imagery service editor application API's Terms of Use, 2010. (http://wiki.openstreetmap.org/w/images/d/d8/Bing_license.pdf)

NearMap Ltd. (2014): http://nearmap.com.

Open Knowledge Foundation (2010): OpenData Historie. (http://www.opendata.at/site/history)

Open Knowledge Foundation (2012): Open Database License (ODbL) v1.0. (http://opendatacommons.org/licenses/odbl/1.0)

Open Knowledge Foundation (2012a): Database Contents License (DbCL) v1.0. (http://opendatacommons.org/licenses/dbcl/1-0)

OpenStreetMap (2014): Copyright and License. (http://www.openstreetmap.org/copyright)

Openstreetmap Foundation (2014): Contributor Terms 1.2.4. (http://www.osmfoundation.org/wiki/License/Contributor_Terms)

Openstreetmap Foundation (2014a): OSMF - About. (https://blog.openstreetmap.org/about)

Openstreetmap Foundation (2014b): License / Community Guidelines. (http://www.osmfoundation.org/wiki/License/Community_Guidelines)

Openstreetmap Foundation (2014c): Substantial Guidelines. (http://www.osmfoundation.org/wiki/License/Community_Guidelines/Substantial_-_Guideline)

OpenStreetMap Wiki contributors (2012): NearMap PhotoMaps. (http://wiki.openstreetmap.org/wiki/NearMap_PhotoMaps)

OpenStreetMap Wiki contributors (2013): Open Data License/Use Cases. (http://wiki.openstreetmap.org/wiki/Open_Data_License/Use_Cases)

OpenStreetMap Wiki contributors (2014): Tile Usage Policy. (http://wiki.openstreetmap.org/wiki/DE:Tile_usage_policy)

OpenStreetMap Wiki contributors (2014a): Common Licence Interpretations. (http://wiki.openstreetmap.org/wiki/Common_licence_interpretations)

OpenStreetMap Wiki contributors (2014b): Open Data License / Community Guidelines. (https://wiki.openstreetmap.org/wiki/Open_Data_License/Community_Guidelines)

OpenStreetMap Wiki contributors (2014c): AND Data. (http://wiki.openstreetmap.org/wiki/AND_Data)

Ramm, Frederik und Topf, Jochen (2010): OpenStreetMap. Lehmanns Media, Berlin,

3 edition. ISBN 9783865413758.

Schmidt, Manuela und Neis, Pascal (2011): OpenStreetMap in der Forschung. In: FOSSGIS-Freie und Open Source Software für Geoinformationssysteme

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Visual analytical approaches for lightning clusters as a case of spatially extended dynamic phenomena

Visuelle Analysemethoden für Blitz-Clustern als Fallbeispiel für räumlich ausgedehnte Phänomene

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This article focuses on the visual analytical approaches for exploring the dynamics of lightning data. The spatio-temporal clustering of individual lightning events can reveal lightning clusters and trajectories which represent a specific type of moving geoobjects, namely the spatially extended objects or phenomena. Several visual analytical solutions are offered for exploring and comparing the movement complexity of lightning trajectories.

■ *Keywords: Lightning clusters, Trajectory complexity gain, Trajectory similarity matrix, Temporal radar plot, Temporal parallel coordinate plot*

Diese Arbeit beschäftigt sich mit der visuell-analytischen Untersuchung von dynamischen Blitz-Daten. Durch räumlich-zeitliches Gruppieren von individuellen Blitzereignissen entstehen Blitz-Cluster und Trajektorien welche eine bestimmten Art von sich bewegenden Geoobjekten repräsentieren, und zwar räumlich ausgedehnte Objekte beziehungsweise Phänomene. Es werden verschiedene visuell-analytische Lösungen vorgestellt, welche dazu dienen, die Komplexität von Blitz-Trajektorien zu untersuchen und zu vergleichen.

■ *Schlüsselwörter:* Blitz-Cluster, Trajektorien-Komplexitäts-Kette, Trajektorien-Ähnlichkeits-Matrix, Temporaler Radarplot, Temporaler Parallel-Koordinaten-Plot

1 Investigating dynamic spatially extended phenomena

The world we live in is highly dynamic. With the increasing availability of big data including large quantities of movement data acquired through sensory devices such as mobile phones, GPS and navigational facilities, the exploration of dynamic geographic data and thus movement pattern detection have become an important research focus (Dykes & Mountain 2003). Movement data are ubiquitous – technically available everywhere to any time. The understanding of dynamic processes is crucial in all fields that have to deal with moving objects or phenomena. It can be strongly supported by appropriate visual analytical methods and tools. Investigating temporal changes of spatial patterns counts as one of the most challenging research tasks for geoscientists because it demands the capabilities of extracting the reliable temporal changes from large datasets, aggregating the extracted information and visualize it in an easily comprehensible way for the target users. Notably, numerous frameworks, strategies, methods and tools for the visual analysis of moving discrete point data such as cars, airplanes, vessels etc. have been extensively investigated in the recent years, but only few approaches have touched the dynamics of spatially extended objects (SEOs) or spatially extended phenomena (SEPs) such as clouds, swarms and herds which change their sizes, shapes and other attributes in time.

The individual instances for a SEO or SEP may demand customized visual analysis solutions. The dynamic lightning clusters which represent the most dangerous part of a thunderstorm, for example, cannot yet been thoroughly studied due to inadequate approaches of visual analysis/analytics and missing interactive visual

Tab. 1: Example of given stroke data

Date	Time (hh:mm:ss)	Latitude (°)	Longitude (°)	Altitude (km)
20130402	10:02:56.747247	41.6565	10.9017	0
20130402	18:11:57.669808	43.8164	14.2545	06.06.15

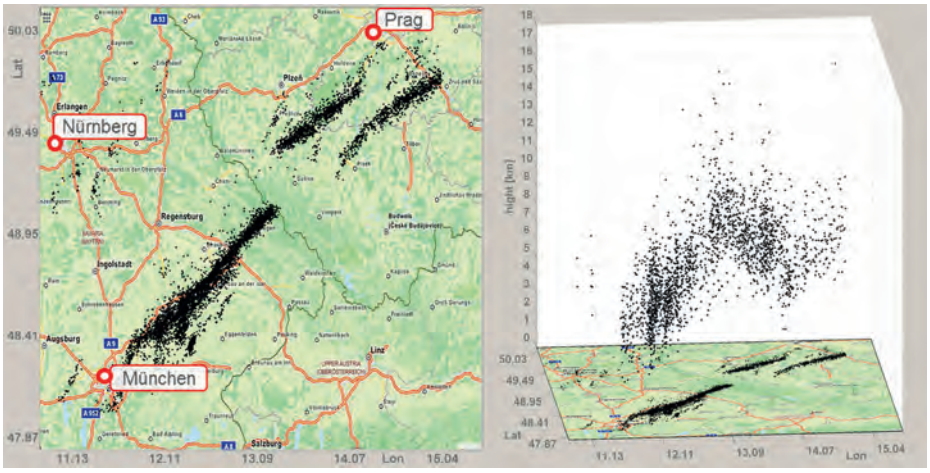

Fig. 1: The test dataset of lightning points: 2D view (left) and 3D view (right); used base map source: openstreetmap.org

exploration tools for target groups such as weather researchers and decision makers (e.g. at airports). On the basis of a generic concept for the visual investigation of SEP and experiments with lightning data as test scenario conducted by the authors at the Chair of Cartography (Peters 2014; Peters et al. 2014; Peters & Meng 2013), this paper is dedicated to the visual exploration of lightning trajectories and their complexity. The spatio-temporal clustering of individual lightning events reveal lightning clusters as well as trajectories and thus represent a specific type of SEOs. Visual analytical approaches are developed to comprehend the dynamics of the spatio-temporally evolving lightning clusters.

2 Test data/scenario description

Lightning is a very complex event. In this work the term lightning refers to a stroke which is a partial discharge consisting of a downward-moving leader streamer of low luminous intensity followed by an upward-moving return streamer of high luminous intensity. A lightning discharge, also called flash, may consist of one single stroke or a series of strokes in the same or adjacent channels (Kitagawa et al. 1962). As test data we used lightning points recorded by LINET, a lightning detection network (Betz et al. 2009). The test dataset is typical for storms that occur in central Europe. It contains altogether 8184 detected lightning in the region between Munich, Germany and Prag, Czech Republic (47°N–49°N Latitude and 10°E–12,5°E Longitude) on April 26th 2013 between 2pm and 7pm. Each point is encoded with its geographic coordinates (longitude, latitude) as well as the exact lightning occurrence time. Furthermore, each lightning point comprises the information about whether the point is an intra-cloud lightning (IC) or a ground-cloud lightning (GC). Our test dataset consists of altogether 5565 CG and 2919 IC lightning points.

A static plot of lightning data as illustrated in Fig. 1 is obviously limited for the investigation of the dynamics in lightning data. Therefore, interactive visual analytical tools are needed which may solve this problem by supporting the visual exploration of the past and predicted lightning cluster- and track attributes.

2.1 Lightning cluster and trajectory pre-processing

Moving SEOs can be geographically -described as polygons whereby each polygon exists at a certain moment of time of time interval. We divide SEOs into two main types: (a) groups of discrete point objects and (b) moving areas. Polygons of type (a) can be either a group of moving points, originated from natural arrangements or they can be constructed based on processing/analysis of point events, for instance by clustering. The corresponding dynamic polygon is shaped via spatio-temporal clustering of detected points. Type (b) could be formed by anything but moving point groups. One example is polygon extraction from raster images (e.g. floods, clouds). In case a dynamic SEO is based on moving points or events, changes of the internal structure within the spatial extension are of particular interest. During movement of the SEO, point distribution and density might change.

In order to investigate lightning movements, we focus on lightning clusters as the smallest meaningful spatio-temporal unit and on lightning trajectories representing the entire lifetime dynamic of a moving cluster. To obtain lightning clusters and trajectories, lightning point events, close in time and space and thus belonging to the same moving thunderstorm, have to be clustered and identified spatio-temporal clusters need to be tracked in time. Lightning point data were divided into 10 minutes time intervals. This commonly used temporal aggregation threshold is suitable to identify movement directions of a weather front. Based on a 2D distance-based clustering method (Jain & Dubes 1988) lightning points of each temporal interval were grouped into lightning clusters by using a threshold of 6 km. Thereby, only x- and y-coordinates of all points (IC and GC points) were used. The common distance thresholds from the lightning cell and thunderstorm tracking domain are between 4 and 10 km (Betz et al. 2009; Hering et al. 2004; Zinner et al. 2008). For the spatial clustering, altitude of IC points was set to zero. In our case, a 2D buffer with a radius of 6 km was applied to each lightning point. All points within overlapping buffers were agglomerated towards the same group. The resulting groups represent lightning clusters within the respective time interval. Point groups with less than 10 points were not considered. In the next step, identified spatio-temporal clusters were tracked. Clusters were allocated if their 2D convex hulls spatially overlap within two time sequences. This tracking method was

based on (Dixon & Wiener 1993; Zinner & Betz 2009). A larger buffer threshold would result in fewer but longer tracks – a smaller threshold in more but shorter tracks. Furthermore, cluster splitting and merging were taken into account. It should be mentioned that we did not aim to establish a perfect tracking solution. Our focus is on enabling users to conduct visual and statistical exploration of tracked lightning cluster.

In addition, statistical data of geometrical and semantic cluster- and track attributes derived from the processed cluster tracking play an essential role for the analysis of lightning cluster. These include among others point cloud coordinates (all points inside a cluster), cluster centroid position, cluster lightning quantity and local density, cluster extension (area, volume), cluster movement attributes (speed, direction) as well as aggregated and average statistical data for each entire trajectory (lifetime, spatial length, average speed, etc.).

2.2 Visual Analysis of lightning data and comparison to similar scenarios

Maps provide excellent information about spatial information. The dynamic data can be expressed using animated maps or map series. Additionally, unconventional visualizations (maplike and non-cartographic displays) map provide a closer look into dynamic geodata and their characteristics. Andrienko et al. (2011) stated that one of the challenges for researchers within geovisualization and visual analytics is to deal with different types of spatio-temporal data (e. g. spatial time series, events, movement data, sequences of satellite images) and find appropriate solutions for the respective data. In our context we face the challenge of handling lightning points, lightning clusters and derived trajectories.

With the recent improvements in lightning data detection and accuracy, there is a growing demand for multidimensional and interactive visualization of such data. Traditional visual investigations on lightning data are mainly focused on source data representation on a 2D cell-grid, where lightning points were temporally aggregated for each grid cell in order to derive local lightning density information for a certain time interval. A recent example is provided by Neuwirth et al. (2012), who aggregated GC lightning data for South-German administrative districts which are colored according the district's lightning density per square kilometer during 2012. Lakshmanan et al. (2004) extended the traditional grid-based point aggregation towards 3D space and integrated a temporal map series into a decision-support system of the lightning warning, where lightning points were temporally averaged and spatially smoothed in order to represent local lightning densities. Furthermore, Resch et al. (2013) suggested a pseudo photo-realistic visualization of lightning points in 3D. They implemented a time slider for a temporal selective visualization of CG lightning points extruded to 3D flash-like pseudo photo-realistic illustrations. Peters (2014) introduced a generic visualization concept for dynamic lightning data, which is basically shaped by two components: Lightning cluster and lightning trajectory visualization. His concept makes a distinction for 2D view, 3D view and Space-Time-Cube (STC). Furthermore predicted lightning data as well as their prediction uncertainty are considered.

With regard to the usage of STC, Turdukulov et al. (2007) worked on precipitating clouds with a set of satellite images (2D) as initial data. They developed a STC with icons whose radius is proportional to the size of the precipitating cloud region. Thus they treated clouds as points. In our work 3D lightning point coordinates are used as initial data and lightning clusters are treated as 2D/3D polygons.

3 Trajectory complexity

Moving objects create trajectories of quite complex spatio-temporal constructs (Andrienko & Andrienko 2013). The complexity of a trajectory can be described using all semantic and geometrical attributes of the moving objects and in particular the degree of their changes, or in other words, by the behavior of object movement. Thus, we could determine complexity differences among trajectories by comparing the change of their movement behaviors in time. Such changes can be derived from database queries or through automatic data analysis. An object moving quite continuously without significant changes in speed, direction and shape reveals a trajectory with a low complexity. According to Güting et al. (2000), it is possible to capture discrete changes such as sudden turns or high acceleration that happen to the continuously moving objects. If these changes exceed predefined threshold, discontinuity occurs. We consider the change of the following geometrical cluster attributes as well as the occurrence of the succeeding situations/events as indicators for lightning trajectory complexity:

Change of geometrical attributes:

- Distance, velocity and acceleration
- Number of lightning points (IC and GC)
- Cluster centroid (latitude, longitude, altitude)
- Cluster extension (2D-area, 3D-volume)
- Movement direction
- Number of neighboring trajectories

Movement events:

- Returns and stops
- Cluster splitting or merging
- Dynamic attributes (time-varying attributes) of interest:
  - Certain instant, interval, and cumulative attributes such as maximum speed, minimum/maximum altitude and lightning point quantity
  - Date/time components of the time references
  - Certain attributes expressing relations to the spatio-temporal context
- Intersection with other context elements (locations, discrete objects) of interest
- 'Speed up - slow down' shift
- Major course change (sinuosity, tortuosity)
- Cluster shape change (2D or 3D)

We define the change from speeding up to slowing down as a significant speed change and thus as movement event indicating trajectory complexity. Furthermore, we consider a major course change as another movement event. Different predefined course descriptions such as continuous, episodic, irregular are combined with the current trajectory course taking for instance the last 3–5 time intervals into account. If the

Tab. 2: Trajectory complexity based on attribute changes

Time interval	distance	velocity	accel-eration	no.of light-ning	area	volume	altitude	direc-tion angle	course direc-tion	speed up/slow down	sum
2	0,2	0,4	0,0	0,3	0,4	0,3	0,5	0,0	0,0	0,0	2,7
3	0,2	0,3	0,6	0,4	0,0	0,2	0,4	0,5	0,0	0,0	2,7
4	0,0	0,1	0,4	0,8	0,3	0,4	0,6	0,1	0,0	1,0	3,9
…	…	…	…	…	…	…	…	…	…		…
38	0,1	0,2	1,0	0,0	0,0	0,0	0,0	0,2	1,0	1,0	3,6
39	0,1	0,0	0,2	0,0	0,3	0,0	0,2	0,2	0,0	1,0	2,0
											sum: 118,6

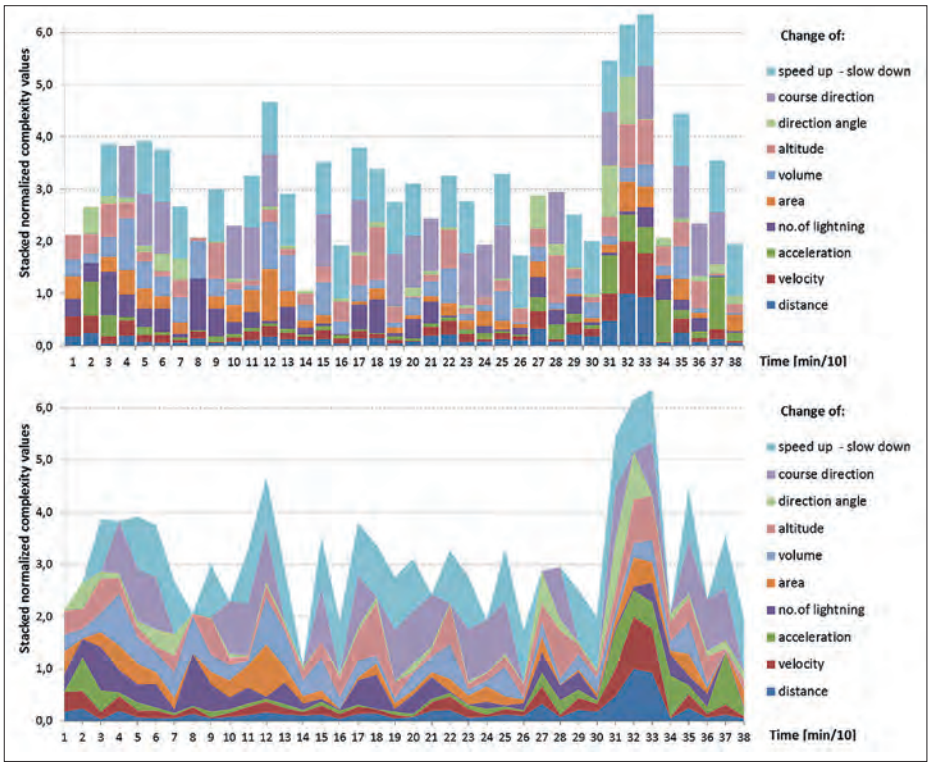

Fig. 2: The bar chart (upper) and the diagram (lower) of the TCG

course template changes substantially with respect to the previous one, we declare the event of a major course change. Alternatively, a movement direction threshold could be used. For other geometrical attributes, predefined thresholds, also for various degrees of complexity, could be used. Moreover, we allocate cluster shapes to predefined templates, such as circle/sphere, ellipse/ellipsoid, 2D/3D irregular shape etc. Based on the coordinates (dX, dY, dZ) of lightning clusters describing the spatial extent, comparable shape templates could be automatically identified/allocated for each spatio-temporal lightning cluster. The change of the shape template will then indicate a movement event relevant for the trajectory complexity. Beside these cluster changes, the trajectory lifetime and its spatial length could also imply trajectory complexity as well as the entire shape of the trajectory path.

Our approach will be explained using one track with altogether 39 temporal steps (6,5 hours duration) of our test dataset as an example. For each time interval we compute the change of geometrical cluster attributes with respect to the previous time interval. We consider distance to previous cluster centroid, velocity, acceleration, lightning point quantity, cluster area and volume as well as movement direction angle. Furthermore, we investigate if movement events are detected, namely, major course change and 'speed up – slow down' shift. Table 2 illustrates a part of these determined values. Attribute change values are normalized by scaling between 0 and 1 and movement change events are set to 1. In the last column all values of one time interval are added up and the sum reflects the momentary trajectory complexity during a certain time interval. The sum of all time interval change values results in the overall trajectory complexity measure value. Thus, Table 2 reflects the complexity gain of a lightning trajectory. We abbreviate that trajectory complexity gain with "TCG". If needed, certain attributes/events in the TCG (e.g. velocity, acceleration) could be weighted with more importance (multiplied with a factor >1), thus, their influence within the complexity sum will be stronger than other attributes/events.

The following figures present multivariate visualizations for the investigation of the TCG. In Fig. 2 (upper) all attribute change and movement event values are stacked for each time interval on a bar chart (TCG bar chart). In the TCG diagram in Fig. 2 (lower) the change of individual attributes can be easily compared through the connected curve lines. Different colors are used to distinguish different attributes, or more precisely, different attribute changes. In our example, it can be seen that a shift from speed up to slow down happens almost during the entire trajectory lifetime. The highest complexity is at the time '33' (330 minutes after start). At this point, distance, velocity and cluster altitude changed dramatically.

Similar to the trajectory wall (Tominski et al. 2012), the stacked complexity values can also be visualized in a 3D visualization, using a geographic map as 2D surface and stacking complexity values in the 3rd dimension (z-axis) along the traveled distance. Thus, spatial information can be presented together with trajectory

complexity information. Fig. 3 illustrates an implementation of that idea. While successive time intervals define the x-axis of Fig. 2, in Fig. 3 the traveled distance of the cluster from its birth defines the x-values. The stacked multivariate complexity attributes at different time intervals are drawn and connected where the time intervals are represented through vertical grey lines. A drawback of the complexity curves based on traveled distance is that the changes (complexity values) are difficult to see for very small distances between two successive time intervals/steps. However, this option has the advantage to show precise information of traveled distances and the associated attribute changes and movement events. Stacked normalized complexity values, visualized as a diagram (or bar chart) are used as z-axis and thus form the 3rd dimension on top of 2D map with track points in orange on cluster centroids in black. Cluster attribute changes are stacked in different colors over and between two successive cluster centroids (black dots on the 2D map). In order to improve visual investigation, an offset along z-axis is used. A geo-referenced open-street-map is used to improve spatial orientation and bar chart complexity colors are slightly transparent.

In comparison with the TCG diagram or bar chart, the trajectory wall has the advantage that temporal differences of each attribute are easier to explore along each band (Andrienko et al. 2014). On the other hand, complexity changes and peaks are easier to detect using the TCG approach (highest z-value) while using the trajectory wall the user needs to visually add brightness values of each temporal step, which is a difficult task with doubtful estimated results. In the trajectory wall, values of one attribute of all (or of a certain amount of selected) individual point objects (moving along a trajectory) are visually stacked for comparison – consequently the trajectory wall contains a constant height (z). Our approach visually stacks several attributes of an SEO moving along a trajectory – thus TCG plot heights differ along/above trajectory positions (spatio-temporal cluster centroids). Moreover, complexity values are based on pre-processed clusters, thus the TCG plot displays aggregated attributes

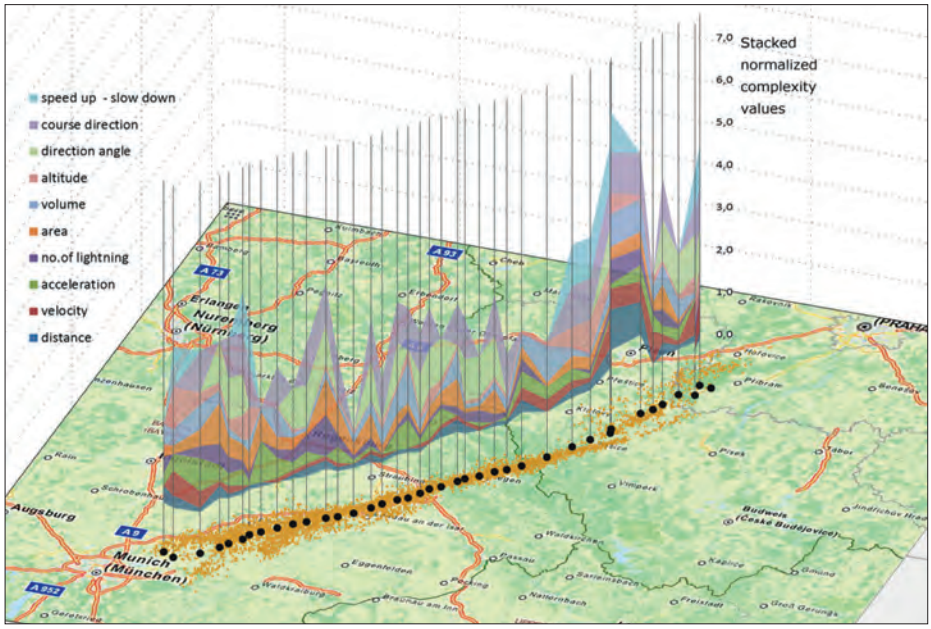

Fig. 3: TCG diagram on top of 2D map

for each spatio-temporal interval. We can conclude that both approaches share the similar basic idea but provide different information.

Instead of attribute changes between successive clusters, the same TCG visualization can be applied to the actual attribute values. Furthermore, the complexity gain concept can be applied to a STC (Peters 2014). Main limitation of the suggested TCG visualization is that it requires strong user interaction with zooming operation when stacking various attributes.

4 Trajectory similarity

Similarity measure of trajectories is a crucial part for the investigation of object movements. Trajectories can be defined (to a certain degree) as similar if they:

- Fully or partly coincide in space or/and time
- Have similar average speed or movement direction
- Have similar spatial lengths
- Have similar shapes
- Have common starts and/or ends
- Have similar dynamic behaviors such as route motions (curve characteristics), speed changes or acceleration changes

"It depends on the application and goals of analysis which of these respects are relevant. Therefore, it is useful to have a clustering tool allowing the analyst to choose an appropriate similarity measure (also called distance function) from a number of alternatives" (Andrienko et al. 2007). An example for an algorithm of such "route similarity" distance function is provided by Andrienko et al. (2007) which repeatedly scans two trajectories, searching for the closest pair of positions. Either the entire trajectories or parts of the trajectories could be clustered. It may also be reasonable to group trajectories by spatial closeness of their starts and ends. Trajectories or compartments could also be clustered by similarities of other attributes than spatial location or time, such as spatial length, shape, duration, average speed, average moving direction and route-behavior. Their respective temporal variations could be then cluster-wise analyzed (Andrienko & Andrienko 2013).

Another important issue during trajectory comparison is to detect similar motions of trajectories in different space regions and at different scales (spatial or/and temporal). A trajectory, large in space and long in duration, could hold similar motions/dynamics as a much smaller one. For trajectory motion comparison, rigid transformations such as shifting, scaling and rotation might be necessary. For instance, transformation of trajectory times for common start times would enable better comparison. Considering space dimensions, similarities of trajec-

Tab. 3: Attributes of two different tracks

	track 4									track 6								
time	dX	dY	dZ	No	A	Vol	v	d	a	dX	dY	dZ	No	A	Vol	v	d	a
1	5	5,9	2,9	22	19	21	0	0	0	9,1	6,3	6,2	19	35	103	0	0	0
2	11	5,4	3,4	15	40	56	6,5	4,8	126	10	10	3,3	18	59	92	7,4	5,2	111
3	12	7	2,8	50	57	88	2,4	1	93	6,3	7,2	8,3	21	29	88	5,4	3,3	106
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
6	15,7	11,8	4,6	111	121	266	6,3	2	88,8	16	8,2	6,5	30	80	212	9,9	5,4	101

tory in 3D can differ from those in 2D. Each group of trajectories, derived from similarity-based clustering, could be aggregated and then again compared/analyzed for similarities/dissimilarities with other aggregated trajectory groups. It can be summarized, that existing approaches focus on similarity measures of line trajectories representing moving points and are mostly based on spatial or/and temporal proximity.

Visual comparison of trajectory similarities (of two or more trajectories) can be done by overlaying one map display over the other one or placing two or more map displays next to one another – each visualizing a different trajectory. Multiple trajectories, which are clustered through spatial or spatial temporal proximity, can be represented by polylines or lanes of different colors. As suggested by Andrienko & Andrienko (2009), similar trajectories can be generalized towards arrows connecting the trajectory 'start' and 'end' in order to avoid overplotting. Thereby, arrows or half-arrows (vectors) show the movement directions and the arrow widths are proportional to the number of trajectories. Further solutions include density map approaches, such as in (Demšar & Virrantaus 2010; Willems et al. 2009) wherein density contour intervals refer to different spatio-temporal trajectory features. Beside traditional map displays, appropriate methods and tools used for visually explore trajectory similarities are STC, trajectory wall, temporal displays, time graph, Radar plot, PCP and Table lenses.

Geometrical and semantic attributes and their changes of selected tracks can be tested for similarities. In order to compare various cluster attributes of two tracks, which change with time, we suggest a similarity matrix in combination with a similarity bar chart as shown in Fig. 4. Our similarity matrix is based on trajectories of constant sample rates (in our case of 10 minutes). Track 4 and 6 occur at the same time (around midnight on 26th of April, 2013) and both tracks are about 80 km away of each other.

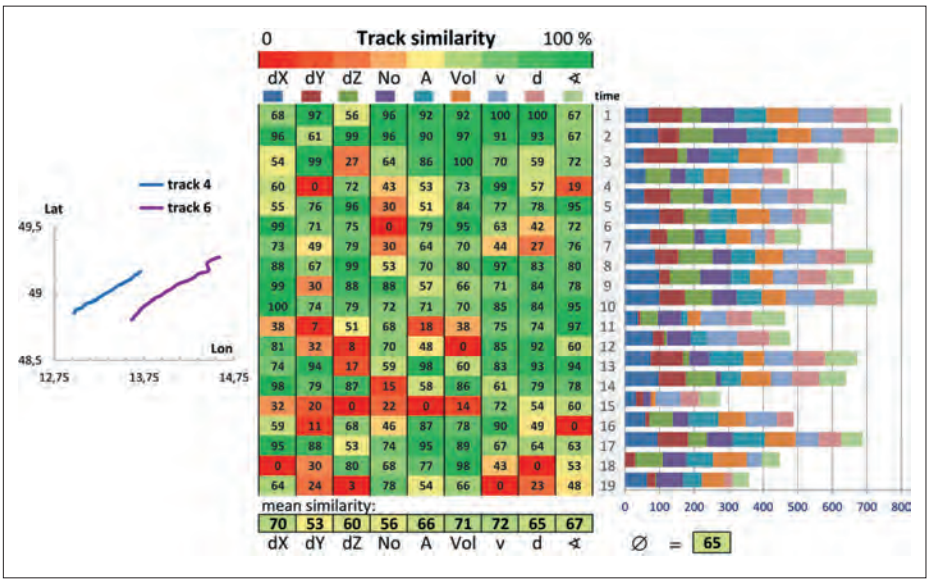

Fig. 4: Similarity matrix and bar chart of two lightning tracks

Comparison is made after 3 hours and 10 minutes, i.e. with 19 time intervals, whereby each row represents one time interval. Altogether 9 cluster attributes are compared: extension (dX, dY, dZ), number of points (No), cluster area (A), volume (Vol), velocity (v), distance to the previous cluster centroid (d) and moving direction angle (a). The attribute values of the first three time intervals are shown in Table 3. As can be clearly seen in the map in Fig. 4, both trajectories nearly move towards the same direction of north-east, have a similar length and follow a similar route. But are they really that much alike as it seems to be?

We can investigate the similarity of individual attributes, of the entire trajectory or of all attributes at a certain moment of time. In the similarity matrix, the attribute values of each time interval are compared with a maximum similarity of 100 %. We deduct the similarity between two tracks – for each time step and for each attribute as follows:

$$sim(ak_{ti}) = (1 - |ak1_{ti} - ak2_{ti}| / \max\{|ak1_{ti} - ak2_{ti}|, \ldots, |ak1_{tn} - ak2_{tn}|\}) \cdot 100\%$$

Whereby $sim(ak_{ti})$ is the similarity of attribute 'ak' of two trajectories at the time 'ti'; it depends on the difference between the two attribute values and the maximum value difference of all attribute value pairs during the entire common lifetime. We can take the number of points (No) as an example while considering only the first three time intervals as listed in Table 3. The largest difference in number of points between track 4 and 6 is detected at time step 6, amounts to '81' (111-30) and refers to the lowest similarity which is hence set to 0 %. Thus, for each of the first three time intervals, the similarity percentages are:

- Time interval 1:
  $(1-|22-19| / 81) \cdot 100\% = 96{,}3\%$

- Time interval 2:
  (1-l15-18l / 81)·100 % = 96,3 %
- Time interval 3:
  (1-l50-21l / 81)·100 % = 64,2 %

This percentage reflects attribute similarity, shown in the table/matrix (middle).

Using a color transition from red (no similarity) to green (identical value) the user can easily identify similarity information in the matrix, identify outliers, similarity changes in a time series and compare similarities of different attributes. The average similarity of each attribute time series is summarized in the table. For example cluster velocity attributes are most similar with an average of 72 %. Moreover, the average of all attribute mean similarities is calculated, in our case 65 %. For each time interval the bar chart on the left of the similarity matrix provides a quantitative overview about track similarity by adding up all determined attribute similarities. To summarize, using our similarity matrix in combination with the similarity bar chart, we can get an insight into their detailed attribute value differences over time. The comparison of trajectory dynamics is difficult when they differ in time and it requires the time transformation of trajectories. If two tracks which should be compared do not start at the same moment of time, trajectories can be shifted in time to a common start time or a common end time in order to enable parallel track periods for comparison. However, this approach is limited to trajectories or trajectory parts of equal duration.

5 Multivariate visual analytics of lightning data

Visual analytics is a comprehensive approach for the visualization-supported analysis of dynamic geodata and their attributes. Often a visual analytics approach doesn't consist of a single graphic method, but of several synchronized complementary methods. We suggest a multivariate visual analytical toolbox for the lightning test dataset, as demonstrated in Fig. 5. As described in (Peters 2014), various visualization techniques can be accessed in the toolbox, such as 2D/3D display for geographic track- and cluster visualization, STC, Spatio-Temporal-Density map, TCG diagram, Trajectory similarity matrix, Temporal radar plot, Temporal PCP, Table lens and time plot. All displays should be synchronized. Thus, when an object in one display is highlighted (e.g. one particular lightning cluster of interest), the object and related information will be highlighted in all other displays. The same applies to enabling/disabling of objects, zooming and panning or using the time slider tool.

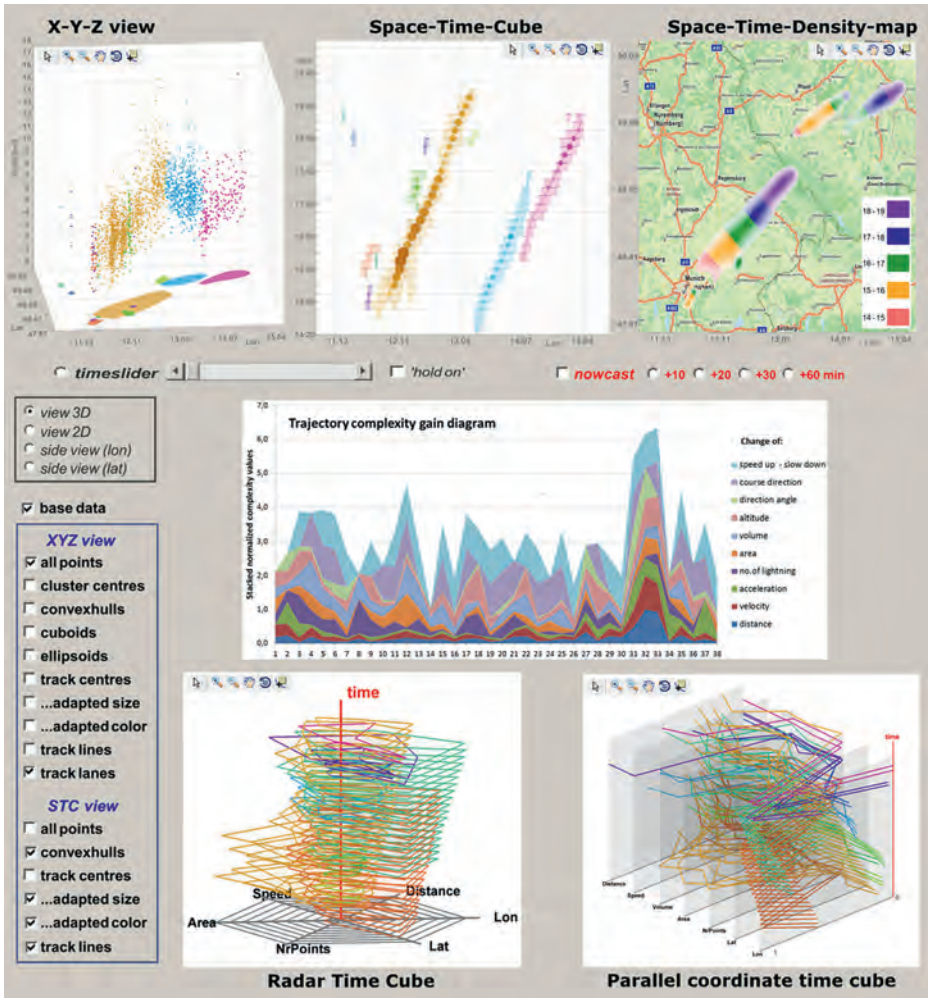

Fig. 5: Multivariate visual analytics of lightning data

6 Conclusion and outlook

Interactive visual analytical tools can provide new knowledge within lightning exploration, hence, support decision-making in thunderstorm analysis, flight scheduling or lightning damage prevention. This work introduced a set of visual analytical approaches to enable interactive visual exploration of lightning data, derived lightning clusters and trajectories, their movement attributes as well as their evolution. We offer a visual analytical solution for exploring the movement complexity of lightning trajectories. Our TCG can be stacked along the trajectory on top of a 2D base map. It also provides an insight into unusual movement behaviors along the trajectory. The similarity matrix assists analysts to compare the similarity of two lightning trajectories. Our approaches demonstrated the capability of interactive visual exploration using a lightning test dataset. We suggested a multivariate interactive GUI, which can integrate and synchronize various visual approaches/displays in order to gain an insight into lightning dynamics as well as to explore events, patterns and trends.

To evaluate our proposed methods, a comprehensive user test is necessary. It is our responsibility to verify the proposed approaches. That will on the one hand refine and thus improve our approaches, and on the other hand it will define which

method is the best for which movement analysis task regarding its usefulness and effectiveness.

References

Andrienko G, Andrienko Gennady (2009) Building a Visual Summary of Multiple Trajectories. In: GeoViz Hamburg 2009 Workshop, Hamburg, Mar. pp 3–5.

Andrienko Gennady, Andrienko Natalia, Keim Daniel, MacEachren Alan M., Wrobel Stefan (2011) Challenging problems of geospatial visual analytics. Journal of Visual Languages and Computing 22:251.

Andrienko Gennady, Andrienko Natalia, Schumann Heidrun, Tominski Christian (2014) Visualization of Trajectory Attributes in Space–Time Cube and Trajectory Wall. In: Cartography from Pole to Pole. Springer, pp 157–163.

Andrienko Gennady, Andrienko Natalia, Wrobel Stefan (2007) Visual analytics tools for analysis of movement data. ACM SIGKDD Explorations Newsletter 9(2):38–46.

Andrienko Natalia, Andrienko Gennady (2013) Visual analytics of movement: An overview of methods, tools and procedures. Information Visualization 12:3–24.

Betz Hans D., Schmidt Kersten, Oettinger Wolf P. (2009) LINET – An International VLF/LF Lightning Detection Network in Europe. In: Betz HD, Schumann U, Laroche P (eds) Lightning: Principles, Instruments and Applications. Springer Netherlands, Dordrecht. pp 115–140.

Demšar Urška, Virrantaus Kirsi (2010) Space–time density of trajectories: exploring spatio-temporal patterns in movement data. International Journal of Geographical Information Science 24:1527–1542.

Dixon M., Wiener G. (1993) TITAN: Thunderstorm identification, tracking, analysis, and nowcasting-A radar-based methodology. Journal of Atmospheric and Oceanic Technology 10:785–797.

Dykes Jason A, Mountain DM (2003) Seeking structure in records of spatio-temporal behaviour: visualization issues, efforts and applications. Computational Statistics & Data Analysis 43(4):581–603.

Güting Ralf Hartmut, Böhlen Michael H, Erwig Martin, Jensen Christian S, Lorentzos Nikos A, Schneider Markus, Vazirgiannis Michalis (2000) A foundation for representing and querying moving objects. ACM Transactions on Database Systems (TODS) 25(1):1–42.

Hering A. M., Morel C., Galli G., Sénési S., Ambrosetti P., Boscacci M. (2004) Nowcasting thunderstorms in the Alpine region using a radar based adaptive thresholding scheme. In: Proceedings of the third ERAD Conference. Visby, Sweden, pp 206–211.

Jain Anil K., Dubes Richard C. (1988) Algorithms for clustering data. Prentice-Hall, Inc., Upper Saddle River, NJ, USA

Kitagawa N., Brook M., Workman E. J. (1962) Continuing currents in cloud-to-ground lightning discharges. Journal of Geophysical Research 67:637–647.

Lakshmanan V., Hondl Kurt, MacGorman Don, Stumpf Gregory J. (2004) The use of Lightning Mapping Array data in WDSS-II. In: 22nd Conference on Severe Local Storms.

Neuwirth C., Spitzer W., Prinz T. (2012) Lightning density distribution and hazard in an alpine region. Journal of Lightning Research 4:166–172.

Peters Stefan (2014) Dynamics of spatially extended phenomena - Visual analytical approach to movements of lightning clusters. In: Department of Cartography. TUM, Munich, p 144.

Peters Stefan, Betz Hans-Dieter, Meng Liqiu (2014) Visual Analysis of Lightning Data Using Space–Time-Cube. In: Cartography from Pole to Pole. Springer, pp 165–176.

Peters Stefan, Meng Liqiu (2013) Visual Analysis for Nowcasting of Multidimensional Lightning Data. ISPRS International Journal of Geo-Information 2:817–836.

Resch Bernd, Hillen Florian, Reimer Andreas, Spitzer Wolfgang (2013) Towards 4D Cartography-Four-dimensional Dynamic Maps for Understanding Spatio-temporal Correlations in Lightning Events. The Cartographic Journal 50:266-275.

Tominski Christian, Schumann Heidrun, Andrienko Gennady, Andrienko Natalia (2012) Stacking-based visualization of trajectory attribute data. Visualization and Computer Graphics, IEEE Transactions on 18:2565–2574.

Turdukulov Ulanbek D., Kraak Menno-Jan, Blok Connie A. (2007) Designing a visual environment for exploration of time series of remote sensing data: In search for convective clouds. Computers & Graphics 31:370–379.

Willems Niels, Van De Wetering Huub, Van Wijk Jarke J. (2009) Visualization of vessel movements. In: Computer Graphics Forum. Wiley Online Library, pp 959–966.

Zinner T., Mannstein H., Tafferner A. (2008) Cb-TRAM: Tracking and monitoring severe convection from onset over rapid development to mature phase using multi-channel Meteosat-8 SEVIRI data. Meteorology and Atmospheric Physics 101:191–210.

Zinner Tobias, Betz Hans-Dieter (2009) Validation of Meteosat storm detection and nowcasting based on lightning network data. In: EUMETSAT Meteorological Satellite Conference.

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Fachberichte

Die Sekunde, das Meter und die Höhenlinie

Heinz Schmidt-Falkenberg, Trostberg

Nach einem kurzen Überblick über die europäische Entwicklung von Kalender und *Zeitzählung* wird die erdweite Entwicklung der *Zeitmessung* dargestellt. Hier ist vorrangig die heutige hochgenaue Zeitmessung mittels *Atomuhren*, insbesondere mittels *Optischer Atomuhren* von Interesse. Optische Atomuhren ermöglichen derzeit die genaueste Definition der *Sekunde*. Die SI-Einheit Sekunde kann gegenwärtig von allen 7 Basiseinheiten des Internationalen Einheitensystems (SI) am genauesten realisiert werden. Bekanntlich wird seit 1983 auch die SI-Einheit *Meter* mit Hilfe der Sekunde realisiert. Und was haben hochgenaue Uhren (hochgenaue Zeitmessungen) nun mit der *Kartographie* zu tun, insbesondere mit der *Höhenlinie*? In kartographischen Darstellungen werden bekanntlich die metrischen Abstände aller Punkte der **Land/Meer-Oberfläche** von einer Bezugsfläche (zenitwärts) durch Höhenlinien und (nadirwärts) durch Tiefenlinien dargestellt (vielfach wird auch zur Bezeichnung beider Linien nur die Benennung Höhenlinie benutzt). Damit zwischen zwei benachbarten Punkten auf einer bestimmten Höhenlinie kein Wasser von selbst fließt, kein Fahrzeug von selbst rollt..., muß bei solchen Höhenmessungen die „Mathematik" und (!) die „Physik" der Erde berücksichtigt werden. Die Sachlage ist dabei folgende: durch jeden Punkt der Land/Meer-Oberfläche verläuft je eine *Fläche konstanten Schwerepotentials*. Diese Flächen werden daher *Niveauflächen oder Äquipotentialflächen* genannt. Aus ihrer Schar