Space-in-Time and Time-in-Space Self-Organizing Maps for Exploring Spatiotemporal Patterns

G. Andrienko[1], N. Andrienko[1], S. Bremm[2], T. Schreck[2], T. von Landesberger[2,3], P. Bak[4], D.Keim[4]

[1]University of Bonn & Fraunhofer IAIS, Germany
[2]Technische Universität Darmstadt, Germany
[3]Fraunhofer IGD, Germany
[4]University of Konstanz, Germany

Abstract

Spatiotemporal data pose serious challenges to analysts in geographic and other domains. Owing to the complexity of the geospatial and temporal components, this kind of data cannot be analyzed by fully automatic methods but require the involvement of the human analyst's expertise. For a comprehensive analysis, the data need to be considered from two complementary perspectives: (1) as spatial distributions (situations) changing over time and (2) as profiles of local temporal variation distributed over space. In order to support the visual analysis of spatiotemporal data, we suggest a framework based on the "Self-Organizing Map" (SOM) method combined with a set of interactive visual tools supporting both analytic perspectives. SOM can be considered as a combination of clustering and dimensionality reduction. In the first perspective, SOM is applied to the spatial situations at different time moments or intervals. In the other perspective, SOM is applied to the local temporal evolution profiles. The integrated visual analytics environment includes interactive coordinated displays enabling various transformations of spatiotemporal data and post-processing of SOM results. The SOM matrix display offers an overview of the groupings of data objects and their two-dimensional arrangement by similarity. This view is linked to a cartographic map display, a time series graph, and a periodic pattern view. The linkage of these views supports the analysis of SOM results in both the spatial and temporal contexts. The variable SOM grid coloring serves as an instrument for linking the SOM with the corresponding items in the other displays. The framework has been validated on a large dataset with real city traffic data, where expected spatiotemporal patterns have been successfully uncovered. We also describe the use of the framework for discovery of previously unknown patterns in 41-years time series of 7 crime rate attributes in the states of the USA.

Categories and Subject Descriptors (according to ACM CCS): H.1.2 [User/Machine Systems]: Human information processing—Visual Analytics; I.6.9 [Visualization]: Information Visualization—

1. Introduction

Spatiotemporal data pose serious challenges to analysts. Firstly, owing to the complexity of the geographical space, data having a geospatial component cannot be adequately analyzed by fully automatic methods, but require the involvement of the human analyst's sense of the space and place, tacit knowledge of their inherent properties and relationships, and space / place -related experiences [AAD*08]. These are incorporated into the analysis through the use of an appropriate representation of the space such as a cartographic map, which serves as a model of the reality through which the analyst can interpret data associated with the space and its places. Secondly, time is also a complex phenomenon. Time flows in a linear way, however the events happening over time can be periodically recurring, with multiple cycles forming hierarchical structures, overlapping, and interacting. Like space, it is heterogeneous; thus, day differs from night and working days differ from weekends and holidays. Humans have good understanding of time, which is very hard to convey to the machine. Hence, data having a temporal component also require human involvement in the analysis through the use of appropriate representations [Peu02].

The analysis of spatiotemporal data may be, however, too complex for humans: the number of distinct places can be too large, the time period under analysis too long, and/or the attributes depending on space and time too numerous. <mark>Therefore, human analysts require a proper support from computational methods capable to deal with large and multidimensional data.</mark>

Comprehensive analysis of spatiotemporal data requires consideration of the data in a dual way [AA05b]:

- As a temporally ordered sequence of spatial situations. A *spatial situation* is a particular spatial distribution of objects and/or values of attributes in some time unit (i.e. moment or interval);
- As a set of spatially arranged places where each place is characterized by its particular temporal variation of attribute values and/or presence of objects. We shall call it *local temporal variation*.

Accordingly, there are two high-level (synoptic) subtasks in analysis of spatiotemporal data:

- Analyze the change of the spatial situation over time, i.e. temporal evolution of the situation.
- Analyze the distribution of the local temporal variations over space.

In order to support both tasks, we suggest a framework for analyzing spatiotemporal data with the use of the computational method called Self-Organizing Map (SOM) [Koh01]. SOM combines clustering with dimensionality reduction: objects are not only grouped but also arranged in one- or two-dimensional space according to their similarity in terms of multidimensional attributes. We have built a visual analytics environment in which it is possible to apply SOM to spatial situations and temporal variations and explore the results obtained by means of various visual and interactive techniques.

An overview of related research concerning the use of SOM for visual data exploration is given in Section 2. Section 3 describes our tools for spatiotemporal analysis with the use of SOM. In Section 4, we describe an application of the tools to real data about city traffic in Milan with previously expected spatiotemporal patterns. We demonstrate that the tools allowed us to detect these patterns. In Section 5, we show how these tools allow uncovering previously unknown spatiotemporal patterns in another real dataset describing crimes in the USA. This is followed by a discussion of our contribution in comparison to the state of the art and conclusion in Section 6.

2. Related work

The SOM methodology is discussed in depth in Kohonen's monograph [Koh01]. The Self-Organizing Map is a neural network type vector projection and quantization algorithm.

By means of a competitive, iterative training process, a network of prototype vectors (or neurons, or cells) is trained (adjusted) to the input vector data. The output of the algorithm is a network of vectors that is approximately topology preserving w.r.t. the input data. The network can be interpreted as a set of clusters and simultaneously as a map to lay out the input data elements (e.g., in the nearest neighbor sense w.r.t. the prototypes). Typically, two-dimensional rectangular or hexagonal prototype vector networks are assumed. The SOM algorithm is usually outperformed in terms of vector quantization capability by algorithms not requiring the network constraint. On the other hand, the capability of SOM to arrange input data in a regular network structure provides good opportunities for visualization. This makes the method very convenient for integration in an environment for interactive visual exploration of multidimensional data. To date, SOM has been successfully used for a number of visual analysis applications.

The SOM method is applicable to any data type that can be represented by vectors. Specifically, complex and multimedia data can be addressed by SOM if represented by appropriate feature vector data. A few example applications to name in this respect include financial data [DK98], text [ND06], images [Bar08], or time-dependent scatter data [SBvLK09]. Vesanto [Ves99] describes the basic analytic tasks that can be addressed with SOM and options for SOM visualization supporting these tasks. The tasks include analyses of cluster structure, of prototype vectors, and of overall data distribution.

The SOM method has been successfully applied in the geospatial data analysis domain, where its data aggregation and sorting properties are leveraged. A wealth of applications are described in a recent book on the topic [AS08]. As the SOM network itself represents an abstract map for data, color-coding can be used to link the location of data elements in SOM space with their respective geospatial coordinates [KK08, ST08]. VISSTAMP is a system linking views based on geospatial maps, SOM maps, parallel coordinate and table plots [GCML06]. Besides using simple linearly scaled two-dimensional color maps, approaches exist for advanced mappings adjusting for non-uniform distributions of SOM distances [KVK00] and considering perceptual issues [GGM*05]. Variants of the SOM algorithm exist that include also geospatial coordinates in the SOM training process, allowing a tradeoff of multivariate and geospatial data properties in the obtained SOM [BLP05]. An interesting way of linking SOM to geographical space and time is described in [Sku08]. A trajectory made by a person in the geographical space is projected onto the space of SOM where geographical places are arranged according to their similarity in terms of multiple attributes.

The most related to our work are the works where SOM is applied to spatiotemporal data. Hewitson [Hew08] applies SOM to time series of spatial distributions of air pressure

values in order to find the archetypal distributions for a region and then looks for certain temporal patterns such as frequencies of the archetypes in dry and wet years. Hewitson does not consider the complementary analytic task, analysis of the spatial distribution of the local temporal variations.

In [GCML06], SOM is applied to combinations of values of multiple attributes characterizing pairs <place + time unit>. Assessing similarities and differences among spatial situations is done by visual inspection of multiple maps (one map per time unit) where each place has the color of the SOM cell containing the particular combination of this place and the time unit. Assessing similarities and differences among local temporal variations is done using a reorderable matrix where the rows correspond to the places, columns to the time units, and cells have the colors of the SOM nodes. Hierarchical clustering groups the rows by similarity; however, the spatial context is missing. We apply SOM to spatial situations and temporal variations; hence, the results directly match the analytic tasks.

3. Description of the tools

We have integrated the SOMPAK SOM engine [KHKL96] in a visual analytics environment for spatiotemporal analysis. The environment supports transformations of spatiotemporal data, controlling the work of the SOM algorithm, postprocessing of the SOM results, and putting the results in the spatial and temporal contexts for human interpretation.

The Self-Organizing Map method is used for grouping and arranging spatial distributions and temporal variation profiles according to their similarity. The results are presented in the SOM matrix display. Two-dimensional color mapping links the SOM matrix with additional data views for supporting multi-perspective data analysis. Thus, the cartographic map display represents SOM results in the geographical context. For this purpose, places in the map are colored according to the positions of the respective profiles of local temporal variation in the SOM matrix. Two types of temporal displays, time graph and time arranger, represent SOM results in the temporal context. For this purpose, segments of these displays are colored according to the positions of the respective spatial situations in the SOM matrix. The time arranger supports detection of periodic temporal patterns in the occurrence of similar spatial situations.

The system also includes interactive tools for spatiotemporal aggregation and other data transformations, which may be needed for preparing data to the application of the SOM method and for interpreting the results obtained. Examples of the use of these tools are given in Sections 4 and 5.

3.1. Parameterization of SOM Algorithm

The SOM algorithm requires a number of parameters to be set. We distinguish between the network size (number of

prototype vectors) and training parameters (including learning rate and neighborhood kernel function). Suitable training parameters can be set according to the empirical rule-of-thumb recommendations [KHKL96]. An alternative is to automatically evaluate a series of different parameterizations and take the best result as judged by an objective SOM quality measure such as quantization or topology error. We regard the network size as a user-chosen parameter. Typically, it will depend on the user task and data size. If the data set is large and data reduction is desired, the number of prototypes is set much smaller than the number of data items, thus providing data aggregation. If the data set is rather small, the network size may be set about equal to the number of data items. In this case, the SOM algorithm mainly acts as a similarity-preserving layout method.

In principle, different parameterizations may give different results in terms of prototype vectors and their layout in the network. However, we practically observe that the results are rather stable even over larger parameter variations. If desired, stability can further be enhanced by data-dependent and supervised training initialization methods (see [Koh01, KHKL96]).

In our system, we apply the rule-of-thumb parameterizations suggested in [KHKL96] for training and let the user select the network size interactively. For simplicity of the implementation, we stick to a rectangular SOM network. While SOMPAK is an efficient implementation, depending on the data size and training parameterization, SOM calculation runtime may not be interactive. While for our data sets, runtimes were quite fast, we note that interactive SOM calculation is not a necessity in our application.

3.2. SOM matrix display

We apply the SOM method to two types of complex objects: (1) spatial situations that occurred in different time units, and (2) local temporal variations that occurred in different places. Accordingly, there are two variants of SOM outcomes called *'space-in-time SOM'* and *'time-in-space SOM'*, respectively. The interactive visual interface to the SOM engine consists of a matrix display of the SOM outcomes and a control panel, which allows the user to set the parameters of the SOM tool and modify the display of the results. The cells of the SOM matrix may include variable numbers of objects depending on data characteristics and the size of the SOM grid; some of the cells may be empty. The number of objects contained in a cell is shown graphically by a bar where the full length represents the maximum number of objects among all cells and the filled part is proportional to the number of objects in the cell. The innovative features of the SOM matrix display are the specific coloring of the matrix cells that reflects the degree of their similarity and two types of automatically generated images representing the contents of the cells, feature images and index images. The images provide a combined representation of the spa-
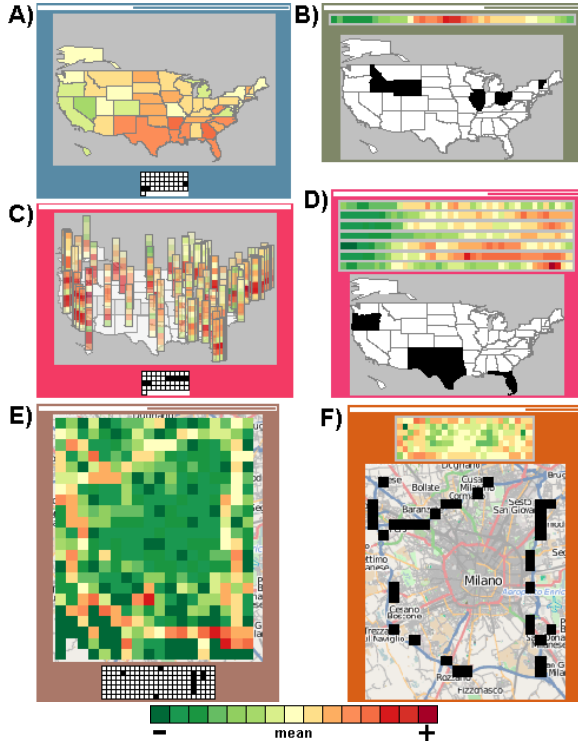
Figure 1: *Possible appearances of cells in a SOM matrix. Left: space-in-time SOM (grouping of spatial situations). Right: time-in-space SOM (grouping of places according to temporal variations of attribute values). A,B: one attribute with values for 41 years. C,D: 7 attributes with values for 41 years. E,F: one attribute with values for 7x24 hours. The upper image in each cell is the feature image, the lower image is the index image.*

tial, temporal, and thematic (attributive) components of the data.

3.2.1. Feature images

Feature images represent the objects to which the SOM tool has been applied, i.e. spatial situations in a space-in-time SOM and local temporal variations in a time-in-space SOM. Spatial situations are represented by maps (Figure 1, left), and local temporal variations by diagrams (Figure 1, right); we call them *'temporal mosaics'*. A map image portrays the attribute values attained in all places in one time unit. A temporal mosaic portrays the attribute values attained in one place in all time units. In both cases, values of space- and time-dependent numeric attributes are represented by color coding. The user may choose one of the multiple color scales available in the system, which include all variants of diverging color scales from Color Brewer [HB03]. Thus, in Figure 1, a Color Brewer's scale is used where shades of green correspond to low values, shades of red to high val-

ues, and yellow stands for values close to the average. In Figure 2, a modified variant of one of the Color Brewer's scales where color brightness is enhanced for more visual salience. Here, shades of blue are used for low values, shades of yellow for medium values, and shades of red for high values. The system also includes some of the palettes suggested in [WVvWvdL08].

It should be noted that feature images are not meant for conveying detailed information about the values of attributes in each particular place and time unit. The system has other tools that enable detailed reading of values. For example, the cartographic map display not only allows the user to decode the colors by means of the legend but also shows the exact values when the user points on a place in the map. The images in the SOM cells are intended for providing an overview, so that the user can approximately estimate whether the values are low, medium, or high and notice major differences between cells.

The cartographic representation technique used in the map images depends on the number of attributes selected for the analysis. Values of a single attribute are represented directly by colors of the map elements depicting the places (territory compartments). Examples can be seen in Figure 1A and E. In case of two or more attributes, the map contains diagrams, called *'multi-attribute mosaics'*, which are positioned in the places (Figure 1C). Each diagram consists of pixels colored according to the attribute values and arranged in a rectangular layout with user-preferred number of columns. Thus, in Figure 1C, the multi-attribute mosaic in each compartment consists of 7 pixels arranged in one column. The pixels correspond to 7 attributes selected for the analysis. Overlapping of the mosaic symbols on the small maps is a serious problem, which is only partly reduced by semi-transparent rendering. Still, the images are adequate for providing an overview: the user can see which colors prevail where.

The temporal mosaics shown in the cells of a time-in-space SOM (Figure 1, right) are built similarly to the multi-attribute mosaics drawn on a map as in Figure 1C. The pixels represent attribute values by color coding. The set of pixels corresponding to one attribute is arranged in a rectangular layout with user-chosen number of columns. Thus, in Figure 1B, the pixels representing values of one attribute for 41 years are arranged in one row. In Figure 1F, the values of one attribute for 168 consecutive hourly intervals (7 days x 24 hours) are arranged in 7 rows corresponding to the days; hence, the columns correspond to the hours of a day. In case of multiple attributes, the respective mosaics are combined in a single image. Thus, the feature image in Figure 1D represents values of 7 attributes for 41 years. The values of each attribute are represented by a mosaic consisting of 41 pixels laid out in one row, as in Figure 1B. The mosaics of the 7 attributes are automatically placed one below another. This produces the overall rectangular layout with 41 columns and
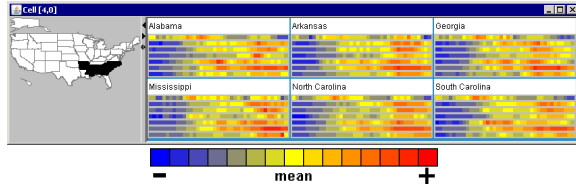
Figure 2: *An additional window displays the content of a cell of a time-in-space SOM.*

7 rows. Although the resulting image is similar to that in Figure 1F, the meaning of the rows is different.

In case of multiple attributes, the values of each attribute are color-coded independently of the other attributes while the same color scale is used. Since the same colors may represent different value intervals for different attributes, feature images are not meant to be used for inter-attribute comparisons. Their role is to give an idea about the relative magnitudes of the individual attribute values.

When a SOM matrix cell contains two or more objects, the displayed image represents the best fitting object, that is, the object with the smallest distance to the cell's prototype vector (nearest neighbor). Images of all objects included in a cell can be seen in an additional window which appears after clicking on the cell (Figure 2).

3.2.2. Index images

Index images show the temporal or spatial positions of the objects included in the SOM matrix cells. In a space-in-time SOM, *temporal index images* show the temporal positions of the spatial situations (Figure 1 left). An image consists of small squares representing the time units, which are temporally ordered and arranged in rows of user-chosen length. The squares representing the objects included in the respective SOM cell are filled in black. Thus, in Figure 1A and B, the temporal index images have 10 columns; hence, the rows correspond to decades. In Figure 1C, the temporal index image has 24 columns corresponding to 24 hours of a day and 7 rows corresponding to 7 consecutive days.

In a time-in-space SOM, *spatial index images* show the spatial positions of the local temporal variations. Each image is a map where the spatial positions are marked by black filling of the corresponding territory compartments (Figure 1 right). The combination of feature images and index images provides a combined representation of the space, time, and values of one or more attributes. The user may arbitrarily switch on and off the drawing of the feature images and the index images.

3.2.3. Distances between SOM cells

In a SOM, not every single neuron necessarily represents a meaningful cluster. In many cases, it is useful to see a com-

bination of nearby neurons as representation for such a cluster. The u-matrix [Ult99], which consists of the pair-wise distances between neighboring cells in the space of the attribute values, is a common way to address this problem. In our implementation, the information about the distances may be conveyed in the SOM matrix display through the shading of the cell borders (Figure 8). The border of a cell is divided into 8 segments corresponding to the 8 neighbors of this cell. The degree of darkness of each segment between white and black is proportional to the Euclidean distance to the respective neighbor in terms of the attribute values. The distances among the SOM cells are also reflected in the coloring of the SOM cells, as explained below. Therefore, the drawing of the so shaded borders between the cells is optional and can be switched off by the user.

3.2.4. Coloring of SOM cells

Coloring of the cells in the SOM matrix is the primary means for visual linking of the matrix display to the other visual displays and thus for putting SOM results in the spatial and temporal contexts. For this purpose, the colors of the cells are assigned to the spatial or temporal positions of the thereby represented objects and used for coloring the corresponding visual elements in the other displays. To enable correct perception of the similarities and dissimilarities from the displays linked to SOM, the coloring of the SOM cells must reflect the distances among them in the attribute values space.

To achieve this, we create for a SOM matrix with m columns and n rows a two-dimensional color map with $10*m$ columns and $10*n$ rows. In the next step, we place the first neuron in the corresponding corner of the color matrix. Then each next neuron is iteratively placed in the color matrix according to the distances to its previously placed neighbors. Using this strategy, neighboring cells with a small distance have more similar colors than cell pairs with a big distance, reflecting the actual data similarity. For a two-dimensional color map, we use the CIELab color space as suggested in [WD08].

4. Validation of the framework: detecting the expected

For testing our framework and tools, we used a dataset where certain spatial and temporal patterns were previously expected. The dataset consists of GPS-tracked positions of 17,241 cars in Milan (Italy) during one week from Sunday to Saturday (April 1-7, 2007). The framework is not directly applicable to this kind of data. We transformed the data by means of spatial and temporal aggregation [AA08], which is suitable for the exploration of the spatiotemporal patterns of the city traffic. We divided the territory of Milan into compartments by means of a rectangular grid with the horizontal and vertical spacing of 1km. We obtained 396 compartments (= 18 columns * 22 rows), further referred to as "places". We divided the time span of the data into hourly intervals and thereby obtained 168 time units (= 7 days * 24 hours). For
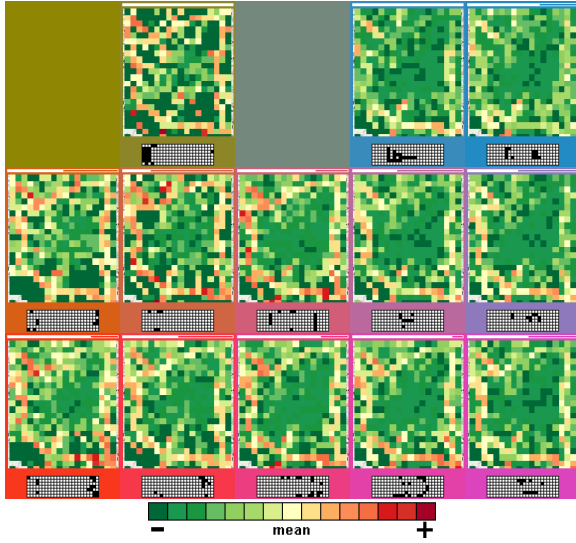
Figure 3: *The space-in-time SOM matrix with the hourly traffic situations in Milan characterized in terms of the mean speeds in the spatial compartments.*

Figure 4: *The Time Arranger exposes periodic temporal patterns in the evolution of the traffic situation in Milan over the week. The columns correspond to the 24 hourly intervals of a day and the rows to the 7 days from Sunday to Saturday. The pixels have the colors of the SOM cells (Figure 3) in which the respective time units belong.*

each pair <place, time unit> we computed the mean speed of the movement. This attribute is adequate for characterizing traffic conditions. The mean speed is high when the conditions are favorable and low when the movement is obstructed, e.g. because of traffic congestion. The data were previously cleaned so that the cars that did not move for 10 or more minutes were not taken into account. The combinations <place, time interval> in which there were no cars have got zero values of the mean speed.

Hence, the spatial situation in each time unit is characterized by the mean speeds in all places. The local temporal variation in each place is characterized by the time series of the mean speeds in this place.

4.1. Detection of temporal patterns among spatial situations

The typical temporal patterns of traffic situations in a big city are well known. Thus, there are particular intervals in the mornings of the working days, called "rush hours", when the major streets are crowded with vehicles and the movement is obstructed. Similar situations occur in the afternoons. Between these intervals, the situation may improve but the movement is not as free as in late evenings and nights. The patterns on weekends and holidays are usually quite different. Situations with heavily obstructed traffic either do not occur or occur in other time intervals. If shops are closed on Sundays, differences between Sunday and Saturday patterns can be expected. We tried to detect these expected temporal patterns by grouping similar spatial situations with the help of SOM.
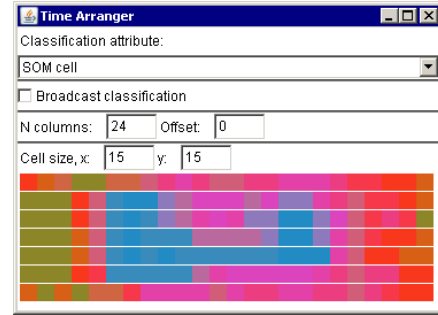
We ran SOM with the following parameters: matrix size 5x3, 300,000 iterations, learning radius 2, learning rate 0.02. The resulting space-in-time SOM matrix is shown in Figure 3. As mentioned before, cell colors in a SOM matrix link it to other displays. Colors from a space-in-time SOM can be transmitted, in particular, to a time arranger display (Figure 4). It consists of rectangular pixels representing the time units and having the colors of the SOM cells the units belong in. The pixels are chronologically ordered and arranged in rows. By choosing suitable row length and indention of the first row, the user can detect periodic temporal patterns in the occurrence of the spatial situations. Periodicity is manifested by vertical alignments of identically or similarly colored pixels. Thus, the pixels in Figure 4 represent hourly intervals within a 7-day period from Sunday to Saturday. They are arranged in rows of the length 24, which corresponds to 24 hours of a day. The prominent vertical alignments of similarly colored pixels mean that the spatial situations were similar in the corresponding hours of different days. It is easy to see that Sunday (first row) and Saturday (last row) differ from the working days. Friday morning is similar to the mornings of the other working days while the color pattern of the rest of the day is more similar to that on Saturday. We found out that this was not a typical working Friday but the Good Friday before Easter, which may explain the difference.

Concerning the typical working days, we can see that the hours from 0 to 3AM are colored in olive green, which corresponds to a cell in the upper left part of the matrix. The feature image shows us that the speeds on the belt roads around the city are high in these hours while there are large areas with no movement (signified by the darkest green shade). The next two hours fit in the region from the lower left corner to the center of the matrix. The speeds on the belt roads remain high while the no movement areas reduce. Starting
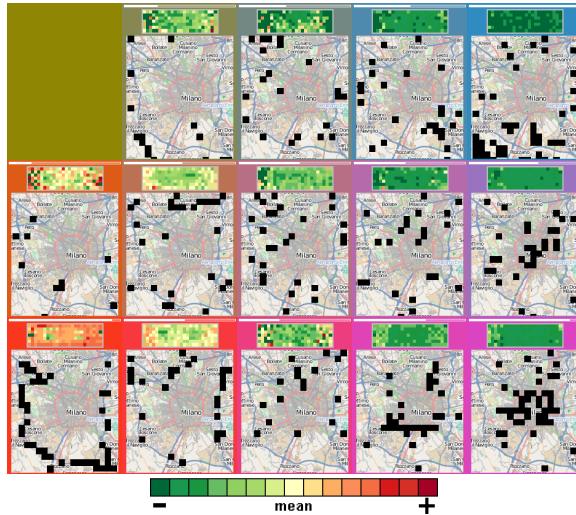
Figure 5: *The time-in-space SOM matrix with the local temporal variations of the mean speeds in the spatial compartments in Milan.*

Figure 6: *The map of Milan with the places colored as the cells of the time-in-space SOM (Figure 5) they belong in.*

from the interval 5-6AM, the pixels are colored in light blue, which corresponds to the upper right corner of the matrix. The speeds are low almost throughout the whole city. Very close to that are the situations in the middle right cell of the matrix (light violet); only on the west and south of the city the speeds are somewhat higher. Apparently, the interval 5-6AM is the beginning of the rush hours, which last till 10AM from Monday to Wednesday and on Friday and till 18 o'clock on Tuesday. From Monday to Wednesday, the obstructed traffic situations repeat from 15 to 17 o'clock. Between and after the rush hours the speeds are higher mainly on the major roads (lower right corner of the matrix). In the evening (from about 20 o'clock), the speeds increase also in other parts of the city (lower left corner).

Hence, we can conclude that our tools allowed us to detect the expected periodic temporal patterns in the weekly traffic in Milan. Periodicity in time-dependent data can also be revealed using other arrangements of display elements; thus, in [SDW08], a diagonal arrangement is used.

4.2. Detection of spatial patterns among local temporal variations

An obvious spatial pattern that can be expected in the distribution of the local temporal variations is that the traffic on the major roads differs from that in the city center. One can also expect a different profile of the traffic variation in residential areas. To detect such patterns, we group the local temporal variations with the help of SOM using the same parameters as in the previous experiment. The resulting time-in-space SOM matrix is shown in Figure 5. In Figure 6, the colors of the SOM cells are used for painting the places on
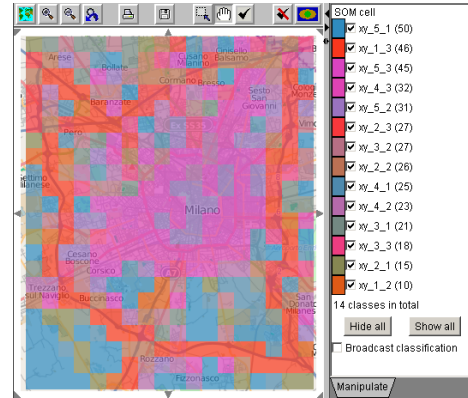
the map of Milan. The places on the major roads are colored mostly in red, which clearly differentiates them from the remaining territory. The speeds in these places are high except for the rush hours (see the temporal mosaics in the lower left corner of the matrix). The places in the city center are colored in pink. Here the speeds are always quite low. Shades of light blue are in places with little or no movement (many of the mean speed values are zeros). It is highly probable that they are in pedestrian or residential areas. Hence, we can say that our tools, indeed, enabled us to detect the expected spatial patterns. We also noticed something unexpected: the speeds on the belt road on the northeast are much lower than typically on the belt roads (see cell 2,2 of the matrix).

5. Application of the framework: discovering the unexpected

In this experiment, we apply our framework to the USA crime dataset published by the US Department of Justice. We downloaded the data from the URL http://bjsdata.ojp.usdoj.gov/dataonline/ in March 2003. For 50 states of the USA plus District of Columbia, there are annual statistics for the years from 1960 to 2000 including the rates of seven types of crime: Murder and non-negligent manslaughter, Forcible rape, Robbery, Aggravated assault, Burglary, Larceny-theft, and Motor vehicle theft. We want to explore the spatial and temporal patterns of these crime rates. Before starting the analysis, we look at the variation of the values of the attributes using a time graph display (Figure 7). For each attribute, there is a graph where the horizontal axis represents time and the vertical axis the attribute's value range. The variation of values in each state is shown by a line; hence, each graph includes 51 lines. The time graph display shows us that District of Columbia has extraordinarily high values of some of the attributes (the corresponding lines are highlighted in white in Figure 7; the pop up window shows the value of the robbery rate in 1996). In order
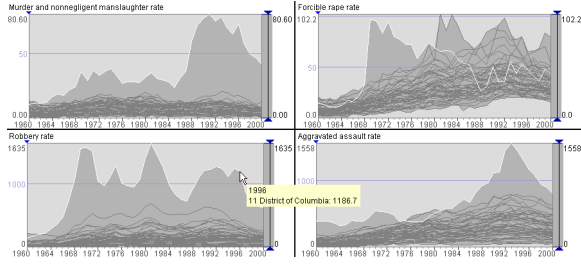
Figure 7: *A fragment of the time graph display of the temporal variations of the crime rates.*
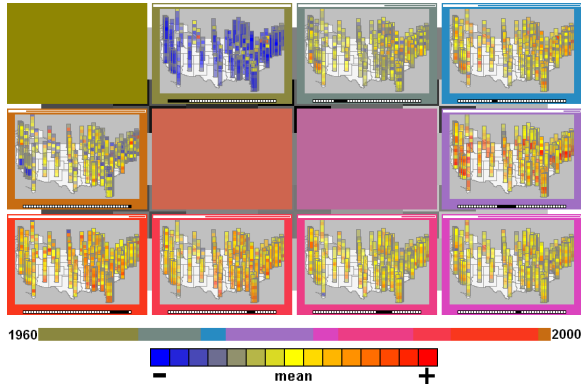

Figure 8: *The space-in-time SOM matrix of the yearly crime situations in the USA.*

Figure 9: *A) A fragment of the time graph display where the original data have been transformed to normalized differences from the mean values. The background painting of the time intervals uses the cell colors from the space-in-time SOM in Figure 8. B) The data have been further transformed to the differences with respect to the previous years. Instead of the lines of the individual states, the 0th, 20th, 40th, 60th, 80th, and 100th percentiles in each year are indicated by the vertical positions of the edges of the alternating stripes with lighter and darker shading, as suggested in [AA05a].*

to make the values in the states more comparable, we transform the original data into differences from the states' mean values divided by the respective standard deviations. For this purpose, we use the interactive interface for data transformation integrated in the time graph display. Figure 9A shows the result for 4 out of 7 attributes. From now on, we use the transformed data.

5.1. Discovery of temporal patterns among spatial situations

To investigate how the spatial distribution of the crime rates values evolves over time, we apply SOM to the spatial situations in the years from 1960 to 2000 where each situation is characterized by the values of the seven crime rates. We use the following parameters: matrix size 4x3, 200,000 iterations, learning radius 2, learning rate 0.02. The resulting space-in-time SOM is shown in Figure 8. In this case, we used a color scale with enhanced brightness for the color coding of the attribute values in order to increase the visibility of the semi-transparent symbols on the maps. Below the matrix, Figure 8 shows a fragment of the time arranger display where the pixels are arranged in one row and have the colors of the respective SOM cells. The pixels in the index images are also arranged in one row. It is well visible that
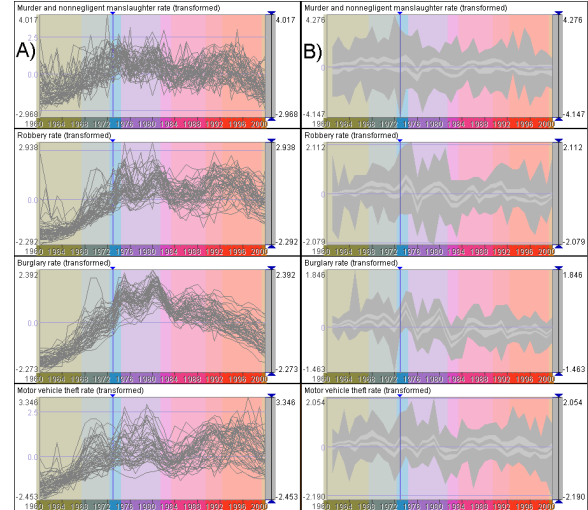
the period 1960-2000 has been divided into continuous intervals. The way in which the colors change from interval to interval indicate gradual or abrupt changes of the crime situations. From the feature images in the matrix it is clear that the crime rates were low in the initial interval and then increased reaching maximums in 1975-1981. After that, there was some decrease in 1982-1983 and 1984-1989 and then increase during the following intervals but without reaching such extreme values as in 1975-1981. In 2000, many of the values go down again.

In Figure 9A the colors of the SOM cells have been transmitted to the time graph display. To understand better the character of the changes from one interval to another, we do a further data transformation in the time graph display: the values in each year are replaced by the differences w.r.t. the previous year. In Figure 9B the differences are represented in a summarized form as suggested in [AA05a]. The vertical lines mark 1973 as a year of substantial change, judging from the remarkable color assigned to the interval 1973-1974. We can see that the burglary and robbery rates (and the larceny-theft rate, which is not shown in Figure 9) highly increased in 1974 in at least 80% states.

With the time graph display, it is easy to note coherent increases or decreases of the values in all or the majority
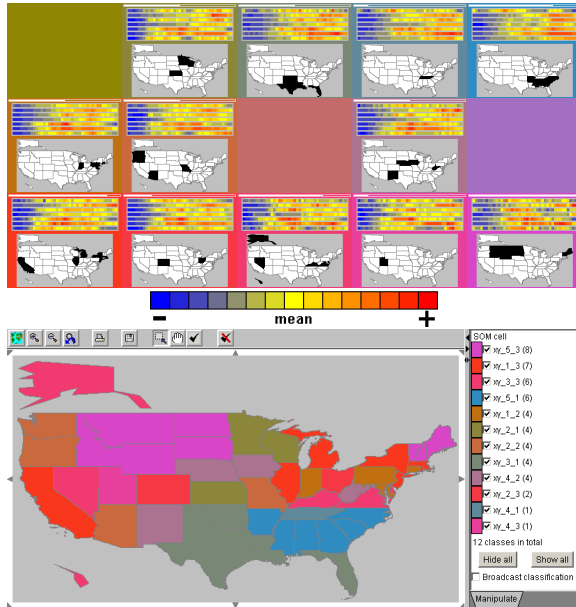
Figure 10: *Top: the time-in-space SOM matrix grouping and arranging the states of the USA according to the temporal variations of the values of 7 crime attributes. Bottom: the map of the USA with the states painted in the colors of the matrix cells.*

of the states. However, this is not the only possible type of situation change; thus, it seems that the change in 1968 was not of this kind. We additionally look at an animated map display presenting the values of the seven attributes. Like the time graph, the map display allows us to transform the values into the differences with respect to previous years, so that we can see where the values substantially increased or decreased. For instance, in 1968 four out of the seven crime rates highly increased on the northwest of the USA.

5.2. Discovery of spatial patterns among local temporal variations

Now we apply the SOM to the local temporal variations in the states using the parameters: matrix size 5x3, 200,000 iterations, learning radius 2, learning rate 0.02. We use the index images in the SOM cells and the SOM-linked map display (Figure 10) to see how the states with similar temporal variations are distributed in space. There are several spatial clusters formed by neighboring states with identical or similar coloring. Some states are not very similar to their neighbors; thus, California is more similar to the states near the Great Lakes. The group of states on the southeast, evidently, differs greatly from the states on the northeast, as indicated by a sharp difference in the colors. The commonalities and differences among the states can be understood by inspecting the feature images and by transmitting the grouping and

colors of the states to the time graph display, as described in [AA05b]. Thus, we found that the values of all crime rates except the first one (murders) in the southeastern states (see Figure 2) mostly increased during the period 1960-2000 and reached their maximums an the last decade. The variation pattern in the other states is different: the highest values were achieved in the middle of the period (around 1975-1985) but than decreased. Only the group of states Texas, Oklahoma, Louisiana, and Florida (middle top cell of the matrix) is somewhat similar to the southeastern states in terms of the temporal variation patterns.

6. Discussion and conclusion

We have demonstrated how our tools, which combine interactive visual interfaces with the computational SOM method, enable comprehensive exploration of multivariate spatiotemporal data and discovery of high-level patterns. Although SOM has been previously applied to spatial, temporal, and spatiotemporal data, our framework uses this method in a novel way. Our main innovation with respect to the state of the art is the support of two complementary analytic tasks based on two perspectives of spatiotemporal data: as spatial situations changing over time and as temporal variation profiles distributed over space. To the best of our knowledge, there are no analogues to our framework in the literature. Previously, SOM has been applied to combinations of attribute values describing pairs <place + time unit> [GCML06]. We apply SOM to higher level constructs, namely, spatial situations and local temporal variations. As a result, the outcomes of the method match the two high-level analysis subtasks much more closely than in the previous approaches.

We have also developed innovative ways to visualize SOM outcomes. While propagating cell colors from SOM to other displays is a common approach, we use special color scales reflecting the similarity among the cells. We put feature images and index images in SOM matrix cells to give a combined representation of the spatial, temporal, and attributive (thematic) components of the data and thereby facilitate understanding of the SOM outcomes. The coordinated spatial and temporal displays with integrated tools for interactive visually-supported data transformations help in preparing data to the application of SOM and in interpreting its results.

7. Acknowledgments

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