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Combining the Automated Segmentation and Visual Analysis of Multivariate Time Series

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Abstract

For the automatic segmentation of multivariate time series domain experts at first need to consider a huge space of alternative configurations of algorithms and parameters. We assume that only a small subset of these configurations needs to be computed and analyzed to lead users to meaningful configurations. To expedite this search, we propose the conceptualization of a segmentation workflow. First, with an algorithmic segmentation pipeline, domain experts can calculate segmentation results with different parameter configurations. Second, in an interactive visual analysis step, domain experts can explore segmentation results to further adapt and improve segmentation pipeline in an informed way. In the interactive analysis approach influences of algorithms, parameters, and different types of uncertainty information are conveyed, which is decisive to trigger selective and purposeful re-calculations. The workflow is built upon reflections on collaborations with domain experts working in activity recognition, which also defines our usage scenario demonstrating the applicability of the workflow.

CCS Concepts

•***Mathematics of computing*** → ***Time series analysis;*** •***Human-centered computing*** → *Visual analytics;*

1. Introduction

The segmentation of multivariate time series into meaningful sequences of time intervals is a highly relevant task in many application domains. The segmentation helps to divide complex structures into smaller and yet more meaningful segments that may reveal underlying mechanisms and foster knowledge generation. Example analysis goals are speech recognition within audio streams, synthesis of human motion based on segmented tracking data, or medical diagnosis using electrocardiography measurements.

This work builds upon ongoing collaborations with domain experts with the goal of identifying different activities in multivariate time series data. For that purpose, we reflect and combine tasks, challenges, and visions of experts working in human motion activity recognition [VKK14], equine biomechanics [WVZ*15], oil drilling processes [ABG*14], and ambient assisted living [RLB*15]. Domain experts in all these use cases share the need for automated segmentation methods to cope with the complexity (size and heterogeneity) of considered multivariate time series. To shift the analysis from time series as a whole to the granularity of segments, a "cascade of algorithmic models" [Fek13] is needed – which we refer to as a *segmentation pipeline*. From our collaborations, we also learned that domain experts need to gain trust of applied algorithms and generated results. This requires a segmentation pipeline that allows the interactive exploration and adaptation of algorithm and parameter selection throughout the pipeline. We further postulate that users may also want to better understand the underlying segmentation algorithms, uncertain areas, appropriate parameterizations, and relations between these aspects. Thus, employing this in a visual analytics approach can ultimately result in a higher acceptance of the segmentation pipeline.

To support optimal algorithm and parameter selection, we focus on three primary types of challenges. The first factor is the choice of algorithms for the segmentation pipeline. Domain experts often have to include important classes of algorithms such as data cleansing routines, sampling approaches, normalizations, descriptor (feature extraction) and feature selection techniques, as well as, naturally, segmentation algorithms. However, the effect of a particular algorithm (or combinations of algorithms) on a particular dataset is not easily predictable [BDB*16]. The second class of challenges to facilitate the segmentation of multivariate time series comes with the parameters of the segmentation pipeline [SHB*14]. Especially when parameter sets become large, choosing adequate parameter values might be difficult [BPFG11] and conventional approaches become increasingly iterative [PBCR11]. The third challenge that domain experts face is the uncertainty inherent in the data [WYM12] or produced by processing or segmentation algorithms across the entire process [GSB*15]. Awareness of inherent uncertainty is mandatory to convey and control robustness of results against variations of input and different user behavior [SSK*16], as well as for the adjustment of algorithms and parameter values.

With this huge design space at hand, the number of possible configurations of segmentation pipelines (and thus different segmentation results) is virtually infinite. Depending on the computational complexity of the segmentation pipeline the calculation of multiple segmentation results can quickly become a time-consuming bottleneck. In contrast to the naïve calculation of large numbers of seg-

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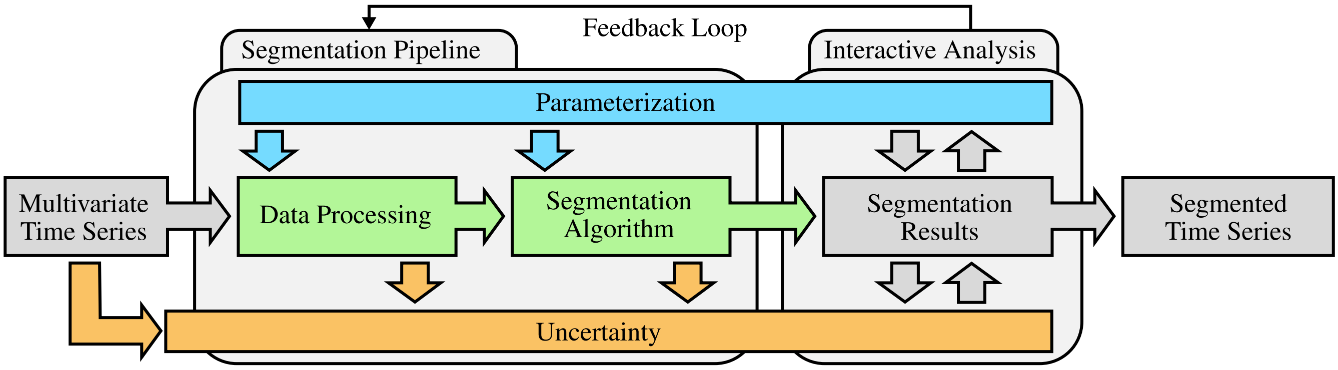

Figure 1: *Pipeline for the segmentation of multivariate time series. Different data processing routines may be applied to make the data usable and useful, followed by a segmentation algorithm. Several parameters are required by the algorithms of the pipeline. Information about value and result uncertainties is collected throughout the pipeline. These uncertainties may influence the initiation of re-calculation in the pipeline.*

mentation results, a careful selection of calculations is desirable. In this connection, the informed refinement of parameter configurations for relevant subspaces can make the workflow of domain experts more effective and efficient. Visual-interactive techniques can support users in the exploration of pre-calculated results to foster informed decisions about which algorithms to choose and which parameter values to prefer.

We contribute a segmentation workflow for multivariate time series data that allows both the calculation of large numbers of segmentation results with a segmentation pipeline and the interactive visual analysis of multiple competing results. The workflow fosters the in-depth analysis of segmentation results as well as refinement of algorithms and parameters and thus facilitates an iterative refinement approach. Domain experts can make informed decisions, effectively using necessary re-calculation cycles for parameter refinements and reducing uncertainty in the results. Our primary contributions are as follows:

- The conceptualization of a segmentation pipeline for selecting and customizing a segmentation process.
- An interactive and iterative analysis approach that fosters the exploration and in-depth analysis of segmentation results along with their influencing algorithms, parameters, and occurring uncertainties.
- A usage scenario of the segmentation workflow demonstrating how domain experts can apply implementations of the segmentation pipeline together with the interactive analysis approach, coupled with a feedback loop.

2. Approach

Our workflow consists of two parts: a *segmentation pipeline* and an *interactive visual analysis* step (see Figure 1). The segmentation pipeline allows building a cascade of algorithmic routines, subdivided into two core steps: time series *processing* and *segmentation* (see Section 2.1). The visual-interactive analysis facilitates the exploration of large numbers of segmentation results from different algorithms, the investigation of parameter spaces, the assessment of different types of uncertainty information, and the re-initialization of the segmentation pipeline based on gained insights (see Section 2.2).

2.1. The Segmentation Pipeline

Design Goals From the collaborations in various use cases in activity recognition, we abstract four design goals for our segmentation pipeline. First, the pipeline is general in a way that it can be applied to various use cases and application domains. Second, it supports the definition of individual algorithmic routines to be specific towards individual data, users, and tasks. Third, parameters are disclosed and can be defined externally, e.g., initiated from a visual analysis environment. Fourth, additional uncertainty information is recorded and propagated alongside the algorithmic routines and segmentation results.

Description of Segmentation Pipeline Research and practice in data mining and machine learning led to a vast amount of algorithms and techniques for processing and transforming multivariate time series. For the sake of compactness, we refer to recent taxonomies and surveys which provide an in-depth overview [Mör06, Fu11]. At a glance, we differentiate between algorithms for processing multivariate time series data [Ber15] and for segmentation modeling [FMH16]. Processing includes cleansing [KHP*11], pre-processing [BRG*12], or sampling [Fu11]. The segmentation algorithm splits the time series into smaller, yet more meaningful intervals, making use of supervised or unsupervised machine learning models [BDV*17], specific time series segmentation algorithms [KCHP04], or feature-based approaches employed in time series data mining [LKLC03]. Parameters required by individual algorithms are collected in a parameter set, and made available to the user. By design, implementations of included algorithms provide default values for every parameter to ease initial segmentation calculations. Finally, the pipeline supports recording of information about data and algorithm uncertainty derived from the processing and segmenting steps.

Supported Types of Uncertainty Correa et al. [CCM09] suggest sourcing uncertainty from (i) the data and (ii) data transformations. Uncertainty can then be utilized to enhance the visual analysis in our interactive analysis step (see Figure 1). We consider uncertainties of the value and the result domain, which are important for an informed execution of the segmentation pipeline. *Value uncertainty* is either obtained from uncertainties inherent in the data input [OM02] or reflects the effect of algorithmic routines applied to the value domain (e.g., noise reduction). *Result uncertainty* is generated by the segmentation algorithms and is represented by the likelihood of segments over time. Changes of result uncertainty over time reflect transitions between different types of segments.

We are currently working with two implementations of the segmentation pipeline, both used for different use cases for activity

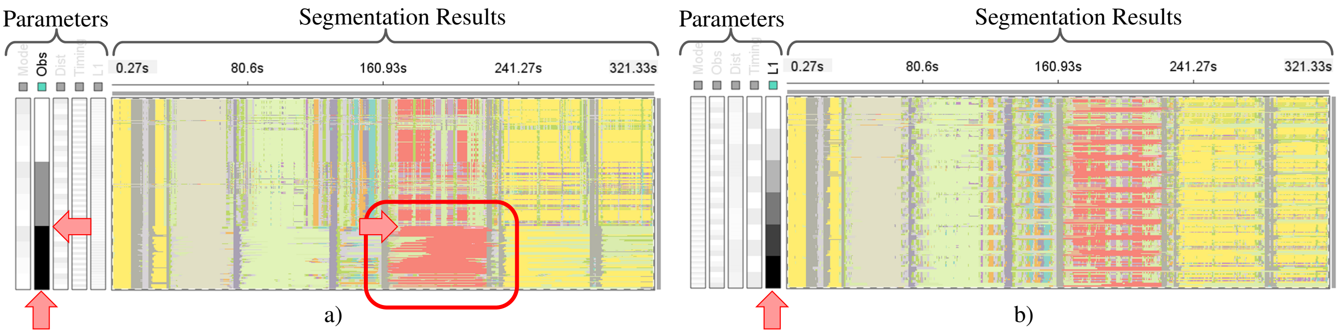

Figure 2: *Visualizations with a parameter sorting for two different parameters. a) Structured segments correlate with the values of the second parameter, indicating a high influence of the parameter. The upper edge of the red structure matches with a change of the parameter values. A resampling in this parameter range is likely to produce new insights. b) Scattered segments signify little influence of the fifth parameter.*

recognition (i) in ambient assisted living and (ii) for human motion capture data. With theses implementations, domain experts can apply our interactive visual analysis approach, and thus close the feedback loop proposed in the conceptual workflow.

2.2. Interactive Visual Analysis

Design Goals According to the working practices of the domain experts, we differentiate two primary design goals to facilitate the selection of a well suited segmentation result. First, the interactive visual analysis should be scalable to large amounts of segmentation results. Second, the automated segmentation should be complemented by the selection and adaption of algorithms and parameter values, as well as the exploration of inherent uncertainty types.

Parameter selection: The influence of different parameterizations might not be easy to understand [TWSM*11]. Thus, an interactive visual analysis is needed

- to investigate the influence of each single parameter as well as sets of multiple parameters on the resulting segments
- to explore the relationship between parameter settings and the quality of segmentation results
- to ultimately select the most appropriate configuration in a systematic way

Uncertainty assessment: To address challenges related to uncertainty, our goal is to communicate different types of uncertainty information captured throughout the pipeline to the user, which can have significant impact on the trustworthiness of an algorithm [SSK*16]. A comprehensive uncertainty analysis means

- to assess value uncertainty and result uncertainty within the segmentation results
- to compare uncertainties of alternative segmentation algorithms and parameterizations
- to obtain detailed uncertainty information if required

Visual Analysis Approach We introduce different views that can be used and combined to interactively analyze multiple segmentation results. The overarching design is a row-wise visualization of segmentation results, where segments are shown as individual color-coded bands. We provide two complementary views to allow the analysis of the parameter space and the investigation of different types of uncertainty. The insights gained from parameter and uncertainty analysis can subsequently be used to change algorithms and parameters of the pipeline.

We provide an overview of the parameter space in concert with corresponding segmentation results (see Figure 2). The parameter settings are located at the left with a column for the value distribution of each parameter. Rows depict values of individual parameter configurations. Just arranging the segmented time series in a row-wise fashion leads to cluttered images. Hence, users can sort the data either w.r.t. segmentation results, or parameter values. Sorting based on segments helps inspecting structures like patterns, similarities, or differences in the segmentation results. In turn, parameter sorting facilitates the investigation of parameter influence. If changes of segments correlate with changes of parameter values, it is likely that the parameter has a high influence. For example, the red box in Figure 2a shows a structure with long red segments that correlate with the second parameter, indicating a strong parameter influence. Figure 2b is sorted by another parameter, but only shows scattered segments. This signifies only a minor influence of that parameter. Significant changes of segment properties can indicate that the used sampling of the parameter space might not be sufficient (e.g., on the edges of observed structures as depicted in Figure 2a). The visualization and sorting strategies help to identify these ranges and thus provide a means to steer the parameterization of re-calculations. However, in this view it is not possible to inspect the impact of uncertainties on the depicted segmentation results.

Thus, we provide another view to communicate different relevant uncertainties in the segmentation pipeline (see Section 2.1). The overview representation (see Figure 3a) allows the exploration and visual comparison of multiple segmentation results calculated with different algorithms and/or parameters. We use color hue to indicate the dominating segment types over time and color gradient (fading color saturation) to depict the result uncertainty of these segments (according to insights gained for the visualization of the value uncertainty [CG14] and temporal uncertainty [GBFM16]). The color gradient technique also scales for the visualization of large numbers of competing results. To compare and explore the uncertainties further, an on-demand detail view is used that also allows the assessment of result and value uncertainties for individual segmentation results (see Figure 3b_{1-2}). We use a standard line chart to depict the likelihood of individual segment types (e.g., different types of activities) over time as calculated by the segmentation algorithm (see Figure 3b_1). High values indicate high likelihood of a segment type. In Figure 3b_1 first the purple segment type is most likely, followed by a short blue segment, until a green segment type is most probable. The value uncertainty is visualized by gray value gradient over time to highlight "hot spots" of high value uncertainty. This type of representation is often used to show data quality metrics [XWRH07] and was used in earlier work to communicate probabilities [RLB*15].

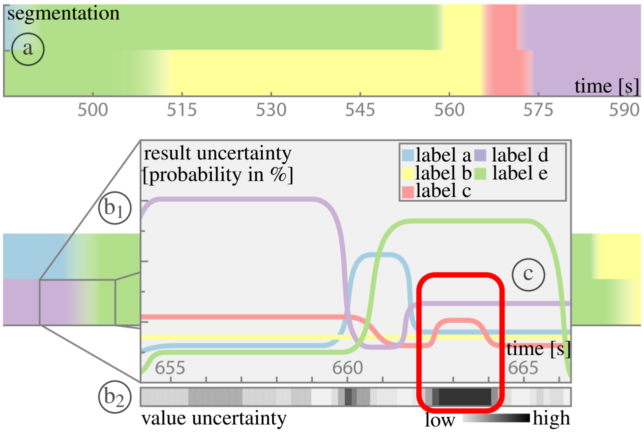

Figure 3: *Interactive exploration of value and result uncertainty. The upper view (a) uses a color gradient to depict result uncertainties of dominating segments over time (for two segmentation results in this case). Details about uncertainties can be obtained with an interactive overlay technique: line charts depict the likelihood of segment labels over time (b_1) and a heat-band technique shows the value uncertainty (b_2). Area (c) shows an interesting combination of result and value uncertainty, that needs further investigation.*

3. Usage Scenario

In this usage scenario, we describe how a domain expert can use our conceptualized segmentation workflow. Given an implementation of the segmentation pipeline (see Section 2.1) and our interactive visual analysis approach (see Section 2.2), the expert can initialize the algorithms and calculate the pipeline with a series of parameter configurations. Next, domain experts can analyze a plethora of segmentation results with a focus on involved parameters and/or resulting uncertainty information. Insights gained in the analysis help the domain expert to effectively trigger the feedback loop, i.e., algorithm and parameter tuning.

In general, domain experts can initialize the segmentation pipeline based on earlier approaches, collaborations with modeling experts, or a first guess (previous heuristic). With the pre-calculation, domain experts obtain initial segmentation results based on default parameters or initial parameter-sampling strategies. In later iterations, domain experts can re-calculate the pipeline with a better understanding of how to refine the parameter configurations, derived from the interactive analysis process. In the interactive analysis step, domain experts may want to gain a comprehensive overview of the segmentation results first. This can be achieved either by focusing on parameter selection (see Figure 2) or under consideration of different types of uncertainty (see Figure 3). Domain experts then can decide whether to approve individual segmentation results or carry out parameter and uncertainty analysis to identify more meaningful parameter configurations.

Interactive Parameter Analysis For a parameter space analysis the domain experts can start by inspecting the influence of each individual parameter. For this, experts can sort segmentation results by the values of individual parameters (Figure 2). If experts infer that a particular parameter hardly has an influence on the results, the parameter is excluded from further inspection. In a next step, domain experts can also investigate parameter combinations by consecutively sorting the rows according to multiple parameter values. Focusing on influential parameters helps to reduce the number of parameter combinations. To find a suitable configuration of an algorithm, new parameterizations need to be recalculated and evaluated. A more fine-grained sampling of influencing parameters is likely to produce new insights. If a particular parameter shows only significant results for one value (see Figure 2a), a narrower scope in value range could present a new direction of analysis.

Interactive Uncertainty Assessment Another way for domain experts to judge the suitability of chosen algorithms and parameter settings is to analyze the uncertainty information provided by the segmentation pipeline. In a first step, domain experts compare the result uncertainty of multiple segmentation results. Considering Figure 3a, a core finding is the disagreement of the (here only) two segmentation results with regard to the green segment type. Next, the experts can focus on more detailed uncertainty information to better understand which parameter values require adaption. Figure 3b shows details about the transition from one dominating segment type (purple) to another (green). The time interval marked by a red border reveals two other findings. First, at the bottom of the view (Figure 3b_2) an interval of particularly high value uncertainty can be observed. Second, this high value uncertainty correlates with an increased probability of the red segment type, as can be seen in the result uncertainty distribution (see Figure 3c). This is a clear indication to investigate the impact of this interesting combination of value and result uncertainty on the employed algorithms and parameterizations.

Triggering the Feedback Loop Informed by the insights gained from parameter and uncertainty analysis, the domain experts can further adjust algorithmic routines and parameter configurations of the segmentation pipeline. Re-calculation of the pipeline with new results leads to the next interactive visual analysis iteration.

4. Conclusion

We presented a conceptual workflow for the segmentation of multivariate times series that tackles challenges associated with the interplay between pre-calculated segmentation results and their visual analysis. The workflow describes the assembly of different algorithmic routines to a segmentation pipeline with parameters that can be triggered externally, e.g., from a visual analysis tool. Moreover, to foster an informed decision process, the pipeline supports the propagation and communication of different types of uncertainty information (inherent in the data or introduced by the utilized algorithms). Finally, we demonstrated how the workflow can be conflated with visual-interactive interfaces for the comparative analysis of multiple segmentation results. The approach overcomes trial-and-error scenarios by allowing users to make informed decisions on algorithm and parameter choices by feeding information about algorithm, parameter, and uncertainty into the analysis. Future work includes the application of the workflow with other user groups. In particular, we assume that it may be interesting to investigate differences between a model-centered perspective of data mining experts and a data-centered perspective of domain experts. In addition, we plan to investigate the usefulness of the pipeline in progressive analytics scenarios.

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