VISUAL ANALYTICS APPROACH FOR CONSIDERING UNCERTAINTY INFORMATION IN CHANGE ANALYSIS PROCESSES

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ABSTRACT:

The classification of remotely sensed data and the follow-up change detection and analysis inherit the problems of large amounts of and possibly uncertain, incomplete and contradictory data, as well as with complex relationships between them. With that a formalization and automatization of necessary processing steps becomes just as difficult as a visual interpretation with standard methods. Hence, there is a need to apply and to further develop analytical reasoning concepts and techniques which are for example known from the field of Visual Analytics. We propose an extended framework for change analysis processes, with a special emphasis on considering uncertainty information, which is then illustrated with some prototypes based on interactive filtering and interactive visualization techniques.

1. PROBLEM

Remotely sensed scenes have a continuously increasing impact on describing, modeling and simulating landscape structures and processes. Nowadays new applications like urban monitoring, city modeling, or classical applications at larger scales can be addressed due to technical developments of satellite or airborne sensing systems concerning their spatial, spectral and radiometric resolutions. With this increased potential a stronger integration of the derived geo data in binding decision and evaluation processes takes place.

On the other hand it has to be stated that automatic and time saving approaches for a thematic interpretation of remotely sensed scenes and series of scenes is by far not operational yet. This status is caused by several reasons (like the variance and complexity of topographic knowledge representation), and will probably be valid for the next ten years or so. From that we draw the conclusion also to "go back" to a visual approach, i.e. to **improve the visual interpretation process** through the adaption of interactive methods and tools that are known from Visual Analytics, a field that is concerned with analytical reasoning supported by interactive visual interfaces.

In the following we will focus on visual analytics approaches for **change detection** purposes with a special emphasis on **considering uncertainty information**. The motivation behind that is the fact that during the classification of remotely sensed scenes we typically obtain overall classification accuracies in the order of 80% to 95%, or vice versa errors in the order of 5% to 20%. On the other hand the rate of changes is in the same order, in most cases even less. Therefore the key question always is whether a change is a real change or just an error. Vice versa, sensitivity analyses performed by Pontius & Lippitt (2006) showed that half of all detected "changes" are caused by actual errors if the overall accuracy of the input data sets is determined to 91%, each.

Some investigations confirm that the **visualization of uncertainties** of complex geo data can actually influence and support the decision making process in a positive manner (e.g., MacEachren & Brewer, 1995; Leitner & Buttenfield, 2000). As Deitrick (2007) states, this influence does not depend on the visualization only, but primarily on the concrete application. This leads to the conclusion that various communication methods have to be developed for different users and purposes. Within this context we will concentrate on experts in the following.

While the introduction of the necessary uncertainty information into conventional visualization approaches is possible (as briefly described in section 2), it is by far not effective, nor efficient. Hence, we propose an extended Visual Analytics framework for this specific task of considering uncertainty information in change analysis processes, which is illustrated with some prototypes incorporating interactive filtering and interactive visualization techniques (section 3).

2. DRAWBACKS OF CONVENTIONAL APPROACHES

In the following we assume the existence of uncertainty information for classified scenes, which for example can be obtained from probability vectors that are generated in the course of a Maximum Likelihood Classification. There are a couple of straightforward options for visualizing resulting uncertainty (or certainty) images together with the original image or classification information (see also MacEachren, 1992), for instance:

- For the display of changes standard side by side views (also known as "trend summary maps") are preferably used (Schroeder, 2007). Adding uncertainty images expands this concept to a **2x2 view** (figure 1). The disadvantage of this option is that the interpretation process becomes very

complex; in particular, focusing on specific locations and comparing the respective content is difficult. This disadvantage can be partially avoided by linking the views geographically (Roberts, 2005).
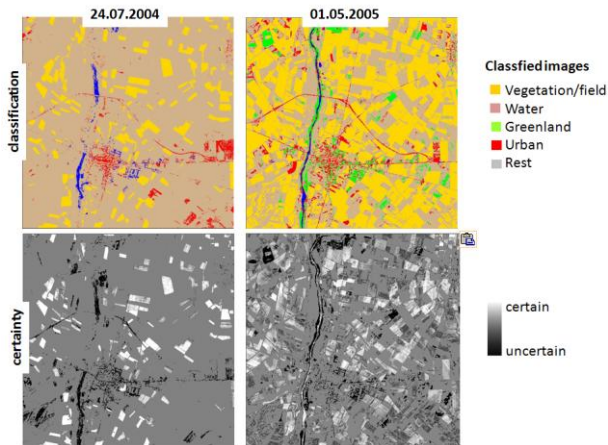

Figure 1. 2x2 view incorporating multi-temporal classified scenes (top) and uncertainty information (bottom)

- By combining classification results (normally by generating the difference image) on one hand and the certainty images (for example, with the minimum operator) on the other hand, we come up with a side-by-side **1x2-view**. Still we have lot of eye movements (saccades) in the visual interpretation process, but now in addition also a loss of class related information.
- A further reduction to a single **1x1-view** can be achieved by several intrinsic or extrinsic methods. For overlaying purposes methods like blending, flickering or swiping can be applied – all leading to a considerable amount of occlusions. Another option is the fog metaphor: The smaller the certainty is, the stronger the fog (or the less the transparency) becomes. The disadvantage here is that the transparency is difficult to design for the various, spectrally heterogeneous background layers. In particular, within classified scenes the appearance of the transparent areas might be mixed up very easily with colors representing other classes.
- Apart from the static representations mentioned so far, quite often **animations** are proposed for the display of multi-temporal scenes. However, animations show several disadvantages like huge efforts for their generation or a too short display of single states which have to be compared with states that are not visible anymore (Andrienko et al., 2005). If uncertainty information would also be integrated, this would lead to an information overload which is contradictory to the interpretation purposes.

3. VISUAL ANALYTICS APPROACH

3.1 Interfacing Remote Sensing and Visual Analytics

Visual analytics is a multidisciplinary field that is primarily concerned with analytical reasoning supported by interactive visual interfaces. It starts from the point that in many applications we have to deal with large amounts of multi-

dimensional and possibly uncertain, incomplete and contradictory data, as well as with complex relationships between them. With that a formalization and automatization of necessary processing steps becomes just as difficult as a visual interpretation with standard methods. Hence, there is a need to develop and to apply analytical reasoning concepts and techniques, for example through different data representation and transformation, user oriented communication and visualization, or suitable interaction techniques (Thomas & Cook, 2005).

The classification of **remotely sensed data** and the follow-up change detection and analysis, with a special emphasis on the consideration of uncertainty, are typical examples for the above described need for Visual Analytics methods. On the other hand, the link between Remote Sensing and Visual Analytics has hardly been dealt with in research and development so far. In this context we want to give some conceptual ideas for visual interfaces, namely interactive filtering and interactive visualization.

3.2 Interactive filtering

As change detection and analysis based on remotely sensed deals with large amounts of multi-dimensional data, it is necessary to reduce this amount and complexity, and with that to increase cognitive resources for interpretation purposes. Our initial hypothesis is that the above presented static and non interactive side by side views (section 2) are not able to satisfy these demands. This statement is valid for answering "simple" spatio-temporal questions of "what", "when" and "where" changes occur (Peuquet, 1994), but it is even more evident for higher level analyses, i.e., for exploring distributions and reasons of changes (i.e., answering "why" questions). For example, it is crucial to know whether a change is of existential character (i.e., an object has completely appeared or disappeared) or whether it just shows only changes in size or form. These effects might have totally different functional reasons. Answering those questions needs a human interpreter who is well-guided and equipped with efficient and effective multiple representations of the underlying data.

In order to apply an interactive filtering on the given data sets, the various spatio-temporal questions occurring in a change detection and analysis process need to be formalized in a structured manner. Based on the work done by Peuquet (1994) and Hornsby & Egenhofer (2000) we firstly concentrate on existential changes between two discrete snapshots of nominal scaled variables (land cover classes) in a local neighborhood. With that, the general case of the "what"-clause in the change process (see also figure 2) can be described as

Transition (*snap1, snap2*)
with: *snap1, snap2* : vectors of object classes for snapshots
1 and 2

It has to be noted that vector *snapi* can contain a single class (e.g., A) or multiple classes (e.g., A ∪ B). Furthermore, a combination of multiple transition actions possible, e.g.:

Transition (A,any) ∪ *Transition (any,A) = Loss_Or_Gain(A)*
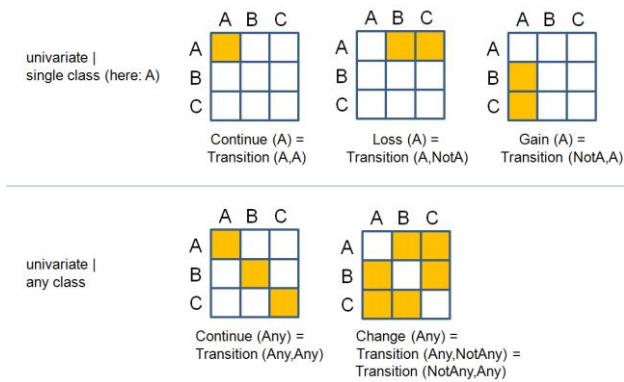
Figure 2. Change description for two snapshots of nominal scaled variables (e.g., land cover classes) A, B and C

Based on this formal description the interactive filtering process can be carried out. With the help of a user interface as shown in figure 3 the filtering starts with defining the dates of the multi-temporal scenes ("when") and the type of change including the specification of topographical classes ("what"). The resulting output ("where") is a simple and comprehensive graphical representation (here overlaid on top of background imagery) of those areas that answer the underlying question. With that the inherent complexity is reduced and cognitive resources for the actual analysis (i.e., answering "why" questions related to changes) are freed.

Those additional cognitive resources can now be used for an integration of additional parameters into the analytical reasoning process. In this context the **consideration of uncertainty information** is of major interest as already pointed out in section 1. Figure 3 demonstrates the specification of the display type (unclassified or classified) of this information source which is then fully integrated into the resulting window as an overlaid choropleth map.
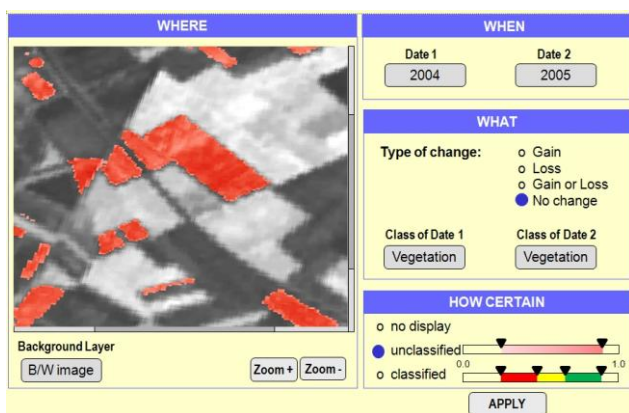

Figure 3. Graphical user interface for interactive filtering including uncertainty information (see bottom right)

3.3 Interactive visualization

Asking concrete questions as implemented through the interactive filtering process as shown in section 3.1 reduces the

graphical complexity significantly and allows for standard and comprehensive visualization methods. Figure 3 has already presented the choice of (possibly overlaid or even transparent) **choropleth maps**, that can be superimposed on top of imagery or thematic information for orientation and interpretation purposes, in an unclassified (i.e., graduated color) or in a classified manner (for example, using the traffic light principle with green light indicating large certainty). Alternatively, uncertainty might be represented through different grades of hachures.

Currently we are also investigating the use of interactive approaches in a single view layout to represent the uncertainty information. One solution which is based upon the above presented interactive filtering method would be the application of **attribute brushing**. This operation allows for an interactive change of the value interval for uncertainties (generally using a slider), and with that for a real-time determination of thresholds in an iterative manner.

Alternatively, **conditional chropleths** are generated through the interactive definition of multiple value intervals for more than one attribute. Figure 4 shows two uncertainty parameters (thematic accuracy, lineage) whose values can be altered iteratively and immediately produce multiple thematic maps in a matrix form. As an example, the lower left map shows only those objects that have a thematic accuracy of more than 85% and which are derived from source A. Comparing the different maps yields information about sensitivities and correlations of the uncertainty parameters.
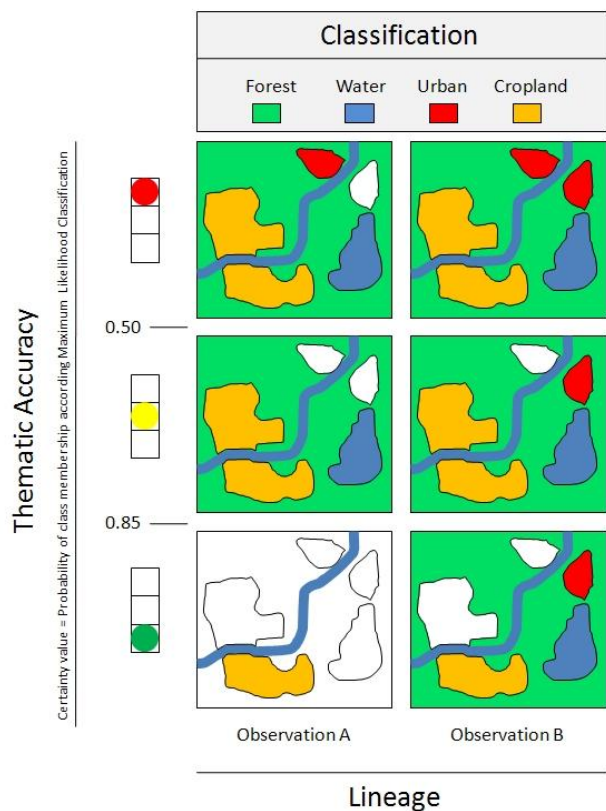

Figure 4. Conditional choropleth map for uncertainty parameters thematic accuracy and lineage

Parallel coordinates also allow for the detection of interrelationships between different uncertainty criteria: The parameters under observation are normalized within a range of 0 to 1, and values of the same object are connected together. Linking this diagram with the cartographic representation yields the spatial reference of class-specific information (figure 5). Evaluating the similarities or variances of the parallel coordinates lead to statements about the inherent correlation.
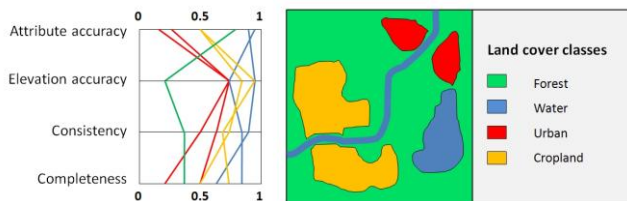

Figure 5. Parallel Coordinates of uncertainty parameters

Many visualization forms inherit the disadvantage that the uncertainty information covers the underlying thematic or spectral information (for example, see figure 3). Hence, we propose the option of a **floating certainty layer.** Based on an oblique perspective) it is possible to view the classification and the related uncertainty values simultaneously. Figure 6 shows a combination of a false color IR scene with a overlaid uncertainty information, which are classified according to the traffic light metaphor.
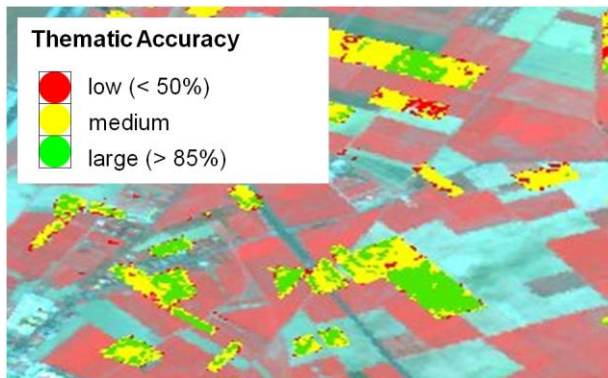

Figure 6. Floating uncertainty layer

4. CONCLUSIONS

There is a couple of reasons why automatic processing methods for the interpretation of remotely sensed scenes and the follow-up change analysis are not operational yet – and will probably not be operational in the near future. Hence, we propose the further development of visual interpretation methods and tools based on approaches and experiences as known from Visual Analytics. As a consequence, cognitive resources shall be freed for the integration of additional information, in particular, of uncertainty information.

This contribution has demonstrated a small selection of specific methods for interactive filtering and visualization. These techniques are suited to guide the operator more efficiently through the complex process and in particular to support the iterative character of an interpretation. Certainly there is not only one perfect interaction or visualization method for the given task. Instead, we propose a toolbox of methods which can be applied for different applications and by different types of users.

Our current work will finish the implementation of selected tools. Based on a prototype we will be able to perform so far missing empirical studies for that field of application and eventually to re-design the specific tools.

So far we have concentrated on existential changes between two discrete snapshots of nominal scaled variables (land cover classes) in a local neighborhood. Going beyond, we will have to deal with more than two snapshots (general case: *Transition (snap1, …, snapn)*) and additional relevant questions (e.g.: Is there any change? Is there always a change? Is there any system in the change?). Furthermore, high-level parameters of change (e.g., in distribution, pattern, clusters) have still to be formalized. It is obvious that the complexity – in terms of the number of possible spatio-temporal questions and the number of inherent uncertainties – is further increased, which on the other hand makes a user support by visual interfaces even more necessary.

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