VISUAL EXPLORATION OF TIME SERIES OF REMOTE SENSING DATA

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ABSTRACT:

The approach described here facilitates the exploration of time-series of remote sensing data by offering a set of interactive visual functions that allows studying the behaviour of dynamic phenomena, events and evolution of phenomena over time. Essentially we simulate the human visual system by decomposing each spatial region into a number of 2D Gaussian functions. The algorithm compares the attributes of each function in successive frames and finds the continuous paths of the spatial object through time. These paths describe the characteristics of the object in each time step and for each object certain interesting 'events' can be described. Examples of events are: continuation, appearance/disappearance, and split/merge of the phenomena. Based on the object paths, a visualization environment with 'temporal functionality' is created with a wide range of tools to support interactive exploration of events and the object's evolution. In particular, the event graph is proposed which in combination with other visualizations will make the process of detection and exploration of the dynamic phenomena independent of the perception and experience of the observer.

1. INTRODUCTION

One of the challenging research areas within GIS is the study and representation of the dynamic phenomena. A commonly used technique for monitoring dynamics in many environmental applications is remote sensing. A recent trend in remote sensing devices is towards higher spectral, spatial and temporal resolution. Further, remote sensing data are often pre-processed by the supplier and coupled with methods and techniques to extract various bio-physical indicators (e.g., water quality parameters, vegetation characteristics, soil properties, climatic parameters). Exploration and analysis of these fast growing spatio-temporal datasets is not a trivial task considering the amount of data being generated today, with remote sensing data alone projected to yield 50 gigabytes of data per hour (Wachowicz, 2000).

The purpose of exploration is to find patterns, trends and relationships in remote sensing data for generating hypotheses and understanding the dynamics of spatial objects. One way of supporting this exploratory process is by developing visualization methods. Visualization enables the researcher to gain insights into large spatio-temporal datasets; leading to better understanding of the phenomena and its modeling.

Generally, visualization includes two important aspects: graphical representation of spatial information and support for the user's visual interaction with this information. Especially, a visual exploratory process is characterized by highly interactive and private use of representations (MacEachren and Kraak, 2001). Currently, there are mainly three types of representations used to depict the temporal aspects of spatial data in GIS: a single static map, a series of static maps and animations. Single maps/images represent snapshots in time and together the maps make up an event. The main problem associated with static maps is that the visualization is restricted to only a few time slices - the dynamism of the phenomena is not maintained and interaction with spatial data is limited.

Animation is often used for large time series to integrate many maps and to add dynamics and interaction to the representation of time. It can be very useful to clarify trends and processes, as well as to provide insight into spatial relations (Kraak, 2000). While animations can be effective in perceiving changes in a single spatial object, they tend to become overwhelming when representing the relationships and evolution of several objects. This is due to the fact that the human visual system has limited bandwidth, and because images fade quickly, it requires an effort to maintain them (Gahegan, 1999). Therefore, even a playback animation, with the user controlling the flow, has two major drawbacks known as change blindness and inattentional blindness (Rensink, 2002). Since dynamics are rarely explored only with respect to the evolution of a single object, many changes go unnoticed by the users of animation (for some amazing example see URL: Visual Cognition Lab).

One way to improve existing visualizations is by providing computational support to human exploratory tasks. Exploratory tasks can be broadly divided into two stages identifying each spatial object in each time step and comparing characteristics of each object for further understanding of the dynamics. Object tracking methods, essentially simulating a human visual tracking process, have a relatively long history in the field of scientific visualization and signal processing. While object tracking is still a field of continuing research, the purpose of this paper is to present an approach for coupling object tracking and visualization in a single exploratory environment and to describe the representations and functionality resulting from such a combination. Therefore, in the following sections we first discuss the object tracking method, followed by a visualization example where we illustrate the principles and interactive support of different graphs designed for visual exploration of events and evolutionary stages of dynamic spatial phenomena.

2. BASIC DEFINITIONS

Each domain has its own set of interesting objects or features. These are usually defined as *regions* of interest in the remote

sensing datasets that satisfy certain constraints: for example an area of low NDVI values may define a stressed vegetation (Samtaney et al., 1994). In the following we consider a scalar function (corresponding to single band image) defined on a 2D set of image pixels. The choice of the function depends on the application domain. Our basic assumption is that this function can be decomposed into a superposition of elementary *building block functions* (b.b.f.) having simple and well defined form. Each b.b.f. corresponds to a single spatial object and may have different properties (spatial extent and magnitude) defined by the function parameters. Choice of a shape of the b.b.f. depends on the process at hand. The most natural function form has a maximum value in the centre of the object and is decreasing as a distance from the centre increases. Important decision should be made whether to choose a b.b.f. with finite or infinite support (corresponding to overlapping or non-overlapping spatial objects to be modelled) for a given application. Overlapping functions should be used when spatially continuous physical problems are studied. In what follows we model spatial objects with a 2D Gaussian function, which is a commonly used model in geosciences (Figure 1). Although Gaussian function has an infinite support, it decays quickly outside of a region defined by the spread of the function.

The advantage of using b.b.f. to model a spatial phenomenon is manifold: firstly, it reduces complex datasets to a description of the overlapping functions (in terms of function parameters), secondly, the overlapping functions can describe region with complex shapes and thirdly, most importantly, it leads to a robust comparison and consequently, to tracking of the functions over time.
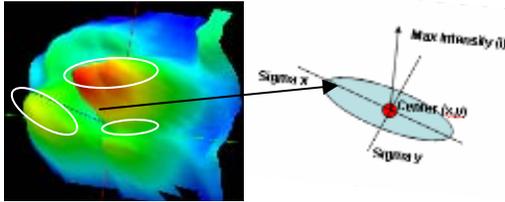

Figure 1. 3D view of hypothetical dataset with the fitted 2D Gaussian functions on the left. Properties of the Gaussian function are shown on the right.

Thus, a set of spatially overlapping 2D Gaussian functions represents the physical phenomenon in the spatial region. The evolution of the spatial object can be described by following its Gaussian building blocks.

3. EXTRACTING AND MODELLING OBJECTS FROM RS DATA

We translated the problem of spatial objects extraction into a problem of decomposition of complex function into a superposition of b.b.f.s having simple form. If the shape of b.b.f. is non-linear (as in the case of Gaussian function chosen in this paper) then such decomposition is a non-trivial problem. The approach described here is based on Gaussian shape of b.b.f. but it might be easily adapted for other functions having continuous derivatives.

We perform the function decomposition in an iterative way. First, the approximate location of the highest magnitude building block is found (by searching for a pixel with highest magnitude). Then a

region of points is sampled around this seed point in such a way that the pixel magnitude in the sampled region is decreasing with increasing distance form the seed point. This ensures that there is no contribution from different building blocks in the sampled region.

Sampled region is used for fitting of the profile with a Gaussian function. The fitting is done in two steps. First, one-dimensional fitting with one-dimensional Gaussian function is performed in vertical and horizontal cut of the sampling region separately:

$$A(x) = C_0 + C_1 \exp\left(-\frac{1}{2}\left(\frac{x - x_0}{\sigma_x}\right)^2\right)$$

$$A(y) = D_0 + D_1 \exp\left(-\frac{1}{2}\left(\frac{y - y_0}{\sigma_y}\right)^2\right)$$

Equation 1

Here $A = A(x,y)$ is the image magnitude at the pixel with coordinates (x,y), $A(x)$ and $A(y)$ are correspondingly the horizontal and the vertical cross-sections of the sampled region, x_0 and y_0 are the coordinates of the seed point, σ_x and σ_y are the parameters describing the extent of the Gaussian profile in horizontal and vertical direction.

The results of this fitting are used to find the approximate parameters of the two dimensional Gaussian function parameters. The second step does the fitting of the whole sampled region with a 2D Gaussian profile:

$$A(x, y) = A_0 + A_1 \exp\left(-\frac{1}{2}\left[\left(\frac{x'}{a}\right)^2 + \left(\frac{y'}{b}\right)^2\right]\right)$$

Equation 2

where x' and y' are the transformed coordinates given by

$$x' = (x - x_0)\cos\theta - (y - y_0)\sin\theta$$
$$y' = (x - x_0)\sin\theta + (y - y_0)\cos\theta$$

a and b denote the extent of the function in the principle axes and θ corresponds to the tilt of the principal axes to the original coordinates (x,y).

The function fitting is performed using steepest gradient descent method (Press et al., 1992).

A check is performed in order to detect artefact objects such as too small or too large objects or bad quality fit (controlled by the fit error). The thresholds are determined in an empirical way for each application domain. If the artefact object is detected, it is destroyed by setting all pixel values in the sampled region to zero. Otherwise, the parameters of the fit are stored and contribution of the object is subtracted from the image. This ensures proper treatment of overlapping objects.

After that the process of object detection and extraction is repeated for next object. Since the algorithm removes the highest magnitude object on each step of the iterative procedure, the result is a sequence of objects sorted by the magnitude in a descending order. We can set a threshold for the process termination being the lowest object magnitude.

As the result of the object extraction each image corresponding to a single time point is replaced by a set of records containing the parameters of 2D Gaussian objects. This significantly simplifies information contained in the image and can be used as an input in the object tracking process.

4. TRACKING OBJECTS AND DETECTING EVENTS

The purpose of tracking is to solve a correspondence (identity) problem and to establish a path of each spatial object over time. The underlying assumption of our tracking process is that the Gaussian functions composing the spatial regions evolve consistently between the successive time steps.

The tracking process consists of two main steps: initialization and tracking. The initialization phase is performed on the first three successive images to form the initial paths of Gaussian functions in time and to extract behavioural information of each identity. In essence, this behavioural information shows the characteristics of each b.b.f. extrapolated into the next time step (mainly position and shape parameters).

In order to describe a pair of Gaussian functions in successive images for their future identity the following characteristics are used: the central position of each Gaussian and attributes representing the overall shape of each Gaussian feature (peak magnitude, spread in the direction of principal axis). Given the object parameters in image *(i)*, the search for the corresponding objects starts in image *(i+1)* from the closest objects till it reaches the limit of the search distance, which is proportional to the spread of each Gaussian. Each object found within the search distance limit in image *(i+1)* is compared to the given object in image *(i)* and a similarity measure is calculated. Similarity is expressed in terms of a probability and the identity is assigned to the function with the highest probability.

$$P(k,l) = P_{magn}(k,l) * P_a(k,l) * P_b(k,l)$$

Equation 3
Where, *P* indicates the similarity probability (the value range between 0 and 1) of two building block functions *k* and *l* based on their magnitude A_1 (see Equation 2), and spread in the direction *a* and *b* as given below:

$$P_{magn}(k,l) = \frac{2 * \sqrt{A_{1k} * A_{1l}}}{A_{1k} + A_{1l}}$$

$$P_a(k,l) = \frac{2 * \sqrt{a_k * a_l}}{a_k + a_l}$$

$$P_b(k,l) = \frac{2 * \sqrt{b_k * b_l}}{b_k + b_l}$$

Equation 4
Once the initialization phase is complete, the extrapolated information of each path can be used for fine tuning of the tracking phase to the next time step. In essence it is the same procedure as the initialization step, but the similarity measure is further constrained by the extrapolated information. The output of the tracking process is the path of each Gaussian building block

in time. These paths are used for detecting events on the level of spatial regions – spatial objects.

Events are stages in the evolution of the phenomena. There exist many different types of events depending on the application, the type of spatial objects, and on the user's interest (Reinders, 2001). Our reasoning on events is based on the identity of each building block function and the total mass of the spatial region. We detect a continuation event if the spatial region on image *(i)* consists of identical Gaussian functions as the region on image *(i+1)* and if the total mass of Gaussian identities composing the region on image *(i+1)* is more than 50 % of the total mass of the region in the previous image. Then it is presumed that the region in the current image is a continuation of the region from the previous image and both regions form a path of the same spatial object. Similarly, a split is defined if the Gaussian identity loses connectivity with the spatial region (see Figure 2). A merge is defined as opposite to the split. Appearance (disappearance) is defined if the region in the current (previous) image fits none of the above criteria or appearance (disappearance) of isolated Gaussian function is occurred.
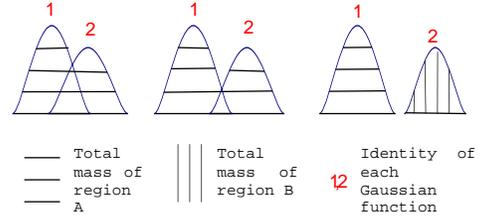

Figure 2. 1D example of a split event in history of region A

The output of the tracking phase is the paths of spatial objects which are essentially tree-like structures, carrying spatial, temporal and relationship information necessary for creating the exploratory visualization environment.

5. VISUALIZING THE EVOLUTION OF THE SPATIAL OBJECT

Though the approach is designed to be generic, we show an example of cloud movement in five time steps of 1 hour. The data used for the study were obtained from the METEOSAT Second Generation satellite with a temporal resolution of 15 minutes. The spatial resolution of the satellite is 3 km and the image has the following dimensions: 550*500 pixels and 20 time steps (subset of the image is shown on Figure 3). Extraction of clouds was done by slicing the band IR 10.8 with threshold value -40 °C (240 °K), as the top cloud temperature is lower than that of the earth surface. Cloud data are often used for rainfall estimation, based on their duration and temperature gradient over time (the clouds with large temperature gradients are more likely to be convective, indicating a high probability of rain).
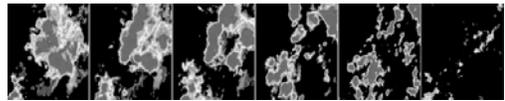

Figure 3: Subset of the example dataset, showing cloud movement at every hour starting at10-00h GMT

The patterns of these cloud regions were extracted and tracked over time to form the object paths. The object paths are input into the visual exploratory system.

The design of visual exploratory system largely depends on the task being supported and it is still a largely intuitive and *ad hoc* process (Ferreira de Olivera and Levkowitz, 2003). In practice however, the exploration tasks often vary depending on the perspective of the expert or the aspect of a phenomenon being studied (Yuan, 1997). Therefore, the best approach towards the design of exploratory environment is the combination of multiple linked views to show different aspect of object evolution.

5.1 Multiple linking representations

In visual environment linking visual representation and interaction forms allows changes in one representation to be reflected in all of them. Linking is usually accompanied with brushing and focusing tools (to be discussed later). The purpose of linking multiple views is to facilitate comparison. Currently, our exploratory environment consists of three main linked representations: an event graph, an animation and an attribute graph.

The purpose of the event graph is to show the evolution of tracked spatial objects. Essentially, our event graph is organized as a space-time cube: the bottom of the cube represents geographic space and the events and regions are drawn along the vertical time axis. Time, always present in the space-time cube, automatically introduces dynamics (Kraak, 2003). The event graph includes iconic representations based on spatial attributes (position and size) of the path-information and time information (Figure 4). The event graph is realized in object graphics, meaning that the three-dimensional cube can be manipulated in space to find the best possible view (known as a focusing technique).
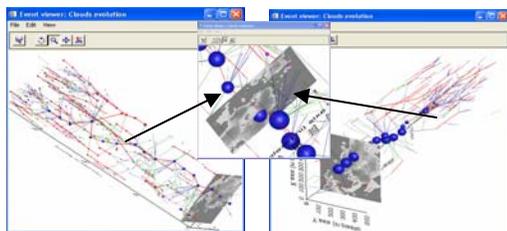

Figure 4: The proposed event graph, combined with iconic representation. On the left the radius of icons is logarithmically plotted, while on the right the radius is directly proportional to the size of the region. In the middle a zoomed section of the event graph.

Each object path (consisting of several regions) has its unique colour. The radius of the icons is proportional to the one of the attribute of the region (in Figure 4 it is proportional to the size). Events are represented by connected tubes of different colour (e.g. red is a continuation event, green – merge and blue – split).
The event graph represents the generalized and abstract view on the evolution of spatial objects. In order to be effective in visual exploration, the event graph has to be linked to other spatial representations, in particular to image animation. While images are animated, the event graph has its sliding geographical space

along the vertical axis synchronized to the individual images in the animation.

5.2 Functionality of linked representations

Besides the functionality already mentioned (linking views and focusing), we implemented an object brushing tool. The object brushing presumes that the users can set queries by the direct manipulation of icons on the event graph. This brushing tool works according to the filtering principle: all objects that were not selected during the user action are removed for the graphical displays. Combined with the linking technique it allows to observe the effect of querying in the other linked views - in animations and attribute graphs. In animation the trajectories and spatial extent of the selected objects can be examined, while attribute graphs can display various characteristics of the objects – rate of change of area (position, etc.) in time. In future, we intend to extend the brushing tool to spatio-temporal domains - allowing the user to highlight specific individual time moments or areas through time or space controls, and view states of the objects at these moments or changes taken place between two time moments.

6. CONCLUSION

The described approach uses advances in the field of scientific visualization and computer vision and can be seen as part of an ongoing trend to integrate scientific visualization methods and methods for exploration of spatial data. This trend has given name to the new discipline - geovisualization and its current research agenda includes both representation aspects of geospatial information and integration of visual with computational methods of knowledge construction (URL: ICA Visualization).

Conceptually, the combination of methods is advantageous: the identification of spatial regions can gain from the research in signal processing and computer vision. Extracting and tracking Gaussian functions reduces the spatial-temporal datasets: each region can be described in terms of its relations (events and b.b.f. identities) and attributes (position, size, total mass etc.). This improves rendering capacity and adds interactivity to the resulting visualizations. Regarding the attributes, the combination can be easily extended to add in other measurements of location and spatial distribution depending on the purpose of the application and the events the user wants to represent (if the event criteria are provided and the detection process is formalized). Also, functionality towards data mining and knowledge construction can be easily added (for example to find objects with large temperature gradients on Figure 3 indicating convective types of clouds).

Object tracking algorithm essentially simulates a low level human visual task of identification of spatial patterns. Contrary to the human visual tracking process, the proposed method detects changes in spatial objects regardless of the numbers of changes present in the scene and does not depend on perception and experience of the observer.

Thus, with proper visualizations, the user can pay more attention to higher order visual tasks – comparison and its related activities: exploration of spatial data and hypothesis generation. In particular, the event graph can show the essence of the object's

evolution and history. Built in three-dimensional space it utilizes the graphical variables (position, form, colour, orientation, size etc.) to portray both events and stages of the object's evolution. Synchronised with other spatial representations, the behaviour of dynamic phenomena, events and evolution of the phenomena can be explored interactively.

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