Explanation of Similarities in Temporal Case-Based Reasoning by Visualization*

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Abstract *Temporal Case-Based Reasoning* (TCBR) relies on time series similarity measures whose global similarity values emerge from multiple local contributions, making the development, validation, and maintenance of similarity models difficult for knowledge engineers. This paper investigates visualization-based explanations for mapping-based time series similarity measures that illustrate how such values are composed. To this end, a systematic literature study on visualization approaches for time series similarities is conducted, and a requirements catalog for similarity visualizations in TCBR is derived. Existing techniques are then assessed against these requirements. Based on the results, an extended point mapping visualization is presented that makes mappings between time series entries explicit and complements them with interactive tools for exploration and inspection. The concept is implemented in the ProCAKE framework and was evaluated in an exploratory user study. The results suggest that the approach is perceived as interpretable and practically useful for supporting the understanding of time series similarity values and their local composition in TCBR.

Keywords: Visualization · Temporal Case-Based Reasoning · Mapping-Based Time Series Similarity · Explainable Case-Based Reasoning

1 Introduction

Similarity is a central concept in *Case-Based Reasoning* (CBR), as it determines which collected cases are most useful for a new problem [6]. Accordingly, several similarity measures exist to identify the most useful case for a case representation. In *Temporal Case-Based Reasoning* (TCBR), relevant case information is often represented as time series data [22, 37]. Such time series occur in settings including complex sensor streams in *Industrial Internet of Things* (IIoT)

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environments for classification and fault detection, as well as medical and energy-consumption contexts [22]. Time series similarity can be assessed by different approaches, including direct comparison methods and approaches based on transformed, abstracted, or learned representations [18, 22, 37, 47]. This paper focuses on mapping-based similarity measures, i.e., measures aligning elements or local regions of two time series, e.g., *Smith-Waterman-Algorithm* (SWA) [44] or *Dynamic Time Warping* (DTW) [32]. Many mapping-based measures follow the local-global principle [6, pp. 106–107], such that multiple local similarity calculations contribute to a similarity value [33]. This makes the resulting similarity difficult to interpret and creates a need for explanation support.

For good retrieval results, the development, validation, and maintenance of similarity measures remain knowledge-intensive and error-prone tasks for knowledge engineers, especially for complex temporal patterns [38]. In TCBR, this challenge is pronounced for mapping-based similarity measures, because a single similarity value may arise from different alignments, heterogeneous local similarity values, and parameter settings of the underlying measure. Consequently, knowledge engineers frequently struggle to understand why a query-case pair yields a similarity value, how the induced mappings affect this value, and which local regions contribute most to it. Within *Explainable Artificial Intelligence* (XAI), explanations are used to support transparency and trust. The subfield of *Explainable Case-Based Reasoning* (XCBR) also addresses explanations of CBR systems, including retrieval results and thus the similarity value [34, 38, 45]. However, knowledge engineers need tool support to inspect and interpret the internal composition of similarity values [38]. Existing work demonstrates that visualization can facilitate this in CBR applications based on other case representations [3, 24, 38]. However, corresponding visualization approaches for explaining time series similarities in TCBR are not yet available.

To address this gap, this paper investigates visualization-based explanations for mapping-based time series similarities in TCBR to make similarity values and their local composition more accessible to knowledge engineers. To this end, a systematic literature study is conducted to identify, structure, and assess existing visualization approaches for time series similarities for mapping-based measures. Based on this, a requirements catalog for similarity visualizations in TCBR is derived, grounded in explainability goals [45] and established principles of information visualization [8, 42, 43]. Existing techniques are assessed against these requirements. From these results, a visualization concept centered on explicit point-to-point correspondences is designed and implemented in the ProCAKE framework [7], and its suitability is examined in an exploratory user study.

The paper is structured as follows. Section 2 provides foundations of TCBR, time series visualization approaches, and related work. Section 3 presents the literature study on visualization approaches for time series similarity, and Sect. 4 derives requirements for such a visualization in TCBR. Section 5 examines applicable literature approaches and adapts them for usage in TCBR. Section 6 evaluates the extended approach by a user study based on a prototypical implementation. Section 7 concludes and discusses future work.

2 Foundations and Related Work

This section provides the necessary background for this research. First, the research field of TCBR is introduced in Sect. 2.1, with a particular focus on time series as case representations and on the role of similarity measures. Subsequently, Sect. 2.2 introduces foundations from information visualization and the visualization of time series as a basis for explaining time series similarities. Finally, Sect. 2.3 discusses related work in XCBR and existing visual approaches relevant to the explanation of time series similarity values.

2.1 Temporal Case-Based Reasoning

TCBR is a subfield of CBR dealing with representing and processing temporal relationships within the CBR cycle [22]. In practice, especially in *Internet of Things* (IoT) applications, temporal case knowledge is frequently captured as multivariate sensor streams, which makes time series the most established case representation form in TCBR [22, 37]. A time series is an ordered sequence of measured values associated with specific points in time, for example, originating from manufacturing sensors as well as from medical monitoring or energy-consumption recordings [22, 37, 40]. While alternative temporal representations such as episodes, graphs, or event sequences exist, time series enable a direct use of original sensor data and can be integrated as local attributes within a higher-level case description [22]. To reduce data volume and complexity, temporal abstraction techniques can aggregate observations to higher-level patterns. However, this comes with a trade-off between compactness and detail, which may be undesirable for fine-grained analyses [37, 41].

Retrieval in TCBR crucially depends on time series similarity measures [22]. Following the local-global principle [6, pp. 106–107], local similarities between time points (or local structures) are aggregated to a global similarity on the time series level and, if multiple series exist, further combined to an overall case similarity. Common syntactic measures include several mapping-based approaches, such as List Mapping [22], SWA [44], and DTW [32]. Among these, DTW additionally compensates stretching and compression effects [22,33]. Many

Table 1. The Three Categories of Syntactic Mapping-Based Similarity Measures for Time Series (according to Malburg et al. [22]).

Category 1	Category 2	Category 3
Similarity measures that can only be applied to time series of the same length, comparing only the values at the corresponding times.	Similarity measures that can be applied to time series of different lengths, considering the values and the time points.	Similarity measures, like those in Cat. 2, but that can detect stretching and compression in addition.
List Mapping [22]	*Smith-Waterman-Algorithm* [44]	*Dynamic Time Warping* [32]

widely used measures are knowledge-poor in the sense that they compare syntactic patterns without incorporating domain semantics [46]. Although knowledge-intensive semantic measures have been proposed, they are rarely used in TCBR practice, where syntactic measures dominate [22]. Tab. 1 summarizes a common categorization of syntactic measures [22], ranging from Cat. 1 to Cat. 3. This increasing complexity also creates a need for suitable explanation support, in particular for understanding how local contributions give rise to the resulting similarity value.

2.2 Visualization of Time Series

Visualizations are a promising means for supporting the understanding of complex issues such as time series similarities. Information visualization studies the computer-supported and interactive visual representation of abstract data, with the primary goal of enabling insight rather than merely producing graphics [8]. By reducing search effort, supporting pattern recognition, and enabling interactive exploration, visualizations can make complex data structures more accessible [43]. In the context of XAI, information visualization can contribute to transparency and trust [21]. Similarly, in XCBR, visual comparisons can support the communication of explanations, e.g., by contrasting a query with retrieved cases [45]. A widely used design guideline in this field is Shneiderman's Visual Information-Seeking Mantra, i.e., "overview first, zoom and filter, then details-on-demand" [42].

The visualization of time series constitutes a broad and heterogeneous research area [1]. Across many application contexts - including IIoT sensor analytics, medical monitoring, and energy-consumption analysis - time series visualizations serve two recurring purposes: (1) providing an interpretable depiction of temporal dynamics and (2) enabling the identification of relevant intervals, events, or anomalies for subsequent analysis. Surveys highlight that time-oriented data can be visualized either as explicit time series or as time-dependent attributes embedded into a broader data representation [2, 10, 27, 43]. For explicit time series, coordinate-based representations such as line charts remain the dominant baseline due to their readability and expressiveness for continuous temporal change [1]. Beyond this baseline, more specialized and often more compact techniques exist, for example, circular, calendar-based, point-based, or matrix-based representations [2, 10, 27]. These alternatives can highlight periodicity, dense observations, or structural patterns, but often trade direct temporal traceability for compactness. Independent of the chosen encoding, interactive components are key to effective time series analysis. Common interaction patterns include filtering and focus mechanisms, linking multiple coordinated views, and providing details-on-demand to inspect specific time points or intervals without cluttering the overall display [10, 43]. Overall, surveys consistently conclude that coordinate-based visualizations remain the practical default for time series, as they provide an intuitive overview and a robust basis for interactive inspection [1, 10]. This is particularly relevant for visualization-based explanations of mapping-based time series similarities, where temporal context and local correspondences must remain visually accessible.

2.3 Visualizations as Explanations in Case-Based Reasoning

XCBR is a subtopic of XAI that focuses on CBR systems which explain their own output by providing additional explanations, for example through visual components [34]. In this context, XCBR differs from case-based explanations that use CBR to explain other *Artificial Intelligence* (AI) systems. Such case-based explanations are thematically related to this work, but address a different goal and are therefore not considered further here. Some publications use CBR to explain other AI approaches, for example, in work by Kenny and Keane [17], or Recio-García et al. [29]. Other XCBR work applies visualizations to explain similarity measures or their configuration, as in Batyrshin et al. [4]. In contrast, this work does not aim to visualize the composition of the similarity value based on the similarity measure. Instead, it focuses on mapping-based time series similarity measures, since they induce explicit or reconstructable correspondences that can serve as visual explanation objects. Furthermore, visualizations are used to depict similarity distributions in case bases or support retrieval-result inspection, for example in Rostami et al. [31] or Namee and Delany [28], and in approaches that visualize retrieval behavior over time [24].

Furthermore, several visualization approaches are related to this work. In CBR research, Massie et al. [25] extend CBR explanations beyond returning a case and a similarity value by using coordinate-based diagrams for cases represented as lists of numerical values. Bach and Mork [3] discuss how visual representations can support the development and inspection of similarity models during retrieval, particularly for computations following the local-global principle. In previous work [38], visualization-based explanations of similarities in *Process-Oriented Case-Based Reasoning* (POCBR) [26] were investigated by deriving a requirements catalog and designing three concepts for cases represented as workflow graphs. Although time series could in principle be encoded as graph structures, transferring these process-oriented visualizations to TCBR would add structure not needed for explaining time series similarity values and would clutter the view with information irrelevant to alignment-based sequence comparison, analogous to Weich et al. [47]. Interactive tools such as SimViz support similarity inspection and maintenance in structured, attribute-based CBR applications [14–16], but they do not support time series as case representations.

Beyond CBR-specific approaches, interactive systems for time series analysis also exist. TimeSearcher [12] and ChronoLenses [49] support exploratory search and transformation of time series data. In these systems, similarity is mainly used for filtering and navigation rather than for explaining similarity values computed by time series similarity measures in TCBR [12, 49].

3 Systematic Literature Study on Visualization Approaches for Time Series Similarities

To provide a basis for selecting and designing a suitable visualization approach for explaining time series similarity values in TCBR, established guidelines for systematic literature studies were followed [30, 48]. The study aims to identify concrete visualization techniques that explicitly address similarity between time series, particularly for mapping-based measures. As a result, the following four relevant approaches are identified.

Gogolou et al. [11] characterize similarity visualization for temporal data as covering both point-based and higher-level structural comparisons. A key observation is that the visualization strongly depends on the underlying similarity measure. In this context, two techniques are emphasized. **(1) Point Mapping Approaches** explicitly highlight correspondences between time points for mapping-based measures such as DTW. Matching points are connected by mapping lines, making local contributions and alignment effects visually accessible. **(2) Normalization Techniques** transform time series to compensate for amplitude differences or vertical shifts by rescaling the values relative to their mean and variability, which makes structural patterns more comparable in a coordinate-based visualization. While this does not change the underlying similarity measure, it makes structural patterns easier to compare visually.

Kumar et al. [19] propose a fundamentally different representation by converting time series into bitmap-like patterns. Their approach first discretizes time series using symbolic aggregate approximation and then maps frequency-based structural properties to a colored raster. Thus, **(3) Bitmap Patterns** enable efficient comparison and browsing of large collections because structurally similar time series yield similar patterns. However, the bitmap abstraction limits interpretability for individual query-case pairs, since relating specific color regions back to original time intervals and local structures becomes difficult. Finally, Chen et al. [9] introduce a **(4) Matching Matrix** for visualizing similar structures between two time series in the context of the spatial assembling distance measure. The matrix places both series on its axes using local pattern representations rather than raw values and marks local pattern matches as diagonal structures. The distribution of these matches provides a visual indication of where and how local patterns correspond across the two sequences.

4 Requirements for Similarity Visualization

To select and design a suitable visualization approach for explaining time series similarities in TCBR, a dedicated requirements catalog is needed. These requirements provide a basis for reviewing existing approaches and for extending them toward the goals of this work. A substantial part of these requirements builds on requirements previously derived for visualization-based explanations in POCBR [38], where knowledge engineers in a focus group were interviewed and the findings were discussed together. In this work, these requirements are examined for their transferability to TCBR, adapted where necessary, and complemented by established principles of information visualization [8, 42, 43], findings from time series visualization research [1, 2, 10, 27], XCBR-related explainability goals such as justification of results [34, 45], and related work [14]. Overall, seven requirements are defined as follows:

Req. 1 Representation of the Underlying Data: The visualization must support time series as the underlying data representation in TCBR [22]. For this work, the focus is restricted to discrete, linear, univariate time series without branching temporal structures or spatial context [1]. The visualization should support primitive local data types, including numerical values, Boolean attributes, and textual strings with an inherent or explicitly defined order, and it should support every mapping-based time series similarity measure.

Req. 2 Explainability of Computed Similarities: The visualization should represent computed time series similarities and their composition in a comprehensible way and provide an explanation for the resulting similarity value. This requirement adapts the explainability requirement from POCBR [38] and is grounded in the justification goal described by Sørmo et al. [45].

Req. 3 Visualization From the Query's Perspective: The explanation should be provided from the query's perspective. In TCBR, queries may cover only a relevant subset of a case, e.g., the pre-failure interval in predictive maintenance scenarios [18]. Attributes or intervals irrelevant to the query should therefore not dominate the visualization and should be visually de-emphasized or excluded.

Req. 4 Task- and Goal-Oriented Representation: The visualization interface should support common tasks of knowledge engineers focussing on time series and their similarities in TCBR. In particular, it should support the cognitively demanding and error-prone modeling and refinement of similarity measures [38]. The interface should facilitate both exploratory search and confirmatory analysis workflows [1] while following Shneiderman's Visual Information-Seeking Mantra [42].

Req. 4a Support of Exploratory Search: The visualization should enable exploratory search without prior hypotheses by providing an overview and interaction mechanisms such as filtering and zooming.

Req. 4b Support of Confirmatory Analysis: The visualization should support hypothesis-driven analysis by enabling comparisons, rankings, and associations between relevant data and similarity values.

Req. 5 Interaction Capabilities: The visualization should not be limited to a static representation of time series and similarity values but should integrate interactive elements that support analysis and model refinement [10, 38].

Req. 5a Filter Functions for Time Series Attributes: It should be possible to hide or filter individual time series attributes or values in order to focus on relevant aspects of similarity inspection [10].

Req. 5b Interactive Adaptation of Similarity Measures: The interface should allow interactive changes to similarity measures on the global and local level to assess their influence on the resulting similarity value [38].

Req. 5c Dynamic Queries on Given Time Series: It should be possible to formulate and execute new queries based on the current visualization, e.g., by selecting subsequences or applying transformations, to investigate their impact on retrieval and similarity values [38].
Req. 6 Relation Between Cases: Similarity explanations should be provided pairwise by comparing the query with one retrieved time series to ensure traceability. In addition, the visualization should support parallel comparison of multiple pairwise similarity visualizations and place the resulting similarity value in the context of the case base similarities [38].
Req. 7 Scalability of Time Series: The visualization must consider large time series with many data points, which are common in practice and pose visual as well as technical challenges [22, 43]. Since non-specialized approaches may hide local structures or cause detail loss [49], the visualization should provide mechanisms for focusing on sub-intervals and reducing the number of visible data points, e.g., by defining a maximum number of rendered elements [13, 16].

5 Visualization Approach for Time Series Similarity

This section presents the visualization approach investigated in this work for explaining mapping-based time series similarity values in TCBR. To this end, Sect. 5.1 identifies a suitable visualization method based on the requirements, which is then conceptually expanded in Sect. 5.2.

5.1 Selection of Suitable Visualization Approach

Based on the requirements defined in Sect. 4, the four approaches for visualizing time series similarities presented in Sect. 3 are evaluated. On a conceptual level, all approaches can be embedded into a pairwise visualization setting and thus address Req. 6. Similarly, Req. 2 and Req. 4 cannot be fully assessed from the visualization technique alone, since task- and goal-oriented support as well as explainability depend on the concrete user interface and therefore require evaluation. Nevertheless, the approaches allow deriving boundary conditions for these requirements. Bitmap patterns are not suitable in this work, since their strong abstraction does not expose explicit correspondences and therefore does not support explaining how a similarity value emerges from local contributions. This conflicts with Req. 2 and limits task-oriented analysis in Req. 4. While bitmap patterns are scalable and support compact comparisons across many cases, they do not allow tracing similarity-relevant structures back to concrete time intervals and value constellations, which is essential for Req. 1 in TCBR. The matching matrix can indicate local correspondences and is therefore related to Req. 2, but it places local pattern abstractions on its axes instead of directly displaying the compared time series and their induced mappings. This weakens traceability regarding Req. 1. This also limits the query-focused perspective required by Req. 3 and complicates interactive refinements such as formulating dynamic queries from the visual representation in line with Req. 5. In contrast, normalization techniques and point mapping approaches retain a coordinate-based view of the compared time series and therefore align more naturally with Req. 1. Both approaches can be aligned with Req. 3 and support typical interaction primitives such as filtering, zooming, and details-on-demand, including interval-focused inspection and dynamic queries in line with Req. 5. However, achieving scalability for long time series (Req. 7) requires additional mechanisms such as restricting the display to sub-intervals. Overall, coordinate-based approaches require only minimal extensions within the scope of this work. Therefore, point mapping is preferred, since it makes induced correspondences explicit and treats them as the primary explanation object, whereas normalization only supports visual comparison indirectly.

5.2 Conceptual Approach

Based on the selected point mapping approach, the extended concept for the visualization of mapping-based time series similarity is presented in the following. Several requirements, derived in Sect. 4, are translated into concrete user interface elements and interaction mechanisms as an extension of point mapping. The concept is described independent of a specific framework so that it can be transferred to different TCBR environments and complemented with application-specific details. As a guiding principle for structuring the interface, the Visual Information-Seeking Mantra by Shneiderman [42] is followed. Therefore, the user interface provides an overview of the relevant information, then enables zooming and filtering for exploration, and finally supports details-on-demand when inspecting local contributions. Whether the overall interface is task- and goal-oriented in the sense of Req. 4 and whether the explanations are perceived as sufficiently informative in the sense of Req. 2 must be validated by evaluation. The following design choices operationalize these requirements at the interface level.

Interface Overview. Fig. 1 illustrates the conceptual interface by the prototype implementation. The interface components are distributed in three sections: 1) a main visualization area with navigation controls (①, ②, ③), 2) a section for displaying information (④, ⑤), and finally, 3) an expandable tool section (⑥). The central idea of the chosen point mapping approach is to treat the mapping itself as the primary explanation object [11]. Instead of only juxtaposing two time series, the visualization makes correspondences induced by a mapping-based similarity measure explicit through mapping lines between query and case points. Each mapping line corresponds to one local comparison that contributes to the resulting similarity value. The overall set of mapping lines provides an immediate visual summary of alignment effects, e.g., shifts, repetitions, and many-to-one or one-to-many correspondences. In this sense, the coordinate system provides temporal context, while the mapping lines convey why specific regions are considered similar. Furthermore, local similarity values are encoded along the mapping using a color range and annotated values. Such encodings

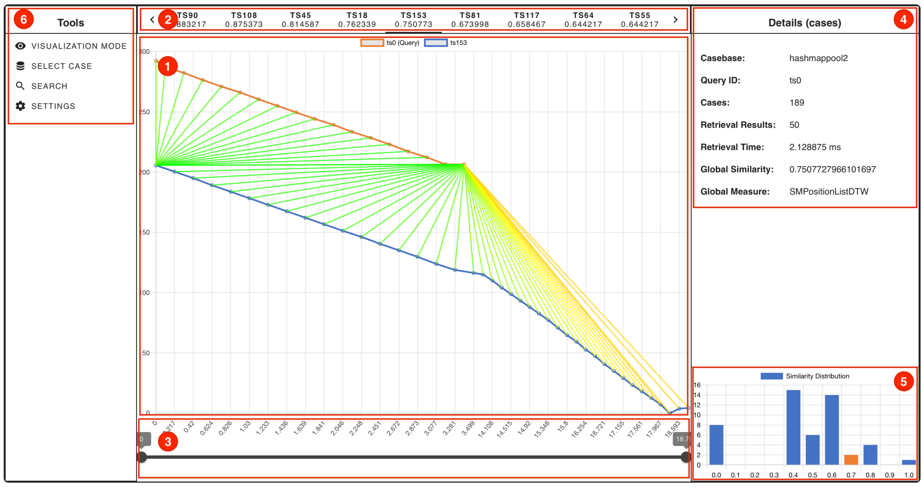

Fig. 1. The Conceptualized User Interface Illustrated by the Implementation.

remain configurable to avoid clutter and keep the visualization usable for exploratory inspection. This design targets Req. 2 by making local contributions and their aggregation into a similarity value accessible at the level of individual mapping pairs.

Coordinate System Visualization. Query and case are displayed in a two-dimensional coordinate system for time series (see ①, Fig. 1) whose entry values are either numerical or can be mapped to an ordinal scale. If the entries contain Boolean values, both series are shown in two vertically stacked coordinate systems, since otherwise the two value states overlap too frequently, especially for very similar time series. In general, the x-axis represents the time attribute, which can be either a timestamp or a numeric value (e.g., time passed since the beginning of the measured event [22]). The y-axis represents the time series values. Use cases for time series whose entry values cannot be represented numerically or mapped to an ordinal scale have not been reported so far [22] and are therefore not considered in this approach. If query and case series have incompatible representations, the interface can fall back to separate displays of both series and communicate that point mapping is not available for the selected pair. The point mapping visualization follows a pairwise explanation setting aligned with Req. 6. The visualization is designed from the query's perspective as required by Req. 3. The query acts as the reference, and the mappings are interpreted as contributions explaining why the retrieved case is similar to the query. Case entries irrelevant for the query should not dominate the explanation so they can be visually de-emphasized, made non-selectable, or hidden by filter mechanisms.

Interaction and Details-on-Demand. Interaction is a core element of the concept and addresses Req. 5. The central view supports inspection of time series points and their mappings. Hover interactions reveal tooltips summarizing time, query value, case value, and the local similarity value. Clicking a point or mapping triggers a details-on-demand workflow by populating an information area with the corresponding local context. The information area (see ④, Fig. 1) supports an overview mode with context about the case base and the retrieval, as well as a detail mode for the selected mapping pair. In detail mode, the interface presents attribute-time-value pairs for query and case entries together with the local similarity value. If the underlying system provides further information about the local similarity computation, the detail mode can offer an entry point to inspect it.

Scalability and Interval Control. Scalability for large time series is addressed by restricting the visualized range to a configurable sub-interval (see ③, Fig. 1), as required by Req. 7. A time slider below the visualization enables users to select lower and upper bounds of the displayed interval. Adjusting this interval updates both time series and the visible mappings immediately. To prevent visual overload, the interface can enforce a maximum number of rendered points and reduce the displayed resolution when needed. This reduction is reflected in the displayed bounds so that users remain aware of the current level of detail. The maximum selectable interval spans the full temporal range of both series, including cases where query and case intervals do not overlap.

Comparison and Case Base Context. To support rapid comparison of multiple query-case pairs, the concept includes a compact selection component for switching between the most similar retrieved cases (see ②, Fig. 1). The component lists cases in descending order, highlights the current selection, and enables comparison without losing context. This supports Req. 6 and can be extended to parallel visualizations when comparing multiple similarity calculations side by side. To place the current similarity value in the context of the case base, the concept further includes an element for visualizing the similarity distribution over the case base (see ⑤, Fig. 1). A histogram-like view allows users to assess whether the current similarity value is typical or exceptional and whether similarity values are concentrated or well separated. This design is adapted from the similarity distribution component used in earlier visualization work [38].

Tool Support and Configuration. Finally, a compact tool palette (see ⑥, Fig. 1) provides additional functions without consuming central screen space. It supports directed search for points, intervals, or attribute conditions, as well as filtering mechanisms to hide irrelevant parts of the visualization, thereby contributing to Req. 4 and Req. 5. The palette also provides configuration options for the similarity visualization itself, such as showing or hiding mappings and enabling similarity color ranges. It further acts as an entry point for interactive similarity-model adjustments and re-running retrieval based on the current configuration, which targets Req. 5 and its subrequirements.

6 Experimental Evaluation

The evaluation investigates whether the proposed visualization is perceived as supporting knowledge engineers in understanding mapping-based time series similarity values, their local composition, and the effects of changes to similarity measures and parameters. Such understanding is an important prerequisite for the refinement and maintenance of similarity models. First, the evaluation setup is presented (see Sect. 6.1), followed by the results and their discussion (see Sect. 6.2).

6.1 Experimental Setup

As a foundation for the evaluation, the conceptual design was implemented as a prototype based on the ProCAKE framework [5, 7]. The framework provides several similarity measures and exemplary datasets for TCBR applications [37, 39, 47]. The implementation is integrated into the `ProCAKE Studio`, which provides a web-based graphical user interface on top of ProCAKE[1].

The evaluation was conducted as an exploratory user study in which participants interacted with the visualization component and assessed the proposed approach against the requirements defined in Sect. 4 as well as by an overall suitability rating. Thus, the requirements serve as an assessment lens for examining whether the transferred and adapted design goals are perceived as addressed by the approach. For the study, a case base [22, 40, 47] from a Fischertechnik Smart Factory in the IoT Lab Trier[2] [23] was used. The case base consists of 189 time series cases with numeric or Boolean entry values, containing between 1 and 59 entries. Numerical time series contain 12.19 entries on average (median 3), whereas Boolean time series contain 1.49 entries on average (median 1). This results from a compact storage variant in which only value changes are represented [22]. This compact representation makes differences between the measure categories visible, for example, whether compression is accounted for by DTW as a Cat. 3 measure. This is particularly relevant because similarity measures from all three categories (see Sect. 2.1) were available in the evaluation and could be selected for visualization. Participants performed guided inspection tasks on example query-case pairs and explored several features of the point mapping visualization. After completing the tasks, they rated the approach using structured questionnaires aligned with the requirements and provided qualitative feedback on strengths, limitations, and desired extensions. Overall, eleven

[1] A demo video illustrating the implementation based on the presented concept for similarity visualization is available at the following link: `https://procake.s.gy/procake-studio-time-series-visualization-demo`

[2] `https://iot.uni-trier.de/`

participants with prior experience in the knowledge-engineering tasks of configuring or analyzing similarity measures as well as prior knowledge of TCBR and the ProCAKE framework took part in the study.

6.2 Experimental Results and Discussion

The evaluation results are primarily reported regarding the requirements defined in Sect. 4. Fig. 2 summarizes the participants' ratings of how well the conceptual visualization approach addresses the requirements. Overall, the concept was assessed as addressing the core requirements for explaining mapping-based time series similarity values to a large extent. The ratings for Req. 2 suggest that the mapping lines and the details-on-demand workflow provide meaningful explanation cues at the level of local contributions. Requirements related to workflows and usability, in particular Req. 4, were evaluated positively, although with more heterogeneous ratings. This is consistent with the fact that task- and goal-oriented support depends not only on the visualization principle itself but also on the concrete interface realization and the users' familiarity with the domain. Scalability aspects (Req. 7) were rated as addressable by the concept, mainly due to the interval-based focus mechanism, while still suggesting a need for careful implementation decisions for large time series. In addition to the conceptual evaluation, participants also assessed the prototype. The implementation ratings were largely consistent with the conceptual assessment in Fig. 2, indicating that the implemented user interface preserves the main properties of the concept. Beyond the requirements-based assessment, the point mapping concept received an average school grade of 1.8 (median 2.0), providing a compact overall indicator of perceived suitability.

The results suggest that point mapping is perceived as a suitable approach for explaining mapping-based time series similarity values in TCBR. Participants reported clear agreement that the concept addresses Req. 1, Req. 3, Req. 5, and Req. 7. In addition, the previously open non-functional requirements Req. 2 and Req. 4 are largely perceived as addressed. In particular, this suggests that the mapping lines and the details-on-demand workflow support understanding of how a similarity value emerges from local contributions. Since such understanding is a prerequisite for refining and maintaining similarity models, the results indicate that the proposed visualization can provide useful support for knowledge engineers in TCBR. At the same time, the results indicate that requirements related to comparison and scalability are most sensitive to prototype completeness rather than to the conceptual approach alone. Ratings for Req. 6 are more heterogeneous, which aligns with participants' feedback that parallel comparison of multiple cases would be beneficial beyond the current pairwise focus. Similarly, more neutral ratings for interaction and scalability requirements point to missing prototype features, such as interactive similarity-model adaptation, dynamic queries, and reduction of visible data points. Detail view and gradient-based mapping are frequently perceived as helpful, whereas the global similarity distribution is rated less useful, likely because its role in the workflow is passive and would benefit from more interactive linking to retrieval results. A

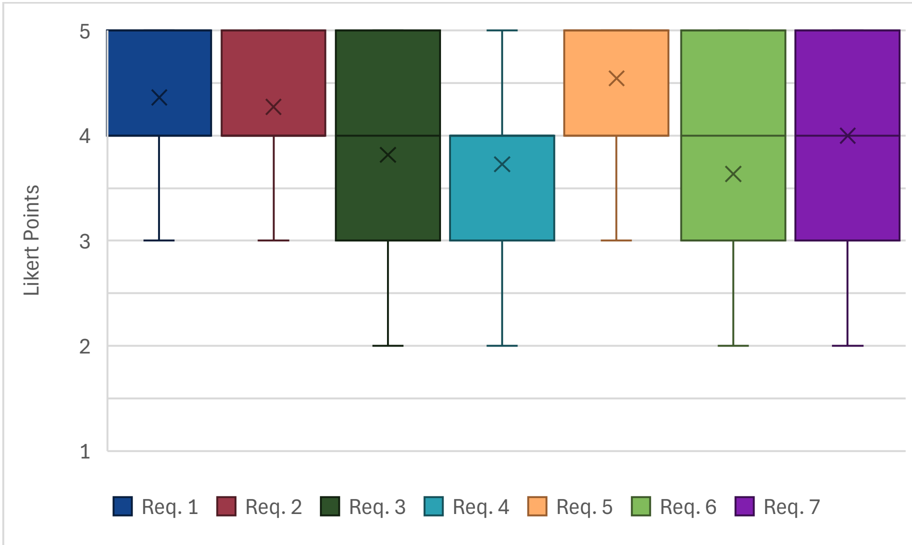

Fig. 2. Results of the Requirement Assessment for the Point Mapping Approach.

limitation of the evaluation is that the prototype is not assessed across a wider range of time series lengths and that the study focuses on perceived suitability rather than objective performance measures. Larger series can increase visual clutter and reduce the explanation clarity provided by the point mappings.

7 Conclusion and Future Work

In this paper, visualization-based explanations for mapping-based time series similarities in TCBR are investigated to make similarity values and their local composition more accessible to knowledge engineers. To this end, existing visualization techniques for time series similarities were consolidated and assessed against a requirements catalog tailored to similarity visualization in TCBR. Based on this, point mapping was identified as the most suitable basis and extended toward a concrete visualization concept for TCBR, which was prototypically implemented on top of the ProCAKE framework. The current concept is restricted to mapping-based similarity measures for discrete, linear, univariate time series. An exploratory user study provides initial evidence that the point mapping concept is perceived as supporting the explainability goal and that the transferred and adapted requirements provide a useful assessment lens for this setting. Overall, the results suggest that explicit visualization of induced mappings is a promising way to support the inspection of how mapping-based similarity values emerge from local contributions in TCBR. The empirical findings are limited by the exploratory nature of the user study.

Future work should address scalability. The evaluation is conducted on comparatively small time series, and future studies should therefore investigate how the visualization behaves for substantially larger series and whether the explanation effect remains stable under higher visual density. Beyond this, the approach can be extended to support multivariate time series, which would require concepts that enable attribute-level inspection and comparison while keeping the explanation of similarity values comprehensible. Dependencies between such multivariate time series within cases, as well as higher-level dependencies across cases, can also be considered, especially if they are relevant for similarity computation (see Kumar et al. [20]). Further, the explanation can be extended by investigating dedicated visualizations of local similarity computations, for example, by providing textual or numerical views. This is particularly relevant because local similarities constitute the basis of the resulting similarity value and could serve as a complementary view to the point mapping representation. Moreover, the approach can be adapted to users without deep CBR expertise. The evaluation indicates that participants with limited prior knowledge of the specific similarity measures still experience some difficulties in understanding them. Future work should therefore introduce explanatory meta-levels for similarity measures in addition to the main visualization. An assistant component based on a large language model could provide context-sensitive explanations of the similarity measures, mappings, and parameters, allowing knowledge engineers or other users to ask questions about the observed similarity patterns. Finally, the approach can be explored in a twin-system setting [17], in which mapping-based similarity measures and their visual explanations serve as an interpretable explanatory layer for more complex methods. For example, such a setting could be used to explain deep-learning-based predictive maintenance classifications [18,35] or to investigate other, non-mapping-based similarity measures through mapping-based explanatory variants.

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