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Spatio-temporal Cartographical Generalization: Conceptual Framework and Algorithmic Extensions

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Abstract

Multi-temporal cartographic generalization poses challenges beyond those of conventional map generalization, requiring methods that not only enhance map legibility but also preserve and effectively communicate meaningful changes over time. This paper addresses two key requirements: (1) a systematic and reproducible framework for describing and comparing multi-temporal generalization processes, and (2) algorithmic extensions of spatio-temporal generalization operations that explicitly account for temporal characteristics while maintaining the legibility of significant change events. To this end, we propose a conceptual framework for spatio-temporal generalization that integrates the temporal dimension into the description of generalization operations, their levels of application, relevant temporal properties (including scale, resolution, duration, and lag), and generalization objectives. Particular emphasis is placed on preserving and emphasizing change events throughout the generalization process. The utility of the proposed framework and its associated algorithmic extensions is demonstrated through two representative operations—data classification and line simplification—which illustrate how temporal considerations can be systematically incorporated to improve both the consistency and interpretability of multi-temporal map representations.

Zusammenfassung

Räumlich-zeitliche kartographische Generalisierung: Konzeptioneller Rahmen und algorithmische Erweiterungen

Die multitemporale kartographische Generalisierung stellt Herausforderungen dar, die über die herkömmliche Generalisierung hinausgehen und Methoden erfordern, die nicht nur die Lesbarkeit der Karte verbessern, sondern auch wichtige Veränderungen im Zeitverlauf bewahren und vermitteln. Dieser Beitrag befasst sich mit zwei zentralen Anforderungen: (1) einem systematischen und reproduzierbaren Rahmen zur Beschreibung und zum Vergleich multi-temporaler Generalisierungsprozesse sowie (2) algorithmischen Erweiterungen räumlich-zeitlicher Generalisierungsoperationen, die zeitliche Merkmale explizit berücksichtigen und gleichzeitig die Lesbarkeit signifikanter Veränderungsereignisse gewährleisten. Zu diesem Zweck schlagen wir einen konzeptionellen Rahmen für die räumlich-zeitliche Generalisierung vor, der die zeitliche Dimension in die Beschreibung der Generalisierungsoperationen, ihrer Anwendungsebenen, relevanter zeitlicher Eigenschaften (einschließlich Maßstab, Auflösung, Dauer und Zeitverzögerung) sowie der Generalisierungsziele integriert. Besonderes Augenmerk wird auf die Erhaltung und Hervorhebung von Veränderungsereignissen während des gesamten Generalisierungsprozesses gelegt. Der Nutzen des vorgeschlagenen Rahmens und der damit verbundenen algorithmischen Erweiterungen wird anhand von zwei repräsentativen Operationen – Datenklassifizierung und Linienvereinfachung – demonstriert, die veranschaulichen, wie zeitliche Überlegungen

systematisch einbezogen werden können, um sowohl die Konsistenz als auch die Interpretierbarkeit multi-temporaler Kartendarstellungen zu verbessern.

Keywords

Generalization; Multi-temporal; change visualization; conceptual framework; data classification; line simplification

1 Introduction

The analysis and visualization of *multi-temporal geodata* are of great **relevance** for understanding dynamic processes across specific time periods. They provide important insights for monitoring, modeling, and decision-making in fields such as climate science, land-use management, epidemiology, or disaster assessment. *Multi-temporal visualization* techniques enhance this potential by enabling an intuitive interpretation of complex spatio-temporal relationships and supporting both exploratory analysis and the effective communication of results (Andrienko et al. 2010, Zhon et al. 2012, Bill et al. 2022).

The increasing need for visualizing complex multi-temporal geodata consequently leads to an increased demand for *generalization* methods that explicitly account for temporal dynamics. Traditional generalization approaches, designed primarily for one point of time, often fail to ensure consistency and interpretability across time (Ortigossa et al. 2025). Spatio-temporal cartographic generalization should bridge this gap by ensuring that spatial features are represented in a coherent and comparable manner across successive time frames, while preserving essential information about change, such as significant value changes (including anomalies), trends, or patterns of change (Panopoulos et al. 2003, Yang et al. 2025). However, as the literature review (Section 2) shows, there are still relatively few studies that explicitly address concepts and algorithms for spatio-temporal generalization.

These limitations expose two key **research gaps** in current approaches to spatio-temporal generalization. First, there is no systematic framework for selecting and documenting appropriate generalization methods and parameter settings for specific datasets and application contexts, limiting the reproducibility, transparency, and comparability of resulting workflows. Second, existing spatial generalization techniques are designed primarily for static representations and therefore do not explicitly consider temporal information. Consequently, they cannot systematically preserve or emphasize significant change events, which are often essential for the effective communication of spatio-temporal phenomena.

Accordingly, the first **objective** of this paper is to develop a conceptual framework for spatio-temporal cartographic generalization that explicitly incorporates the temporal dimension into the generalization process (Section 3). The framework is developed primarily for the generalization of thematic maps, reflecting the observation by Raposo et al. (2020) that cartographic generalization has received comparatively little attention in thematic cartography and geovisualization. Although the discussion focuses on thematic map series and animated maps, which represent the most common forms of spatio-temporal visualization, the proposed concepts are largely transferable to topographic mapping. Furthermore, this study concentrates on cartographic generalization, while recognizing that model generalization (i.e., data abstraction) constitutes an essential prerequisite. Because integrating both aspects would substantially broaden the scope of the study, model generalization is not considered further.

The second objective of this paper is to demonstrate how the proposed conceptual framework can be applied to specific cartographic generalization operations and to derive the algorithmic extensions required to improve map legibility while preserving significant temporal changes. To illustrate this approach, we examine two representative operations: aggregation, exemplified by data classification (Section 4), and line simplification (Section 5). These case studies demonstrate both the practical applicability of the framework and its potential to guide the development of spatio-temporal generalization methods.

Section 6 summarizes the results and limitations, and gives an outlook to necessary future work.

2 Previous Work

2.1 Conceptual framework

Although a substantial body of research has addressed the generalization of multiple map representations, most studies focus on representations across different geometric scales rather than across time. Explicit approaches to the generalization of temporal map series remain comparatively scarce. One of the earliest systematic contributions to the cartographic representation of temporal change was presented by Monmonier (1990), who argued that temporal generalization should incorporate several forms of abstraction, including the following:

- Temporal selection and filtering to emphasize "significant moments" or critical thresholds that represent meaningful changes;
- smoothing and aggregation (e.g., by using moving averages) to highlight long-term trends over short-term volatility;
- visual Efficiency to improve visual perception, e.g., by reducing temporal resolution.

Andrienko et al. (2003) proposed a comprehensive framework for exploratory spatio-temporal visualization. With respect to spatio-temporal generalization, they argued that purely visual representations, such as animations and space–time cubes, become increasingly affected by visual clutter and cognitive overload as data volumes grow. To address these limitations, they advocated computational generalization, particularly task-driven data aggregation, as a means of reducing noise in high-resolution spatio-temporal datasets while preserving information relevant to the user's analytical objectives. Together, the works of Monmonier (1990) and Andrienko et al. (2003) establish the importance of temporal generalization and identify several of its key operations. However, neither study provides a systematic conceptual framework that defines the objectives, principles, and tasks of spatio-temporal cartographic generalization.

Panopoulos et al. (2003) proposed a framework for spatio-temporal generalization based on the premise that time should be abstracted in a manner analogous to space. They define *"temporal information abstraction"* as the transformation of a spatio-temporal schema into a new schema with different spatial and temporal levels of detail, determined by the "temporal scale", which they interpret as the granularity of time. To support this process, they introduce four operators adapted from traditional map generalization: temporal selection, temporal class generalization, change aggregation, and temporal topology association. While this work represents an important step toward integrating temporal abstraction into generalization, its definition of *temporal scale* is conceptually inconsistent (see Section 3.2). Moreover, the proposed framework primarily addresses the generalization of spatio-temporal data models (information abstraction) rather than cartographic generalization, although the authors explicitly acknowledge that effective spatio-temporal generalization must support both data modeling and visualization.

As mentioned above, the general requirement for multi-temporal generalization is not only to preserve important geometric and thematic features, but also to maintain their essential changes in values and patterns over time. It is clear that the methods depend heavily on the type of visualization. Examples include the generalization in "Space Time Cubes," as discussed by Mioc et al. (2013; using a hierarchical Voronoi data structure) or by Yang (2025; for reducing trajectories). This paper focuses on map series and animations, which have so far been addressed in only a very small number of scientific studies - an exception is the work by Traun & Mayrhofer (2018), who performed value generalization of choropleth time-series data while taking into account global spatio-temporal auto-correlation.

Among other things, deep learning methods are being widely used and tested for change detection, particularly with raster data (for displaying, for example, land cover or historical developments). With regard to topographic vector maps, Zhou et al. (2026) noted that neural networks can efficiently generalize individual, isolated features over time (such as the outlines of buildings); however, they struggle to preserve the complex, changing context between multiple overlapping features. Furthermore, Yan et al. (2025) pointed to a major hurdle in current automated systems—maintaining contextual relationships between overlapping layers: When an algorithm generalizes different layers independently across multiple temporal map frames, this often leads to topological errors because temporal relationships are not considered explicitly.

Finally, within this broader context, user-oriented evaluation is essential for assessing the extent to which generalized representations effectively support interpretation and decision-making. Relevant examples include the work of Cybulski (2022), who investigates the perception of temporal trends in spatial patterns in choropleth maps, and Traun et al. (2021), who examine the detection of outliers and trends in animated choropleth maps. However, a systematic discussion of evaluation methods lies beyond the scope of this article and is therefore not pursued further.

2.2 Example: Data Classification

Data classification is the process of grouping relative values at cardinal scale into classes for reducing complexity and enhancing the visual appearance (in particular, the contrast). Typical methods for classifying data in *mono-temporal* datasets define class boundaries based purely on the data itself, for example by using equal intervals along the numerical line (e.g., equidistant) or by taking the data distribution into account (e.g., quantiles, natural breaks). However, these methods do not explicitly account for whether significant changes between two map frames are "translated" into different class values or whether insignificant changes are assigned the same class value. Possible consequences include the loss of significant changes (false negatives) or the overemphasis of insignificant change information (false positives; Zhang & Maciejewski 2017). Consequently, Halpern et al. (2021) argued that data classification should be individually tailored for each application. However, relatively little has been published in this area; an older overview was provided by Armstrong et al. (2003).

Harrower (2003) recommended a high level of aggregation into two or three classes; however, for many applications, this is an overly simplified approach. It is noted that the even greater number of visual stimuli resulting from multiple map sections and change events makes it difficult to find a suitable solution for data classification (Harrower 2007; Goldsberry & Battersby 2009). Cybulski (2022) empirically found that temporal trends are generally recognized better than spatial patterns. In the field of (information) visualization, the topic is typically addressed as part of larger systems (such as visual analytics tools) or in combination with aspects of uncertainty or interaction (Li et al. 2014), but less so with the further development of data classification algorithms themselves.

The developments by Brewer & Pickle (2002) considered neither specific nor different change tasks. The quantile method, which here has been found to be optimal, is certainly well suited to represent

only very few, large changes - but a classification based on significant change values has not been taken into account. Schiewe (2024a; 2024b) proposed an extended data classification that explicitly attempts to preserve change information. The quality metric POCC (Preservation of Change Classes) is introduced, which weights and standardizes the difference between required class changes and actually implemented class changes. This approach is addressed in Section 4 again.

2.3 Example: Line Simplification

Line simplification reduces the number of vertices in polylines while preserving their essential geometric structure, thereby supporting efficient visualization, storage, and analysis across multiple scales. Classic algorithms include the Douglas–Peucker algorithm (Douglas & Peucker, 1973), which is based on iterative vertex elimination; the method of Wang & Müller (1998), which emphasizes curvature preservation; and the approach of Visvalingam & Whyatt (1993), which applies an area-based weighting strategy.

There are a few approaches to line simplification for multi-temporal data. Huang et al. (2024) focused on preserving temporal structures during the spatio-temporal simplification of trajectories. Amiraghdam et al. (2020) proposed a locally adaptive method for line simplification that adjusts generalization parameters based on local shape or visual significance, rather than using a single fixed tolerance for the entire dataset. What these methods have in common is that they do not explicitly focus on preserving changes in map series or animations. In addition, there are methods for multi-scale simplification (e.g., Ware & Jones 1998) or topology-preserving simplification (Tienaah & Coleman 2015), whose approaches, however, have not be applied to the multi-temporal case yet (see Section 5).

In summary, previous research on line simplification has primarily focused on preserving geometric, topological, and thematic characteristics. In contrast, the preservation of these characteristics in time series simplification remains largely unexplored, representing a notable gap in the existing literature.

3 Conceptual Framework

Spatio-temporal generalization – based on Schiewe (2025: 294) and emphasizing on the temporal aspect – refers to theories and methods for the reduction, alteration or emphasis of multi-temporal cartographic information for an improved usability. In the following, a proposal for an extended concept will be presented und put up for discussion that explicitly integrates the temporal dimension. The key components of this concept are objectives, temporal properties, as well as operations and levels.

Spatio-temporal generalization, based on Schiewe (2025: 294) and putting now the emphasis on the temporal dimension, refers to the theories and methods for reducing, modifying, or emphasizing multi-temporal cartographic information to improve its usability. Building on this definition, the following section proposes an extended conceptual framework that explicitly incorporates the temporal dimension. The proposed framework consists of the following key components: objectives, temporal properties, operations, and the corresponding levels of operation.

3.1 Objectives

Conventional spatial cartographic generalization pursues two primary objectives: the preservation of important geographic objects, their properties, and spatial patterns, and the preservation or enhancement of map legibility through the reduction of the complexity of the displayed content. Accordingly,

spatio-temporal generalization has – apart from preserving or improving **legibility** – to preserve not only the static properties as described above, but also to **preserve "important" changes.** These changes, for example, in environmental, urban, epidemiology and socio-economic time series, can be manifold:

- Value differences in geometrical or thematic attributes (expressed by anomalies, maximum, minimum, average or even Null differences),
- pattern changes,
- trends, or
- existential changes (gain, loss).

The type of changes requires different generalization operations, so that they have to be predefined in advance of the application of those.

3.2 Temporal properties

The conventional spatial generalization strongly depends on the choice of the cartographic scale, which describes the ratio between a distance on the map and the distance in reality. It has to be noted that there is no unique definition of "temporal scale" in literature; in fact, in many cases, it is simply understood as duration. The definition used here is closely related to the concept of spatial scale in Cartography.

Consequently, the *temporal scale* should be defined as the ratio between a time extent as displayed in multiple maps (t) and the corresponding time extent in reality (T). These time extents can refer to

- the time for the entire scene (*total duration*),
- the time spacing between directly consecutive data frames (*time resolution*), or
- the time delay between two related change events (*time lag*).

The temporal extent represented in maps may, for example, correspond to the duration (or temporal resolution) of an animation or, in the case of a map series, to the user's reading time, which is considerably more variable and difficult to quantify. Nevertheless, relative comparisons of reading times, for example as a function of the number of maps or screen size, are feasible.

Temporal scale and total duration are particularly important in the context of **legibility**. As an example, a shorter duration of an animation (Δt) representing the same real-time duration (ΔT) leads to smaller temporal scale ($\Delta t/\Delta T$) – which typically makes the visual and cognitive perception more difficult.

Focusing on the aspect of **preservation of changes**, also the temporal parameters duration, resolution and lag should be considered. Here it is important that the time resolution is not necessarily coordinated with actual rate of actual changes $\Delta X/\Delta T$ or $\Delta x/\Delta t$ (Fig. 1). For example, it is possible that there is no change at all, or a maximum change within a certain period of time. Time lags express the time delay between relevant change events. Typically, such changes are derived from a bi-temporal composition of scenes. "Bi-temporal" does not necessarily mean consecutive map frames – also larger time differences over many frames are possible. Trends, however, need more than two map frames, whereby this number does not necessarily have to include all frames and must also be determined in advance.

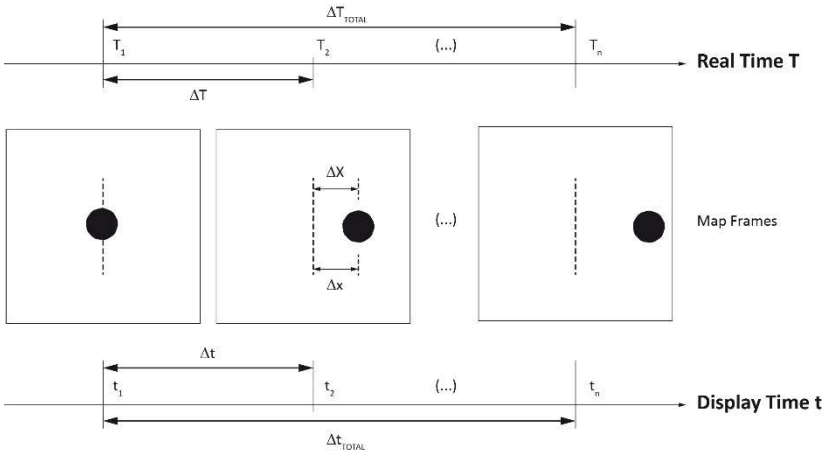


Fig. 1: Time and change parameters for dynamic representations (based on Schiewe 2025:229)

3.3 Operations and levels

The classic spatial generalization operations involve modifying individual components of geo-objects (e.g., deleting vertices in lines to simplify them) or altering entire objects (e.g., by deleting them), which can also be performed in conjunction with other, adjacent objects (e.g., during displacement or merging).

This concept can be transferred to spatio-temporal generalization: The well-known **operations** (simplification, deletion, enlargement, emphasis, displacement, aggregation, degradation; Schiewe 2025:297) are retained, but they also need the specification of one of the following three **operation levels** (Fig. 2) - i.e., a generalization of

- *object components* over time (e.g., deletion of selected vertices of a line at multiple points of time),
- *objects* over time (e.g., deletion of entire objects at specific time points), or
- complete *time frames* (e.g., deletion or summarizing of one or more frames containing all objects).

In principle, all known operations can be applied at these three levels. By definition, however, there are the following exceptions for the third level (frame-wise generalizations), as these operations are logically not meaningful:

- simplification (which would correspond to a deletion over time),
- displacement (which would entail an undesirable change in chronological order), and
- degradation (since there is no “dimension” for frames).

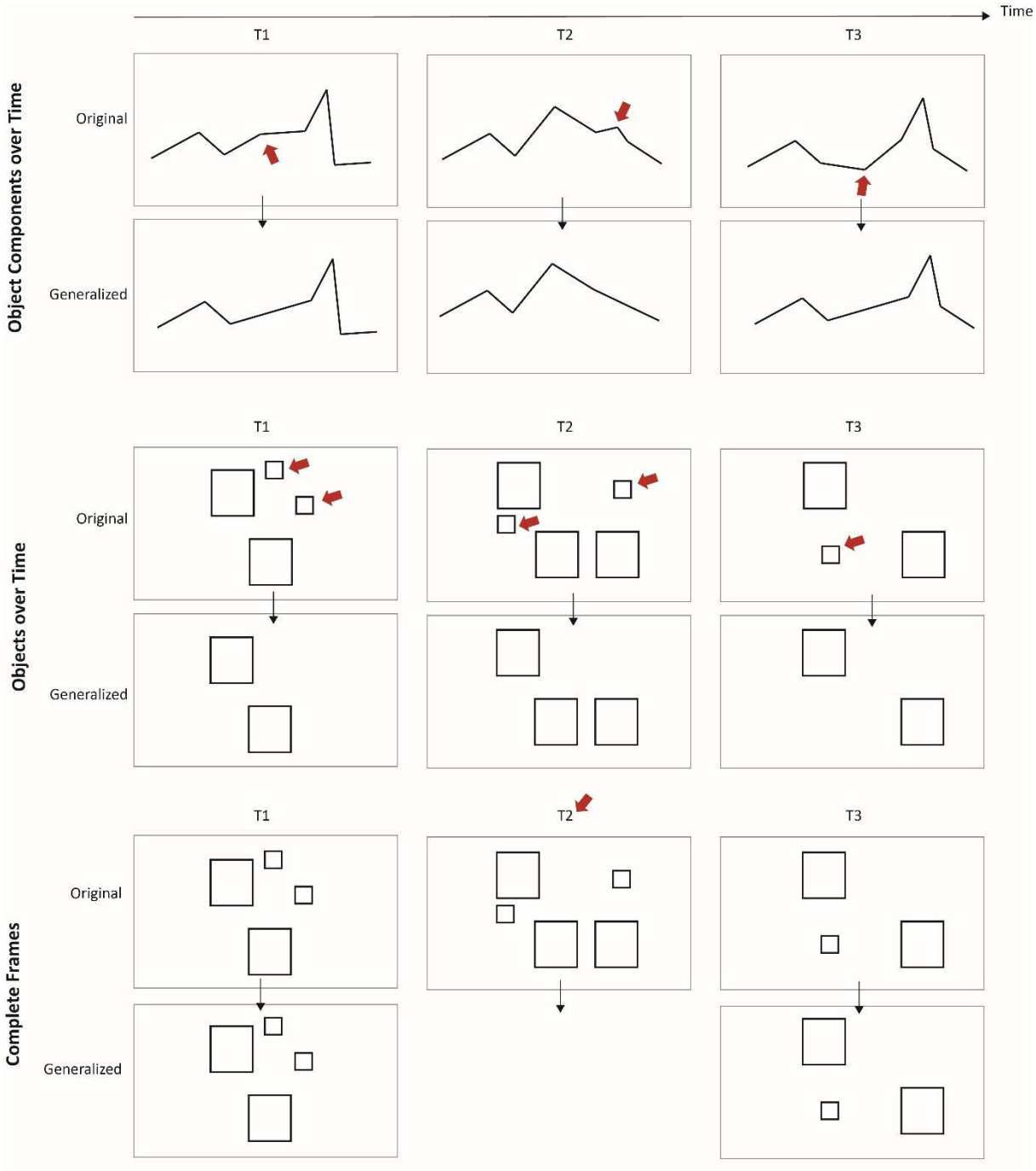


Fig. 2: Different levels of spatio-temporal generalization for time fames T1, T2 and T3: Generalization of object components, objects, frames (arrows point to features to be generalized, without explaining any rules here)

4 Example: Multi-Temporal Data Classification

4.1 Integration into the Overarching Concept

Considering the generalization operation “aggregation” in a spatio-temporal context, the following operations and their respective levels (rf. Section 3.3) are of relevance:

- The *object-over-time reclassification* leads to a summary of data at nominal scale by considering selected classes across multiple frames of the time series (typically: all time frames) and possibly the dissolving of borders.
- The *object-over-time data classification* summarizes data at cardinal scale by harmonizing class boundaries across multiple time frames.
- The *frame aggregation* merges entire time frames into coarser intervals by applying rules for aggregating objects (e. g., min/max, average; Moellering, 1976).

In the following, the operation "object-over-time data classification" will be dealt with. It can be integrated into the aforementioned conceptual framework as follows:

- **Operation and level:** The task of multi-temporal data classification is to assign class values c for given attribute values at enumeration units at time t. Consequently, one obtains class differences Δc for given value differences Δx between two time frames (Fig. 3). It is assumed that there is *one* common classification scheme for all epochs of the time series in order to ensure comparability (Brewer and Pickle, 2002; see also paragraph on "Objectives" below).

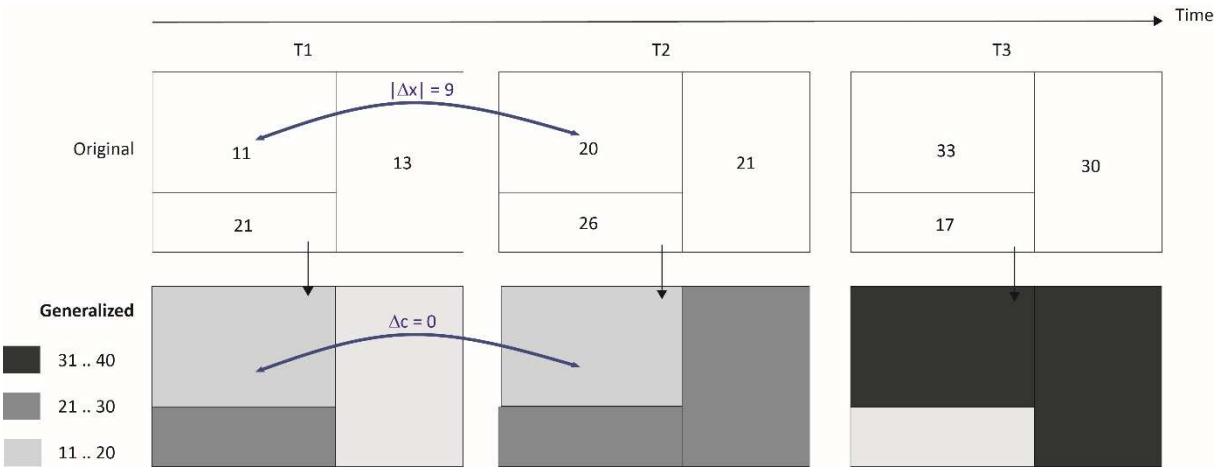


Fig. 3: Concept of the generalizing operation "multi-temporal data classification": One classification scheme for all time frames T1, T2 and T3 (here: equidistant method)

- **Temporal properties:** Typically, data classification with multiple scenes considers all time frames. Of the utmost importance with regard to temporal properties is the time lag that describes relevant change events. However, for simplification purposes, time lag is simply set as the difference between two consecutive frames in most cases.
- **Objective:** According to the aforementioned overall objective of spatio-temporal generalization, the aim of multi-temporal data classification is to determine a set of class breaks that is able to preserve as many significant changes (and with that, to improve legibility). Typically, the loss of large values differences should be avoided – such as in Fig. 3 the marked, quite large value change ($|\Delta x|=9$), which is lost after data classification through the allocation to the same class (i.e., $\Delta c=0$). Due to the limited number of classes, there is no perfect solution in general. To find an optimal solution, the *POCC data classification* method has been proposed (Schiewe 2024a), which is briefly addressed in the following.

4.2 Extended Algorithm

Basic idea of the POCC algorithm for preserving important changes after data classification is to compare the desired or required class changes in a data set with the actually achieved class changes after applying the classification process.

In order to introduce the change information, the required class changes can – for example – be derived as follows (Fig. 4): All value changes Δx with a given time lag (typically, between all possible, consecutive time frames) within the data set are transformed into several, equally spaced class differences. The top class starts at the threshold value Δx_{UPPER}. If the classification is calculated for k classes (k is given a priori), the required class difference $\Delta c_{required}$ results from

$$\Delta c_{required} = INT\left(\frac{k-1}{\Delta x_{UPPER}}\Delta x\right)$$

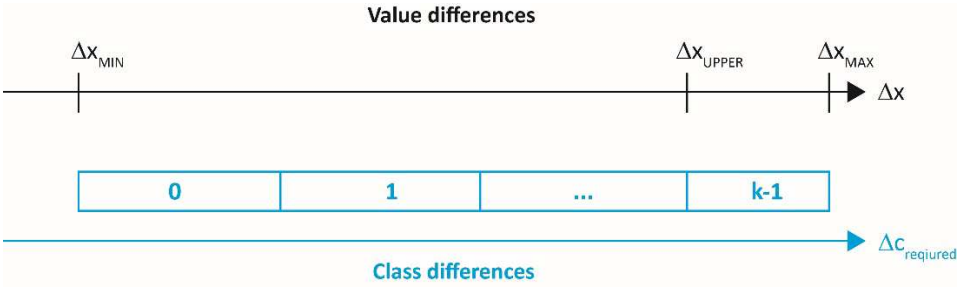


Fig. 4: Option for determining required class differences $\Delta c_{required}$ based on given value differences

In the example given in Fig. 3, Δx_{MIN} equals 5, Δx_{MAX} equals 13. If Δx_{UPPER} is set to 11 (in order to emphasize the largest difference by putting this into a separate class), the required class differences $\Delta c_{required}$ equal 1 (for $\Delta x \geq 8$) and 2 (for $\Delta x \geq 11$), else 0.

After applying any data classification method, the requested class differences $\Delta c_{required}$ can be compared with the actually obtained differences $\Delta c_{achieved}$. Applying a normalization, one obtains the *Preservation Of Change Classes (POCC)* metric as follows (the weighting factor w_i is used to emphasize certain changes):

$$POCC = 1 - \frac{\sum_i |\Delta c_{required,i} - \Delta c_{achieved,i}|}{\sum_i w_i \cdot \Delta c_{required,i}}$$

This POCC value can take values in the interval of [0; 1], with POCC=1 representing the optimal preservation. This metric can be used to evaluate results derived from different classification methods. It can also be used to guide an optimized classification – the POCC method. This method uses a sweep line algorithm, where the respective diagram (Fig. 5) shows the attribute values x on the right axis, while all attribute differences Δx between two lags are plotted as intervals below. An intersection of such an interval with the sweep line represents a possible class boundary between the lower and upper breaks of the interval. As more than two classes are possible, k-1 sweep lines have to be generated. For each sweep line, the corresponding number of intersections with value intervals $|\Delta x|$ can be counted. At the end, for each interval the total number of intersections (i.e., the class difference $\Delta c_{achieved}$) is counted and compared to the required value $\Delta c_{required}$ using the POCC measure. Given an a priori fixed

number of classes (k), the optimal solution is obtained using a brute force approach that considers all possible combinations of sweep lines (i.e., all class boundaries).

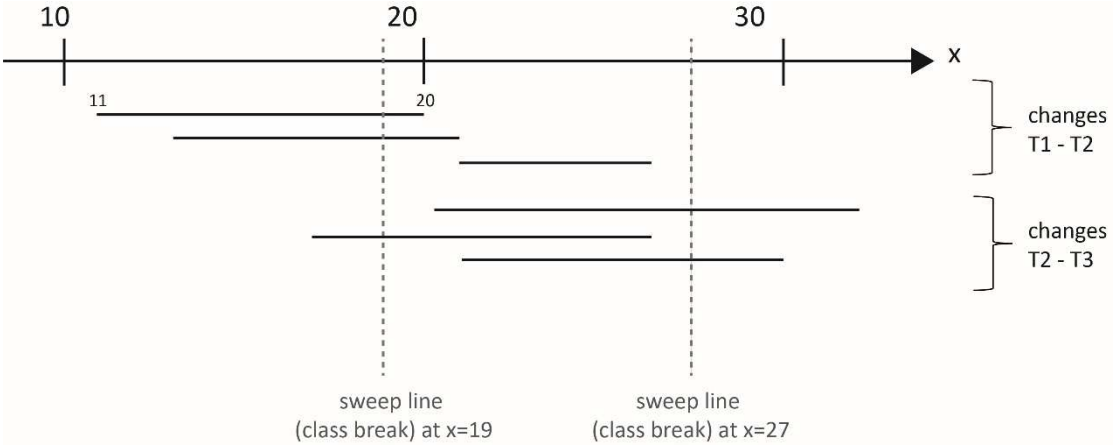


Fig. 5: Finding class breaks by intersection of multiple sweep lines with "important" value intervals Δx (for the classification example in Fig. 3)

Tab. 1 summarizes the workflow for the example given in Fig. 3 in numerical form, also showing the improved preservation of required changes with the POCC versus the equidistant method (expressed by the POCC value for both cases). However, it also demonstrates (as mentioned above), that there is no guarantee that even POCC delivers a perfect preservation (which would be POCC=1). Fig. 6 shows the cartographical the result.

Tab. 1: Numerical description of POCC value determination for equidistant method (class breaks at 20, 30; Fig. 3) and POCC method (class breaks at 19, 27; Fig. 6) – violations of required class difference are marked in red

time	x_i	x_j	$\lvert\Delta x\rvert$	$\Delta c_{required}$	**equidistant** $\Delta c_{achieved}$	**POCC** $\Delta c_{achieved}$
T1 – T2	11	20	9	1	0	1
	13	21	8	1	1	1
	21	26	5	0	1	0
T2 – T3	20	33	13	2	1	1
	26	17	9	1	1	1
	21	30	9	1	0	1
				POCC values	1-(4/6)=**0.33**	1-(1/6)=**0.83**

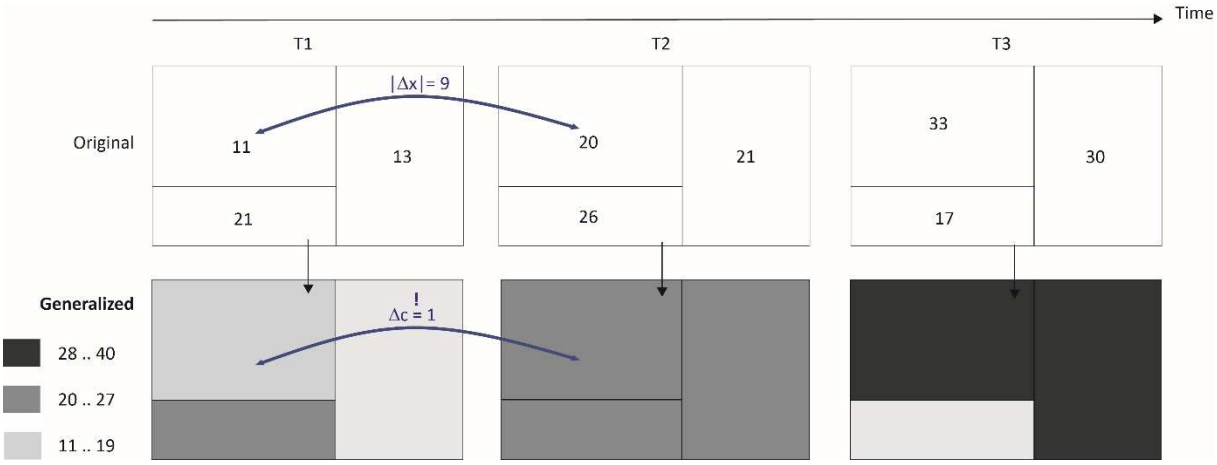


Fig. 6: Result of POCC classification method (compare with result of Fig. 3: For example, the large value interval in upper left corner between T1 and T2 is now depicted in different classes)

It has to be noted that for improving the visual perception of changes in animations or map series, not only the suppression of large change differences (false negatives) is of importance, but also the suppression of smaller value differences (false positives) that ideally should not be represented by different classes as these false positives make it harder to detect important changes because they serve as a distraction. The POCC classification can also consider this requirement (not applied in the example above): The sweep line diagram then also integrates the small difference intervals, counts the intersections with these (which represent “bad cases” then), and compares this number with the required class difference of zero.

It should be noted that, to improve the visual perception of changes in animations or map series, it is important not only to suppress large change differences that remain undetected (false negatives), but also to suppress small value differences (false positives). Ideally, such smaller differences should not be assigned to different classes, as they distract from the detection of more substantial changes. The POCC classification can also account for this requirement, although this functionality was not applied in the example above. In this case, the sweep-line diagram additionally incorporates the intervals representing small value differences, counts the corresponding intersections (i.e., undesirable cases), and compares this number with the target class difference of zero.

4.3 Further developments

The basic version of the POCC classification as described before (Schiewe 2024a) is currently undergoing further development. This involves, on the one hand, the flexibility to select a range for the number of classes (rather than a single value only). On the other hand, alternative approaches to the brute-force method are being explored, since this approach results in unacceptable computation times on the order of minutes if the number of classes exceeds 5.

For the latter topic, the branch-and-bound method appears promising, which is an exact solution method for combinatorial optimization problems in which the solution space is recursively divided into subproblems (branching) and systematically searched using borders (bounding) (Land & Doig 1960). During the recursive search the class boundaries are added step by step. Here, the POCC function is not used immediately; instead, an equivalent error function is used, which also takes into account the weighted difference between the required and achieved class differences. A lower bound of the achievable error is computed for partial solutions. If this bound exceeds the current best solution, the

branch is pruned. The number of breakpoints inside each interval is tracked incrementally to avoid re-computation. Ongoing work is examining and improving the applicability and, in particular, the runtime behavior of this approach.

5 Example: Line Simplification

5.1 Integration into the Overarching Concept

From a geometric perspective, simplification refers to the reduction of the (intermediate) points on a (perimeter) line and the connection of the remaining points. In the context of a time series, line simplification can be categorized as follows within the aforementioned conceptual framework:

- **Operation and level:** Line simplification belongs to the group of *component-over-time generalizations*. The parameters for this simplification may be derived from a single frame, from each frame independently, or through an integrated analysis of all frames.
- **Temporal parameters:** Typically, line simplification with multiple scenes considers all time frames. While temporal scale is important for legibility, time lag is important for preserving the changes. However, in most cases, the time lag is simply defined as the difference between two consecutive frames.
- **Objectives:** In addition to improving legibility, the simplification aims to preserve the original geometric structure, which can be expressed in terms of the shape, length, or point density of lines, as well as the shape and size of areas. In a multi-temporal context, these objectives remain unchanged; however, certain "significant" changes to a line (e.g., a coastline) should also be preserved or even emphasized. Here, too, changes to the structural features mentioned above (shape, length, etc.) must be taken into account.

5.2 Extended algorithm

5.2.1 Problem setting

A very commonly used method for line simplification is the *Douglas-Peucker (DP) algorithm* (Douglas & Peucker 1973), which aims to remove selected vertices while still preserving the characteristic shape of the line. Metrics that guide the preservation or deletion of vertices can include, for example, the perpendicular distance between the original points and the approximating line segment, or the interior angle between a point's predecessor and successor. Large distances or small interior angles indicate significant changes in the line's path—therefore, the corresponding vertices should be retained. The degree of deletion is controlled by threshold values. Those are typically determined iteratively and lead to rules such as "Eliminate points with a distance of more than 10 m," "Eliminate points with an interior angle of less than 120°," or "Eliminate 50% of all points."

When applying the DP algorithm to a *time series of lines*, one should not use just a single line (e.g., the first in the time series) to determine the threshold value, because the curvature behavior could change significantly over the following time frames. As an example, Fig. 7 (2) shows the selection of a rather low threshold value, that is derived from the line at time t(1) (with the goal of eliminating 50% of the vertices in this line). The result is a very small reduction of vertices in the subsequent lines t(2) and t(3), which are characterized by larger distance deviations or more pronounced bending behavior. The total reduction of all three generalized lines t(1), t(2), and t(3) is now only 25% (6 out of 24). If, on the

other hand, the threshold is set too high (e.g., derived from line t(3) only; Fig. 7(3)), a very strong simplification occurs in lines with low bending behavior (here at t(1) and t(2)).

In both cases significant changes in the lines over time are distorted or even lost. Consequently, the lines from *all* time frames should be included when determining the necessary threshold values.

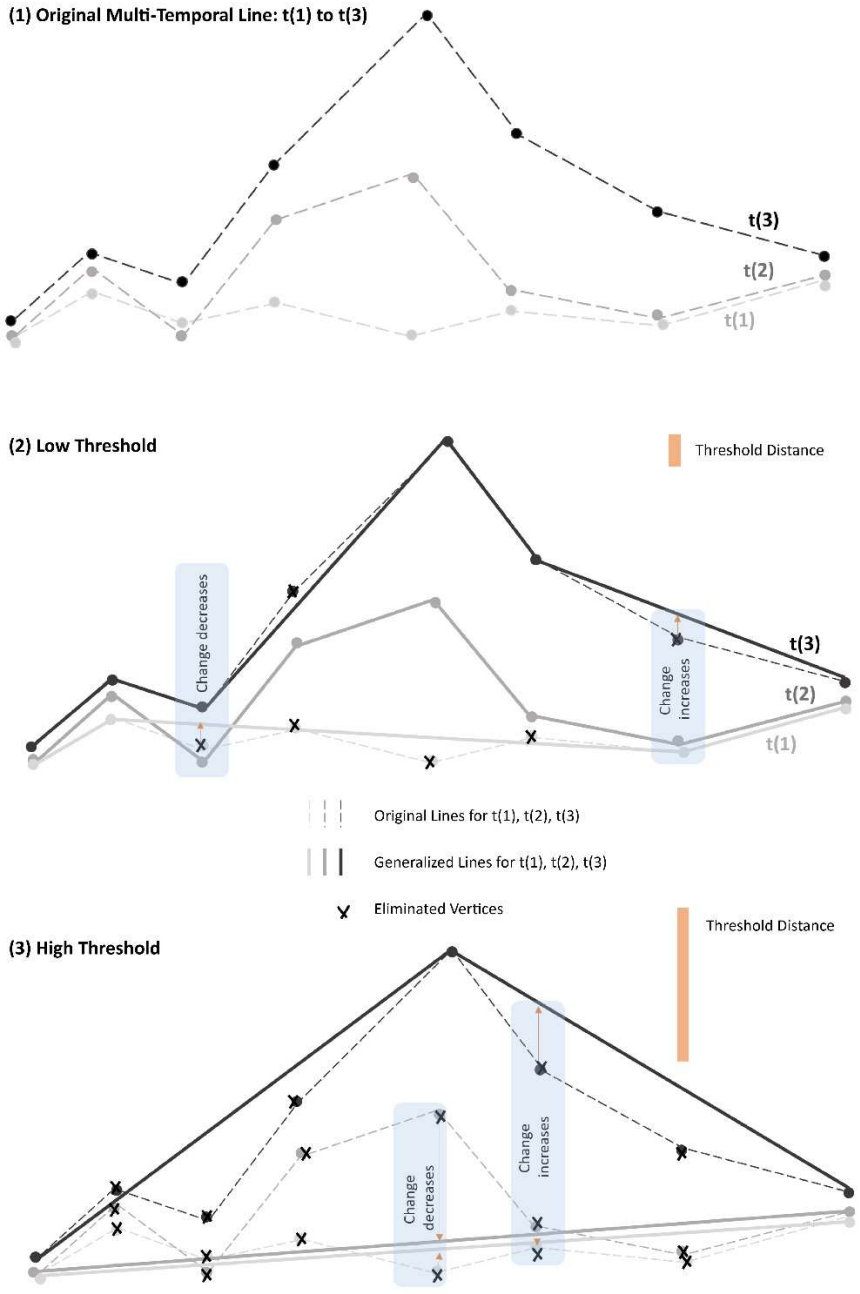


Fig. 7: Based on given multi-temporal original line (1): Application of a rather low threshold value (2) and a rather high threshold value (3) in the DP algorithm for a time series t(1) to t(3) – leading to distorted changes over time after applying the simplification (marked as "change increases" or "change decreases")

5.2.2 Constraint-based approach for preserving large positional changes

In line with the conceptual framework of spatio-temporal generalization, it is necessary to account also for changes of a line given for time frames t(i) and t(i+j) (typically between consecutive time points, i.e., j=1). As an example, these changes can be defined by large positional changes of corresponding vertices of one and the same line over time using a respective threshold (Fig. 8). The choice of this change threshold can be based on application-specific requirements and taking the map scale into account (e.g., a deviation of 20 m might be considered significant in reality, which is represented as a deviation of 1 mm on a 1:20,000 map). All vertices at which the positional shift exceed such a threshold should be retained and are treated as "constraint vertices" in the following. After setting these constraints vertices, the actual DP algorithm is applied separately to the segments between them.

To date, such a constraint-based approach has been used in mono-temporal datasets to preserve dominant directions of line segments or to avoid violating topological properties (e.g., not allowing road segments to intersect with buildings or roundabouts; Tienaah et al. 2015). This idea is now transferred to the preservation of changes in multi-temporal lines. Of course, this concept can also be applied to other line simplification methods, such as Visvalingam-Whyat or Lang.

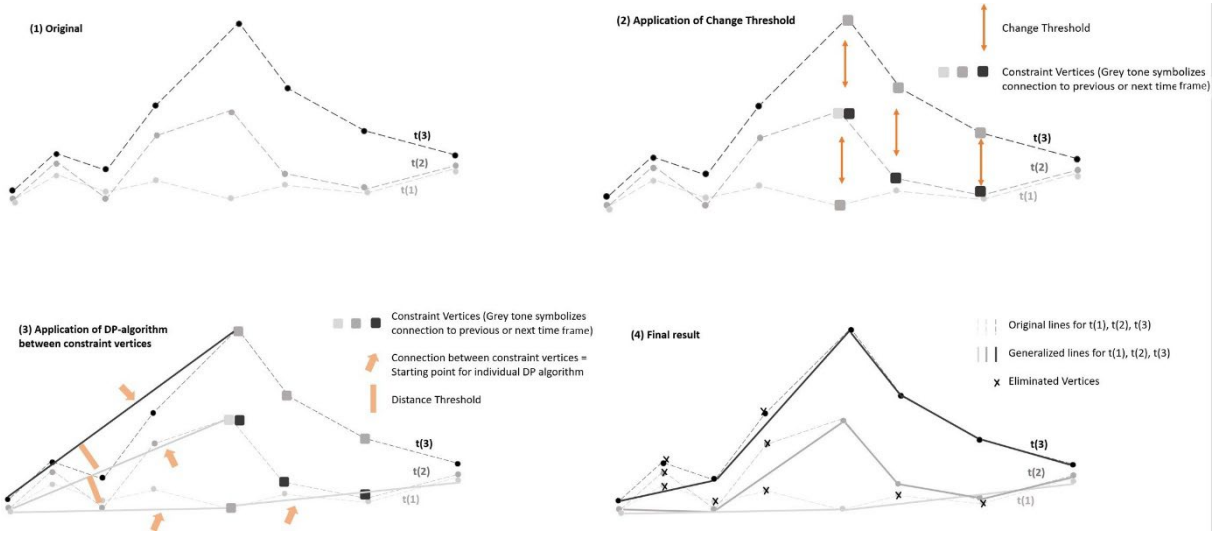


Fig. 8: Based on multi-temporal original line (1): Applying a change threshold to identify constraint vertices (2), then applying the DP algorithm to subintervals (3) and merging these to final result (4); note the functional difference between "Change Threshold" in (2) and "Distance Threshold" in (3)

5.2.3 Constraint-based approach to suppress very small positional changes

The mental load associated with perceiving changes in time series can be reduced by preventing "distractions" caused by small or even actually negligible deviations between two time frames that are typically visually perceived as a kind of "flickering." For this reason, it makes sense not only to preserve major changes (Section 5.2.2) but also to suppress these "unimportant" changes—defined by a "non-change threshold" for corresponding vertices at times t(i) and t(i+j). If a distance falls below this threshold, the vertex at time t(i+j) is shifted to the position at time t(i) (Fig. 9) – this vertex is also introduced as constraint vertex. Similar to 5.2.2, the DP algorithm is then applied to the sub-intervals between these constraint vertices, and the resulting, simplified sub-lines are merged to the total line.

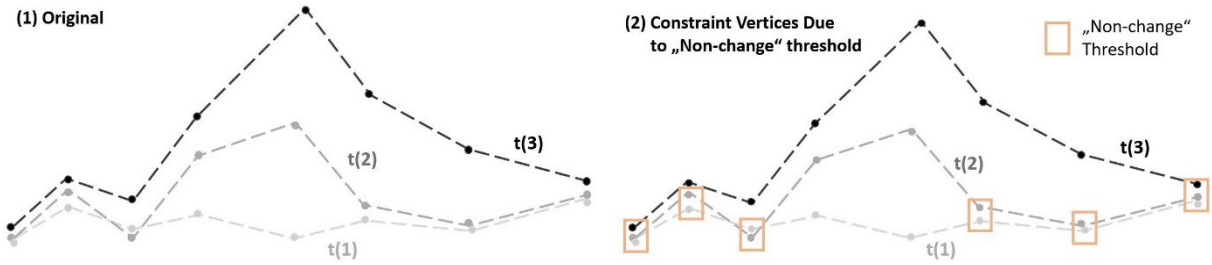


Fig. 9: Based on multi-temporal original line (1): Determining constraint vertices based on "non-change" threshold in order to avoid flickering effects (2)

5.2.4 Constraint approach for line features

Depending on the application, it is not (only) the preservation of positional shifts over time that is of interest, but also the preservation of certain line features such as line length, line shape, or the area of a closed line.

When preserving changes in *line length*, it must be taken into account that a simplification (i.e., the deletion of intermediate vertices) always results in a shortening of the total line length. In a multi-temporal context, the task is therefore to preserve the relative ratio of line lengths between two time frames. Fig. 10 (1) shows an example in which the original line length remains unchanged between times t(1) and t(2), but the generalization (using the same threshold value) significantly shortens the line at t(2). There are now two options: Either the line that has become too short after generalization can be lengthened again by reinserting points (*reinsert*), or the relatively too long line can be shortened by further deletions of intermediate points (*delete*).

Fig. 10 (2) demonstrates the reinsert process. For this purpose, the loss in line length resulting from each single vertex deletion during the application of the DP algorithm is recorded, creating a list sorted by magnitude of length loss. The reinsert then processes this priority list sequentially. The step-by-step reinsertion of vertices continues until the required relative length ratio is achieved (in the example in Fig. 10, this already happens after the first reinsert).

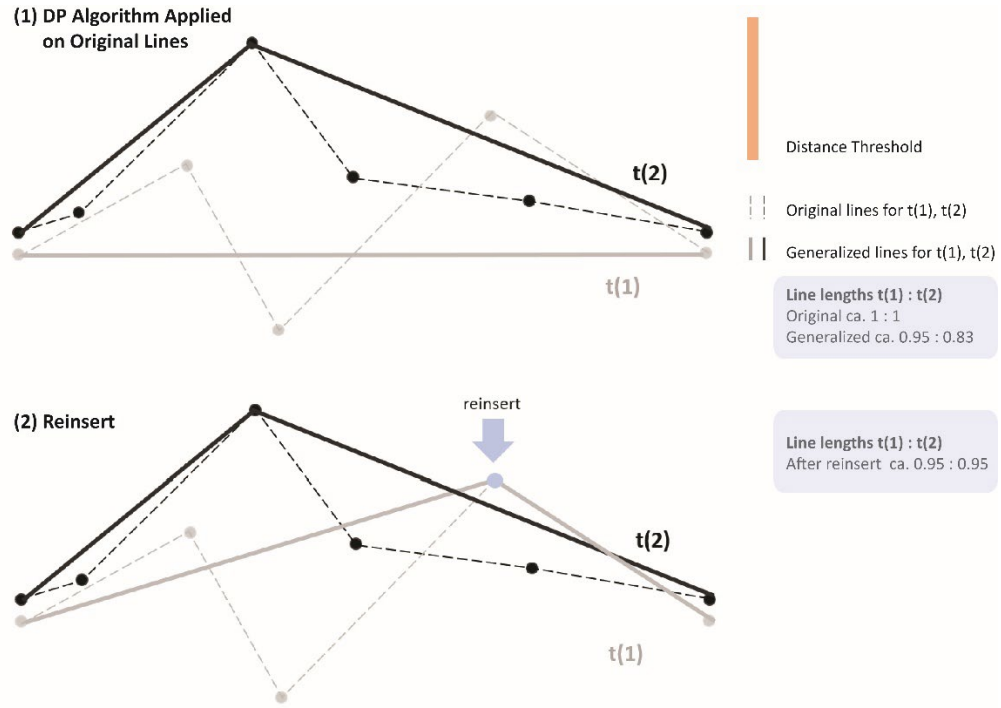


Fig. 10: Principle of restoration of line length ratio by reinserting a vertex (2), which has been deleted by DP algorithm before (1)

Just as line length ratios are preserved over time, this same approach can be used to handle changes in line shapes (through individual angle changes or overall parameters such as concavity or convexity) or the areas of closed line loops (through normalized areas).

5.3 Further developments

So far, the work on multi-temporal line simplification with the focus on preserving important changes and avoid small ones has remained at the conceptual stage. Currently, implementation and testing activities are being carried out to gain practical experience regarding the appropriate configuration of threshold parameters. In parallel, investigations are being conducted with the objective to assess the extent to which quantitative preservation metrics correspond to visually observable changes and to identify threshold settings that provide a reliable balance between numerical performance and perceptual detectability.

6 Conclusions and Future Work

In **summary**, the objectives of this contribution have largely been achieved. A comprehensive conceptual framework has been developed that enables the systematic, detailed, and reproducible description and comparison of multi-temporal generalization processes. The presented examples demonstrate the applicability of this framework. Furthermore, the study shows that achieving the primary objective of spatio-temporal generalization—the preservation or enhancement of relevant changes—requires extensions to conventional mono-temporal generalization methods. The examples of data classification and line simplification illustrate that such extensions are both feasible and effective. In

addition, variants such as the suppression of minor changes, which may distract from the perception of more significant changes and therefore need not be visualized, were presented.

Future work will focus on extending the proposed conceptual framework to additional generalization operations, including deletion, enlargement, emphasis, displacement, and degradation, as well as combinations thereof. Furthermore, the corresponding algorithms – focusing on the preservation of changes – will be implemented and systematically evaluated. Particular attention will be given to analytical investigations of parameter settings, such as the number of classes and upper-class constraints in data classification, as well as distance thresholds defining significant and insignificant changes in line simplification. Furthermore, there is more to learn about the relationship between legibility and preservation. In addition, empirical studies will be conducted to assess the relationship between parameter configurations and the visual perception of changes. These investigations will consider the difference between animated representations and map series, taking into account their different temporal and spatial constraints.

The primary **scientific contribution** of this work is the development of a holistic conceptual framework that integrates the key characteristics of multi-temporal generalization. By providing a structured theoretical foundation, the framework addresses a gap in the existing literature and supports the generation of reproducible and comparable generalization results. Moreover, the proposed framework may also serve as a basis for future AI-driven generalization approaches by offering a systematic representation of relevant processing characteristics. For actual practical purposes, the algorithmic extensions in multi-temporal data classification and line simplification contribute to more informative and effective visualizations of temporal changes.

Conflict of Statement

The corresponding author states that there is no conflict of interest.

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