Spatio Temporal Density Mapping of a Dynamic Phenomenon

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***Abstract*— Visualizing density and distribution information is a key support for understanding spatio-temporal phenomena represented by point data. However, the temporal information is not yet adequately handled in existing density map approaches. In this paper, we propose a novel approach for the creation of a 2D density surface - using contour intervals – for dynamic points or phenomena. Our method is based on a rainbow color scheme, which enables the user to visually extract spatio-temporal changes of point density and distribution. Furthermore, we present various possibilities for extending and improving our approach.**

Keywords-spatio temporal density map; rainbow color scheme; visual analysis; dynamic data.

I. Introduction

Visualization helps to investigate and understand complex relationships in a spatial context. Maps account as one of the most powerful visualization forms. They represent geographic information in abstract ways that support the identification of spatial patterns and the interpretation of spatial phenomena.

Furthermore, the visual presentation and analysis of dynamic data and dynamic phenomena is currently a hot research topic [1].

Hence, in today's society, the need for data abstraction along with the growing amount of available digital geodata is rapidly increasing. One reasonable way of abstracting data is provided by density maps [2].

Density maps can be applied for point data in various fields, for instance, in physical or human geography, geology, medicine, economy or biology [3, 4]. How to present the density for dynamic data/phenomena is, however, not yet adequately addressed.

In this paper, we introduce a novel density mapping approach for spatially and temporally changing data.

In the next section, the state of the art related to density maps, in particular, an overview of approaches considering the dynamics of movement data in the density visualization is given. In the section afterwards, our own approach is described in detail, followed by implementation processes, discussions of the results and a conclusion.

II. Density maps - State of the art

One of the most straight forward ways to visualize point density is a scatter plot or a dot map. Graphic variables for point symbols, such as size, shape, color and transparency, can depend on point's attribute value. In order to discern the density distribution, these graphic variables can be iteratively adapted to the given map scale, but still the occlusion of neighboring points cannot be always desirably avoided. The density value of each point can be obtained by counting all points within a buffer around the point or within a grid cell the point is located in.

In the following, the density estimation and map principles are shortly presented and the state of the art of density maps with static or dynamic data is given.

A. *Kernel Density Estimation (KDE)*

The Kernel Density Estimation (KDE) [5] is a classic method widely used to determine densities of individual points that represent a continuous surface. The KDE approach is described in detail in [5, 6, 7]. The standard KDE, a normal distribution function, uses a Gaussian kernel. A certain bandwidth (search radius) is defined for the kernels, located around each point. For each cell of an underlying grid (defined by a certain resolution) a density value is calculated and hence a smooth surface is provided [8]. The bandwidth value strongly influences the density surface [9]. A formula for an optimal bandwidth is proposed by Silverman [6]. Kernel density estimates have been used for cluster detection in various fields, such as crime analysis. Kwan [10] uses geovisualization of activity patterns in space–time and displays the results as a continuous density surface. She applies the density estimation as a method of geovisualization to find patterns in human activities related to other social attributes. Assent, Krieger, Müller, and Seidl [11], Krisp and Špatenková [12], and Maciejewski, et al. [13] investigate the classic kernel density estimation and define it as a visual clustering method. In these works, KDE maps were created in order to visually provide a better overview and insight into the given data.

B. *Contour lines and intervals*

A common technique to map point densities calculated using KDE are isopleth maps with filled contour intervals. The term "isopleth map" (isopleth = equal in quantity and number), refers to one of two types of isoline maps (also called isarithmic or contour maps). In the first type of isoline maps each contour line indicates a constant rate or ratio derived from the values of a buffer zone or kernel area. In this sense, the continuous density surface is derived from an originally discrete surface. In the other type of isoline maps (commonly referred to "isometric map"), contour lines (isometers) are drawn through points with directly

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measurable equal value or intensity such as terrain height or temperature [14]. It is assumed that the data collected for enumeration units are part of a smooth, inherently continuous phenomenon [15]. In this paper, we only use contour lines to delimit the intervals (the areas between contour lines). Furthermore, Langford provides a good overview of density surfaces used in Geographic Information Systems (GIS) as choropleth population density maps, population density on grids, population density surfaces, and pseudo-3D population density surfaces [16]. In several works as [3, 4], the KDE concept is adapted for the 3D-Space density mapping of static 3D data.

C. *Dynamic data and density information*

In the last years, we published several papers related to visual analysis of moving objects with a focus on the representation of dynamic lightning data [17, 18, 19]. In these works, different visualization methods were proposed for moving lightning point data. However, density surfaces were not yet taken into account.

In the following sub-sections, an overview is given about existing works related to density maps of dynamic points.

1) *KDE for dynamic points*

A straightforward way of visualizing the density of dynamic points would be a sequence of density surfaces (one per time interval) as reported in [20]. The change of the density in time could be better discernable by means of an animation of these density maps. Another option would be to use an individual Kernel density map with a unique color scheme that fills the areas between the contour lines. Due to the movement of points (as for example swarms), however, the tinted intervals may spatially overlap and make the map reading a difficult endeavor.

2) *Dual KDE*

Jansenberger and Staufer-Steinocher [21] analyzed two different point data sets recorded within the same area, but at two different moments of time. The authors suggest a Dual-KDE approach, which results in a map illustrating the spatio-temporal density difference of the two datasets. The absolute difference is used, that is, the absolute density of the second point data set subtracted from that of the first point data set.

3) *DKDE*

The approach called Directed Kernel Density Estimation (DKDE) that is able to take the dynamics of moving points inside density maps into account was suggested in previous works [22, 23, 24, 25, 26]. The DKDE is applicable for discrete moving points and it considers two moments of time. Instead of an upright kernel as in the KDE method, a titled kernel is used. The tilt depends on the movement direction vector of the respective point. The resulting DKDE-map shows the so-called “ripples”, which can be interpreted as an indicator for the movement direction and density change of points that are located closely to each other with very similar movement speeds and directions. These ripples are visible among overlapped contour lines. The tinted contour intervals do not contain the information about movement or density change.

4) *3D density map using space time cube*

Nakaya and Yano [27] suggest a method using a space–time cube to visually explore the spatio-temporal density distribution of crime data in an interactive 3D GIS. In order to investigate the dynamics and density change, an interactive use within a 3D environment is essential.

5) *KDE for trajectories*

In a comprehensive review of the existing visual analysis [1], methods, tools and concepts of discrete objects point data were introduced. A section is dedicated to continuous density surfaces (fields) derived from trajectories or from point-related attributes. Density maps of moving objects were created on the basis of aggregated points of trajectories. A trajectory is understood as a function of time or a path left by a moving object in space. Moving objects can be confined within a network (such as cars along streets of a traffic network) or float freely over a region (boats) or in space (airplanes). Spatio-temporal density maps of trajectories were investigated in [28, 29, 30, 31]. In these approaches, the KDE method is adapted to trajectories as a function of moving velocity and direction. The resulting density maps can reveal simultaneously large-scope patterns and fine features of the trajectories. This mapping idea was extended to the 3D space in [29] where the trajectory densities are visualized inside a space-time cube.

Another possibility of displaying density information of trajectories is to use derived discrete grid cells, whereby each cell color refers to the amount of trajectories passing through the cell [32, 33].

D. *Research questions*

In the existing 2D density maps based on KDE, the time is either frozen on a certain moment or confined within a certain time interval. Consequently, the resulting contour lines do not carry information of temporal changes. Although various approaches for density visualization of trajectories have been investigated, an appropriate method for 2D density maps of moving point clouds is still missing. Can the dynamics of spatially extended phenomena - represented by points - be adequately expressed in a single contour map? This research question remains unsolved. In the following sections, we will tackle this question and introduce a new approach termed Spatio-Temporal Density Mapping or STDmapping.

III. METHODOLOGY

A. *Test data*

We used lightning points recorded by LINET, a lightning detection network [34], as the test data set. It contains altogether 7100 detected lightnings in the region of Upper Bavaria (47°N–49°N Latitude and 10°E–12,5°E Longitude) on 22.07.2010 between 2pm and 9pm. Each point is encoded with its geographic coordinates (longitude, latitude) as well as the exact lightning occurrence time. The recorded height information is not considered within our approach.

Figure 1 illustrates the provided lightning point coordinates projected onto a plane surface a using black dots.

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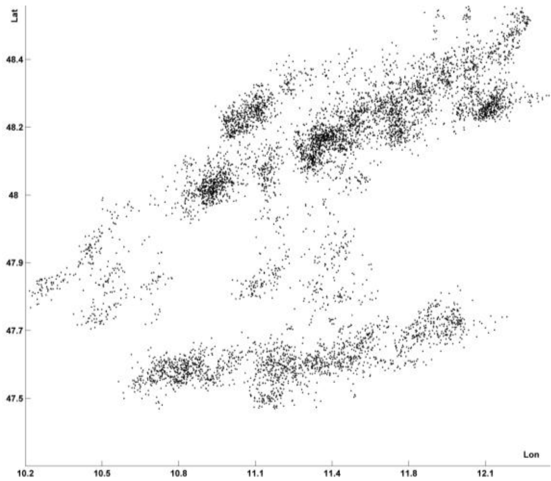

Figure 1. Initial test data set.

Visual analysis methods for these lightning points, which represent the moving phenomena of a thunderstorm, were published in [17, 18, 19].

B. Initial situation and basic idea of the new approach

First of all, we applied KDE using Silverman's formula for calculating an optimal kernel bandwidth [6] to the given test data set. On top of the resulting density contour map, we overlay the initial points, which change colors whenever a time interval has been crossed. In doing so, we used a time interval of 10 minutes starting at 2 pm for the temporal clustering. Additionally, we applied a buffer threshold of 6 km for the spatial clustering.

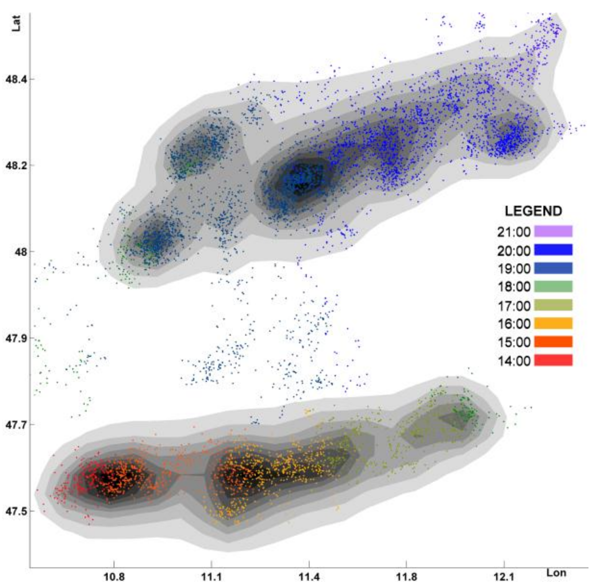

Figure 2. KDE map and clustered points.

Details of the temporal and spatial clustering including explanations for thresholds can be found in [17, 18, 19].

The resulting map is shown in Figure 2. The density layers in grey tones in Figure 2 do not bear any temporal information. But, the overlaid lightning points are segmented and colored according to the different time intervals, thus reveal the dynamic changes. In Figure 2 two moving lightning clusters are perceivable within the test area. Their geographic and temporal locations are apart from each other with one formed lower left starting around 2pm and the other upper left occurring around 6pm. The initially lower left point cluster is moving north-eastwards from 2pm (red dots) to 6pm (green dots). The initially upper left cluster is also moving north-eastwards from 6pm (green dots) to 9pm (purple dots).

C. Workflow

In Figure 3, an overall workflow of our approach is illustrated.

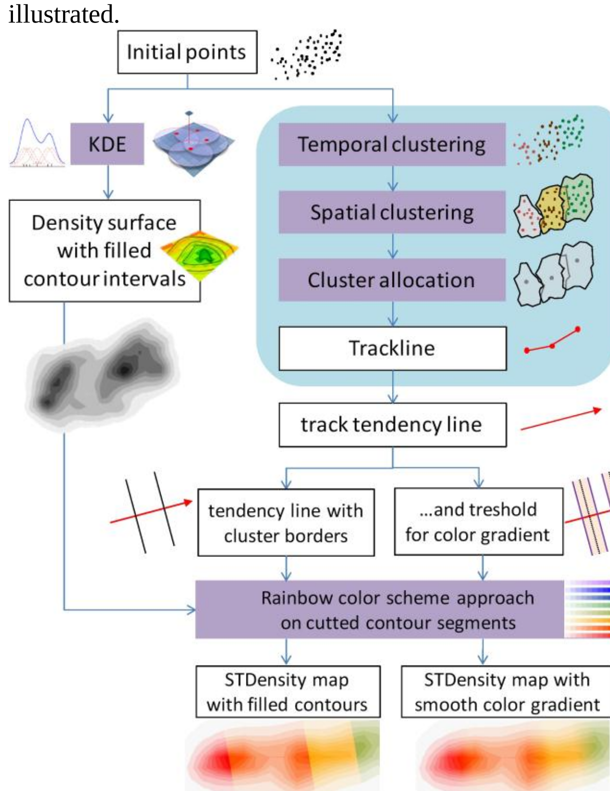

Figure 3. Workflow of STDmapping of lightning data.

Initial lightning point data are explained in Section III.A. As described in Section III.B, first of all a density contour map using KDE is created. Additionally, the given point data set is temporally and spatially clustered. In the next step, the overlapping clusters (in case they are temporally successive) are detected and allocated towards independent tracks. Cluster centroids are embedded in the trajectories. A detailed description about these steps can be found in [17]. A linear approximation of each track trajectory results in a tendency line, which represents the average moving direction of the point cluster. The linear approximation can be based either only on the cluster centroids or on the entire point data sets of a track.

Based on this new approach, we have on the one hand the density surfaces represented by layered tints between neighboring contour lines and on the other hand we have the tendency line with either abrupt or smooth transition at borders of temporal clusters. This temporal border is a line that lies perpendicular to the tendency line passing through the average locations of all points within 10 minutes before and after a full hour. If the phenomenon is moving, all points between the “1 pm line” and the “2 pm line” are grouped into the temporal interval “1 pm - 2 pm”.

The question being addressed now is how we can incorporate the dynamics inside the density map. The idea is to divide the tendency line into temporal parts, which in turn guide the segmentation of the density surface. Different surface segments carry different color hues. Within the same surface segment, the color hue remains the same but its intensity varies with the change of density.

In our approach, we adopted the “rainbow color scheme”, which is essentially the visible and continuous electromagnetic spectrum. Its main color hues transit from red, orange, yellow, green, blue to violet. The spectrum can be divided into an arbitrary number of intervals. Users may easily anticipate and comprehend the color transitions. In our approach, we assign each time interval to a certain color hue – the medium color of the rainbow subinterval. Figure 4 illustrates 8 different rainbow color hues with each being displayed in up to 9 different color intensities from light to dark. For instance, the red color scheme refers to the time from 1 to 2 pm and contains 9 different red tones, which are related to 9 different density values/ value intervals. We split the entire time of our dynamic dataset into equal time intervals. Interval size can be determined based on the user’s interest.

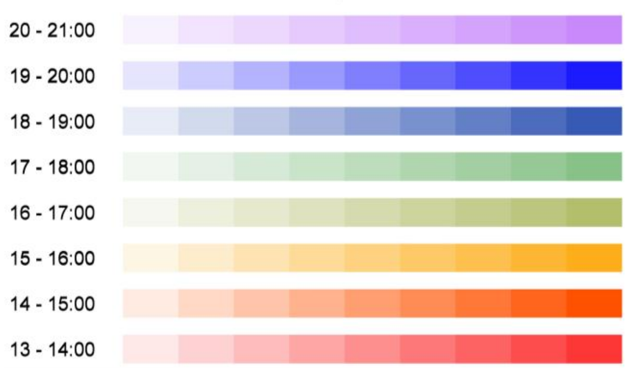

Figure 4. Rainbow color scheme.

With regard to the division of density surface by means of the temporal tendency lines, we introduce the perpendicular line to each tendency line as the temporal border between the two neighboring time intervals of the underlying KDE map. The color transition between two temporal segments can be either abrupt or smooth. In case of smooth temporal borders between temporal KDE segments, a defined threshold for the smooth color transition is set. The threshold refers to a certain time before and after the abrupt temporal borders. That leads to two parallel border lines – one on the left hand site of the abrupt border line and one at the right hand site of the abrupt border line. The distance (time) between each smooth border line and the respective abrupt border line is equal and variable.

IV. Results and Discussion

As shown in Figure 5 Figure 5. the density visualization option (KDE with dynamic points) described in Section II.C.1) is applied to our test dataset. For each spatio-temporal cluster, a segment of density map with layered tints was produced.

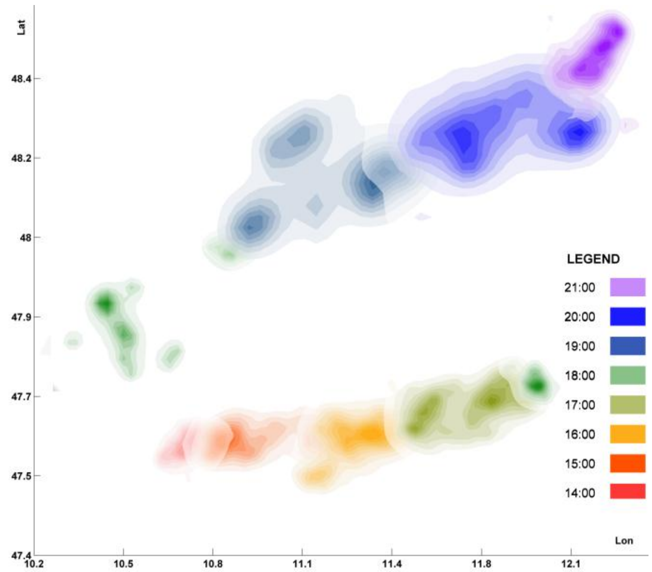

Figure 5. Segmented KDE in one map.

However, the results in Figure 5 are not satisfying due to map overlays and occlusion – even if transparency is applied. It leads to a loss of the overall density information.

Applying the new approach following the workflow in Figure 3, we created two different output maps:

A. STDmap with abpruptcolor transition

Figure 6 presents a STDmap with abrupt color transition. Obviously the entire density information is kept while temporal information (and zhus information about phenomena dynamics: speed and moving direction) is the added value: Both lightning clusters are moving north-eastwards and in particular around 8 pm the upper cluster is moving faster than at any other time, while points in the blue colored contours are less dense and more distributed in southwest-northeast direction.

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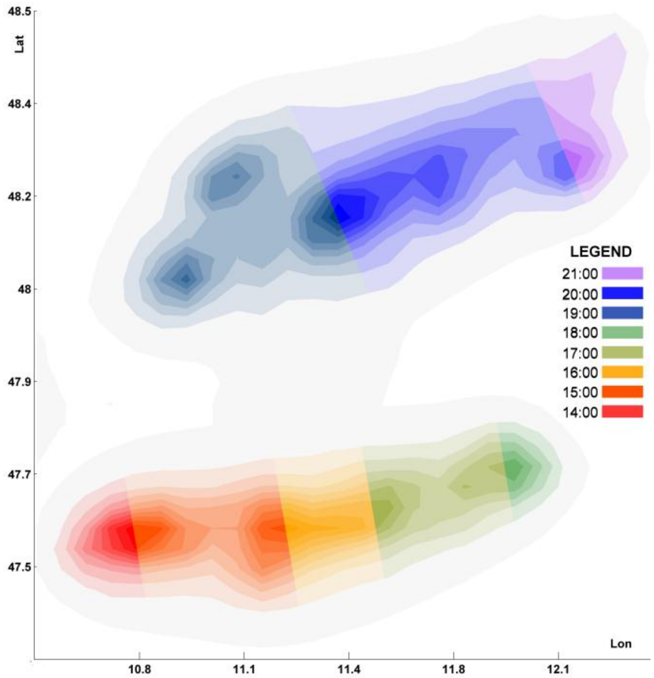

Figure 6. STDmap with abrupt color transition.

The clear-cut temporal cluster borders reveal another advantage: Density information in layered tints within each specific time interval is clearly visible and separable from neighboring segments.

B. Smooth STDmap

Figure 7 presents the STDmap with smooth color transition.

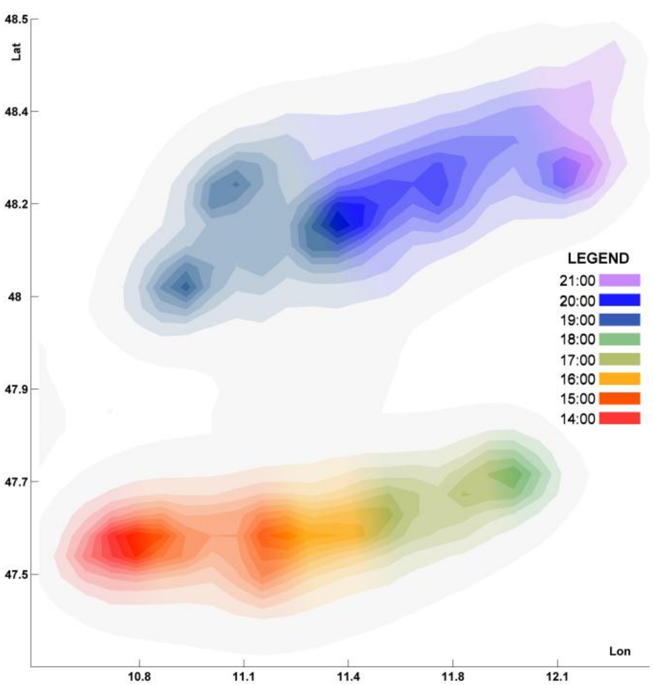

Figure 7. Smooth STDmap.

The smooth color transitions between neighboring segments are closer to the reality and correspond better to the visual perception: lightning points occurring for instance some minutes after 2 pm can be located inside the 1-2 pm segment and points appearing some minutes before 2 pm might be placed inside the 2-3 pm segment. With the help of an adaptive slider tool, the smoothing effect can be set for either a small time interval (e.g., 13:55 – 14:05) or a large one (maximum smoothing interval: half of the time interval left and right of the temporal border, e.g., 13:30 – 14:30). In our case we used a threshold of 20 minutes (10 minutes before and after each abrupt border line). For an easy comprehension, we suggest to limit the number of colors (time intervals) to no more than about 10. In case of very extensive temporal range, the brightness of the same tone within the same interval can be adopted. For instance, 24 hours can be cut into six by four hours intervals. With each four hour interval four different brightness of the same tone can be used.

C. Comparison with existing approaches

The 3D density space time cube suggested by Nakaya and Yano [27] is a comparable approach, where a series of time steps is taken into account within density information visualization with the aim to illustrate the change of point density in time. However, the density changes in time can only be explored by using interactive tools such as panning, zooming and rotating of the space time cube. If a cluster of interest is surrounded by other clusters, it can be hardly explored. Our approach has overcome this drawback by storing and presenting temporal information in different colors in a STDmap (in 2D).

V. CONCLUSION AND FUTURE WORK

In the existing approaches for visualization of dynamic phenomena represented by moving point datasets, temporal information is not yet adequately handed. This research gives a try to close the gap by incorporating and visualizing the temporal change of point cluster in a 2D density map. Our approach is termed as STDmapping according to which a density surface of layered tints can be divided into different temporal segments. Each segment is then visualized by a color hue with varying intensities. The resulted STDmaps contain not only the information about the spatial density distribution, but also the changes in time about moving direction and speed of dynamic point clusters. Therefore, they can support the pattern detection/extraction of spatio-temporal phenomena without having to activate interactive tools.

In future work, we will investigate the relation between the characteristics of initial data (density, distribution, spatio-temporal change of point coordinates) and their modeling parameters (movement tendency, time interval, boundary lines) with the purpose to describe the dynamic phenomena with minimum information loss or distortion for the subsequent visualization and use of STDmaps. Furthermore, an adaption of our approach for 3D point data is also possible.

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Moreover, an interesting relative topic could be the dynamic mapping for sensor-based systems: in this case, the contour line must be computed from values regularly sent by sensors (e.g., temperature data).

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REFERENCES

[1] N. Andrienko and G. Andrienko, "Visual analytics of movement: An overview of methods, tools and procedures," *Information Visualization*, vol. 12, 2013, pp. 3-24.

[2] W. A. Mackaness, A. Ruas, and L. T. Sarjakoski, *Generalisation of geographic information: cartographic modelling and applications*. Amsterdam, The Netherlands: Elsevier Science, 2007.

[3] K. Romanenko, D. Xiao, and B. J. Balcom, "Velocity field measurements in sedimentary rock cores by magnetization prepared 3D SPRITE," *Journal of Magnetic Resonance,* 2012, pp. 120-128.

[4] S. Stoilova-McPhie, B. O. Villoutreix, K. Mertens, G. Kemball-Cook, and A. Holzenburg, "3-Dimensional structure of membrane-bound coagulation factor VIII: modeling of the factor VIII heterodimer within a 3-dimensional density map derived by electron crystallography," *Blood*, vol. 99, 2002, pp. 1215-1223.

[5] J. W. Tukey, *Exploratory data analysis*: Addison-Wesley, 1977.

[6] B. W. Silverman, *Density estimation for statistics and data analysis* vol. 26: CRC press, 1986.

[7] N. Cressie, "Statistics for spatial data," *Terra Nova*, vol. 4, 1992, pp. 613-617.

[8] D. W. Scott, *Multivariate density estimation: theory, practice, and visualization* vol. 383: Wiley. com, 2009.

[9] D. O'Sullivan and D. J. Unwin, *Geographic information analysis*: John Wiley & Sons, 2003.

[10] M.-P. Kwan, "Geovisualisation of activity-travel patterns using 3D geographical information systems," in *10th international conference on travel behaviour research (pp. pages pending), Lucerne*, 2003, pp. 185-203.

[11] I. Assent, R. Krieger, E. Müller, and T. Seidl, "VISA: visual subspace clustering analysis," *ACM SIGKDD Explorations Newsletter*, vol. 9, 2007, pp. 5-12.

[12] J. M. Krisp and O. Špatenková, "Kernel density estimations for visual analysis of emergency response data," in *Geographic Information and Cartography for Risk and Crisis Management*, ed: Springer, 2010, pp. 395-408.

[13] R. Maciejewski, *et al.*, "A visual analytics approach to understanding spatiotemporal hotspots," *Visualization and Computer Graphics, IEEE Transactions on*, vol. 16, 2010, pp. 205-220.

[14] C. F. Schmid and E. H. MacCannell, "Basic Problems, Techniques, and Theory of Isopleth Mapping*," *Journal of the American Statistical Association*, vol. 50, 1955, pp. 220-239.

[15] T. A. Slocum, R. B. McMaster, F. C. Kessler, and H. H. Howard, *Thematic cartography and geovisualization*: Pearson Prentice Hall Upper Saddle River, NJ, 2009.

[16] M. Langford and D. J. Unwin, "Generating and mapping population density surfaces within a geographical information system," *Cartographic Journal, The*, vol. 31, 1994, pp. 21-26.

[17] S. Peters, H.-D. Betz, and L. Meng, "Visual Analysis of Lightning Data Using Space–Time-Cube," in *Cartography from Pole to Pole*, ed: Springer, 2014, pp. 165-176.

[18] S. Peters and L. Meng, "Visual Analysis for Nowcasting of Multidimensional Lightning Data," *ISPRS International Journal of Geo-Information*, vol. 2, 2013, pp. 817-836.

[19] S. Peters, L. Meng, and H. D. Betz, "Analytics approach for Lightning data analysis and cell nowcasting," in *EGU General Assembly Conference Abstracts*, 2013, pp. 32-3.

[20] Z. Zhang, *et al.*, "Nonparametric evaluation of dynamic disease risk: A spatio-temporal kernel approach," *PloS one*, vol. 6, 2011, p. e17381.

[21] E. M. Jansenberger and P. Staufer-Steinnocher, "Dual Kernel density estimation as a method for describing spatio-temporal changes in the upper austrian food retailing market," in *7th AGILE Conference on Geographic Information Science*, 2004, pp. 551-558.

[22] J. M. Krisp and S. Peters, "Directed kernel density estimation (DKDE) for time series visualization," *Annals of GIS*, vol. 17, 2011, 2011, pp. 155-162.

[23] J. M. Krisp, S. Peters, and F. Burkert, "Visualizing Crowd Movement Patterns Using a Directed Kernel Density Estimation," in *Earth Observation of Global Changes (EOGC)*, Munich, Germany, 2013, pp. 255-268.

[24] J. M. Krisp, S. Peters, C. E. Murphy, and H. Fan, "Visual Bandwidth Selection for Kernel Density Maps," *Photogrammetrie - Fernerkundung - Geoinformation*, vol. 2009, 2009/11/01/, 2009, pp. 445-454.

[25] J. M. Krisp, S. Peters, and M. Mustafa, "Application of an Adaptive and Directed Kernel Density Estimation (AD-KDE) for the Visual Analysis of Traffic Data," in *GeoViz2011*, Hamburg, Germany, 2011, pp. 1-1.

[26] S. Peters and J. M. Krisp, "Density calculation for moving points," in *13th AGILE International Conference on Geographic Information Science*, Guimaraes, Portugal, 2010, pp. 10-14.

[27] T. Nakaya and K. Yano, "Visualising Crime Clusters in a Space time Cube: An Exploratory Data analysis Approach Using Space time Kernel Density Estimation and Scan Statistics," *Transactions in GIS*, vol. 14, 2010, pp. 223-239.

[28] MOVE. *WG 4: Visual Analytics for Movement and Cognitive Issues (retrieved: January, 2014)*. Available: http://www.move-cost.info/

[29] U. Demšar and K. Virrantaus, "Space–time density of trajectories: exploring spatio-temporal patterns in movement data," *International Journal of Geographical Information Science*, vol. 24, 2010, pp. 1527-1542.

[30] R. Scheepens, *et al.*, "Composite density maps for multivariate trajectories," *Visualization and Computer Graphics, IEEE Transactions on*, vol. 17, 2011, pp. 2518-2527.

[31] N. Willems, H. Van De Wetering, and J. J. Van Wijk, "Visualization of vessel movements," in *Computer Graphics Forum*, 2009, pp. 959-966.

[32] P. Forer and O. Huisman, "Space, time and sequencing: Substitution at the physical/virtual interface," *Information, Place, and Cyberspace: Issues in Accessibility*, 2000, pp. 73-90.

[33] G. Andrienko and N. Andrienko, "A general framework for using aggregation in visual exploration of movement data," *Cartographic Journal, The*, vol. 47, 2002, pp. 22-40.

[34] H. D. Betz, K. Schmidt, and W. P. Oettinger, "LINET – An International VLF/LF Lightning Detection Network in Europe," in *Lightning: Principles, Instruments and Applications*, H. D. Betz, U. Schumann, and P. Laroche, Eds., ed Dordrecht: Springer Netherlands, 2009, pp. 115-140.