Structure Across Scales: Hierarchical Decomposition of Spatiotemporal Data Using A Scale-Space Approach

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Abstract

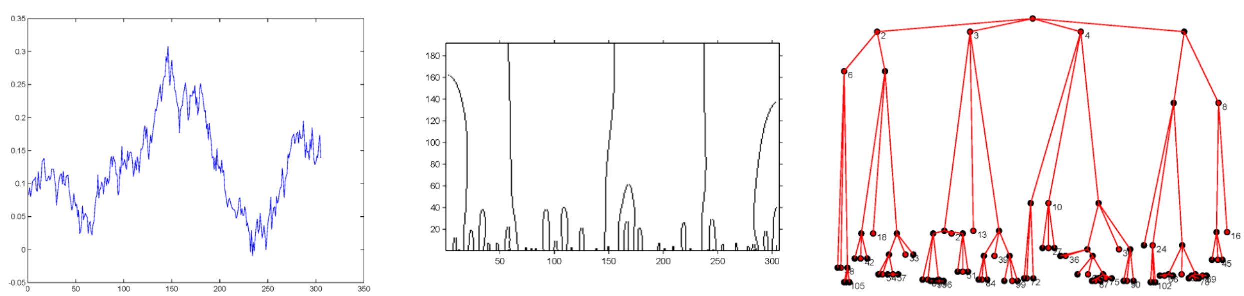
The ability to derive relationships between parts (granules) of a phenomenon that extends over space and time at different scales is essential in numerous application areas. Currently, the task of deriving a hierarchical decomposition of a spatiotemporal phenomenon relies on expert domain knowledge and is driven by a human operator. With the increased availability of spatiotemporal data this approach is quickly becoming impractical, thus requiring the development of automated tools for spatiotemporal data mining over multiple granularities. This presentation will review the problem of partitioning a spatiotemporal phenomenon into salient granular parts over multiple scales, and will introduce a novel analytical approach for reconstructing a multi-scale hierarchical decomposition of a given spatiotemporal data set.

Introduction

Many phenomena in virtually all areas of natural sciences involve the study of change, and in particular, change in space and time. A primary reason for this interest in change is simple: change has a fundamental role in our perception and understanding of the world as it provides a systematic approach to the evolution of things in space and time. The identification and formalization of change patterns allows us to achieve what is often taken for granted: formalize rules, apply reasoning, and predict future behaviors of a given phenomenon. Consequently, the study of change in spatial data over time is essential in various areas, such as meteorology, geophysics, forestry, biology, and epidemiology. The study of change in all these disciplines is closely related to the study of events and processes. The description of change in terms of events (and processes) is natural to us – as humans we intuitively tend to perceive an activity as consisting of discrete events (Zacks and Taversky, 2001). Yet the way spatiotemporal data should be decomposed into salient events and processes is often unclear and difficult without expert a-priori knowledge. Furthermore, our perception of events and processes is directly influenced by the scale by which we perceive and analyze the data (Galton, 2000), making the distinction between salient events and processes and the discovery of relations between them even more challenging. In light of this, the primary motivation of this work is to develop an analytical approach that would provide a hierarchical decomposition of spatiotemporal data into salient features (events and processes) while retrieving the hierarchical relations between the features using little or no a-priori knowledge.

The proposed approach

The proposed approach is based on a decomposition of spatiotemporal data using a scale-space representation of the data. The construction of a scale-space representation is carried out by imbedding the signal f into a one parameter family of derived signals, in which the scale is controlled by a scale parameter t. More formally, given a signal $f(x):\Re\rightarrow\Re \ \forall x\in\Re^N$ and a scale parameter $t\in\Re_+$, the scale space representation $L:\Re\times\Re_+\rightarrow\Re$ is defined as $L(x,t)=g(x,t)*f(x)$, such that $L(x,0)=f(x)$, and $*$ is the convolution operator (Lindeberg 1994). Typically, $g(x,t)$ is taken as a Gaussian kernel (Witkin, 1983),(Lindeberg 1990) but in the general case $g(x,t)$ can be any well-defined waveform (e.g. a wavelet). A primary advantage of the scale-space representation is its ability to provide an insight into the inherent inner structure of the data across different scales. By following inflection (extremum) points in the scale-space representation, and by using these inflection points as event/process indicators it is possible to generate a scale-space "sketch" in which the evolution trajectory of events and processes across scales becomes evident (Fig. 1(b)). A formal representation of the scale-space inner structure can then be constructed by generating an interval tree from the scale-space sketch (Witkin, 1983). A detailed outline of the proposed scale-space approach can be found in Croitoru et al. (2006). Once created, the interval tree can be analyzed using the granularity tree formalization (Reitsma and Bittner, 2003). Here, several forms of analysis can take place in addition to the reconstruction of the event/process hierarchy (Fig. 1(c)), for instance: (a) pattern detection, in which a search for a particular subset of the granularity tree is carried out; (b) change detection, in which two granularity trees are compared and differences are indicated.



(a) (b) (c)

Figure 1: Hierarchical decomposition using scale space. (a) a tidal time series; (b) the corresponding scale-space sketch; (c) reconstruction of the granularity tree (each node represents an event or process).

Results

In order to evaluate the proposed approach two types of data were analyzed: meteorological (storms) and ocean data. In the case of meteorological data the evaluation of the proposed approach was carried out using satellite data from NASA-GFSC's GOES project (http://goes.gsfc.nasa.gov) that provides GOES-12 imagery. A total of five storms were collected, and for each storm four additional permutations were generated with a varying level of noise resulting in a set of 25 time series. Then, using the proposed approach, the data set was clustered in an attempt to recover the five storm clusters. In this case the proposed approach was able to correctly cluster the data and showed resistance to noise. In the case of ocean data wave height time series were analyzed in an attempt to detect and characterize a change in the measure phenomenon. The data was derived from GoMOOS - a buoy sensor network operating in the Gulf of Maine (http://www.gomoos.org). Using the proposed approach a granularity tree was derived and analyzed for change detection, resulting in the successful detection of change. It should be noted that in the proposed approach change is detected across scales and not a single scale.

Conclusions

Recent years have been characterized by unprecedented amounts of spatiotemporal data. As we become more reliant on spatiotemporal data, the need to develop a sound analytical foundation for processing and inferring knowledge from such data becomes evident. In this work the problem of processing spatiotemporal data over multiple granularities was addressed. The proposed approach builds on scale-space theory in which multiple scales (instead of a single scale) are utilized, thus reducing the need for a-priori domain-specific knowledge in order to process the data. Furthermore, the proposed approach is specifically geared towards dealing with events and processes at multiple granularities, and allows reconstructing the inherent structural hierarchy of spatiotemporal phenomena. This work outlined and demonstrated how scale-space theory together with granularity trees can bused to mine spatiotemporal data, and eventually lead to the discovery of knowledge from such data.

The work presented here could be expanded in several directions. First, the scale-space approach presented could be expanded to simultaneously consider multiple object attributes. This would result in a multi-dimensional granularity tree structure, and would enable the discovery of multi-dimensional event patterns across scale. Work in a two-dimensional space has recently been presented in the context of object analysis and detection (Siddiqi et al., 1999), but further expansion into multiple dimensions is needed. A second area in which this work could be expanded is the development of modeling and analysis tools for intra and inter-object events and processes. The work presented here focuses on a single salient objects (i.e. a hurricane cloud mass) and assumes that the topology of the object remains unchanged (i.e. the cloud mass does not split, or merge with another storm's cloud mass). However, various application areas, such as transportation, meteorology and homeland security, require the capacity to detect events and processes that include changes in the composition of an object or in the relation between objects over time, space, and scale (McIntosh and Yuan, 2005). In order to accommodate such a capacity change in topological relations over time should be incorporated, and temporal ordering rules should be applied (Peuquet, 1994). Potentially, this could be done through a conceptual neighborhood graph based approach (Cohn et al., 1997). In addition, a framework for describing topological relations over multiple granularity levels should be developed.

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