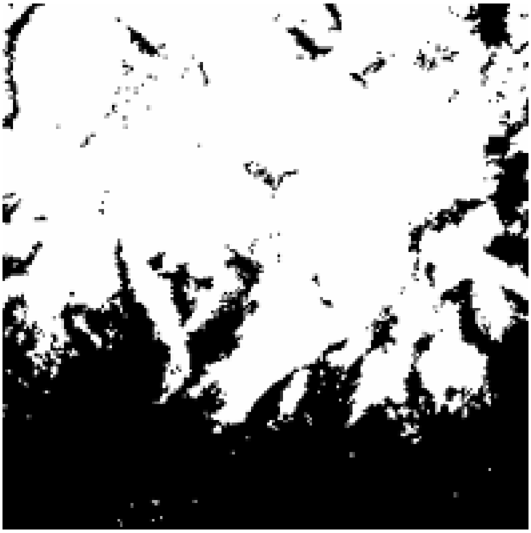

Figure 6: virtual image corresponding to august, 13th

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