Fuzzy Feature Tracking: Visual Analysis of Industrial 4D-XCT Data

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Abstract

In-situ analysis is becoming increasingly important in the evaluation of existing as well as novel materials and components. In this domain, specialists require answers on questions such as: *How does a process change internal and external structures of a component?* or *How do the internal features evolve?*

In this work, we present a novel integrated visual analysis tool to evaluate series of X-ray Computed Tomography (XCT) data. We therefore process volume datasets of a series of XCT scans, which non destructively cover the evolution of a process by in-situ scans. After the extraction of individual features, a feature tracking algorithm is applied to detect changes of features throughout the series as *events*. We distinguish between *creation, continuation, split, merge* and *dissipation* events. As an explicit tracking is not always possible, we introduce the computation of a *Tracking Uncertainty*. We visualize the data together with the determined events in multiple linked-views, each emphasizing individual aspects of the 4D-XCT dataset series: A *Volume Player* and a *3D Data View* show the spatial feature information, whereas the global overview of the feature evolution is visualized in the *Event Explorer*. The *Event Explorer* allows for interactive exploration and selection of the events of interest. The selection is further used as basis to calculate a *Fuzzy Tracking Graph* visualizing the global evolution of the features over the whole series.

We finally demonstrate the results and advantages of the proposed tool using various real world applications, such as a wood shrinkage analysis and an AlSiC alloy under thermal load.

Keywords: in-situ test, 4D-XCT, uncertainty calculation, uncertainty visualization

1. Introduction and Motivation

In recent years a clear trend has formed in industry towards designing tailored materials and components as well as enhancing existing ones. No matter if it is the understanding of specific manufacturing procedures or the aging of components under extreme conditions, a characterization of both internal and external structures is essential. In order to gain insight into materials and components, non-destructive testing (NDT) techniques are the methods of choice, in order to reuse the specimens for further processing or testing.

A well known NDT method is 3D X-ray Computed Tomography (XCT). XCT non-destructively generates a 3D volumetric representation of the specimen from a series of 2D X-ray attenuation images. The specimen is placed on a rotary plate between X-ray source and detector. The detector acquires 2D projection images at each angular position of the rotary plate, recording the attenuation of the X-rays through the specimen. After acquiring the series of 2D projection images, a 3D volumetric dataset is reconstructed. XCT allows the domain experts to gain new insights into material systems and has thus become a highly attractive method in various engineering disciplines.

When using a series of XCT scans, even *processes* may be investigated for in-situ analyses, e.g., over time or under certain load conditions. We refer to the resulting *4D-XCT data* as *series* where each *step* corresponds to a single *dataset*, respectively a single XCT scan.

For in-situ analysis in our work, XCT scans are acquired at predefined stages of a process. The process is either continuing during the whole data acquisition (in-situ), e.g., continuously heating the specimen and XCT scanning at predefined temperature steps, or the process is interrupted (interrupted in-situ), e.g., keeping load conditions constant during the XCT scan and then continuing the process. In either case analyzing the individual steps and their correlations leads to an improved understanding of the material or its manufacturing procedure.

Regarding the analysis and visualization of industrial XCT data, various techniques are used for analyzing a specimen at a defined condition (at a single step), but not a process the specimen is exposed to. Thus, in this work we go one step further and consider this new dimension: the evolution of a specimen being subjected to an ongoing process. This additional dimension leads to new challenges for both analysis and visualization: *Features* have to be identified and tracked throughout the complete dataset series. Such features may be voids, inclusions, particles, etc.. Features may as well change throughout the process, e.g., voids grow and merge under thermal loading. We refer to these changes as *events* which need to be determined from one step of the process to the next regarding the *creation, continuation, split, merge* and *dissipation* of features. Thus an event may be considered as the connection of features from one step the other. Since features also may move over time, an explicit tracking is not always possible. For example, Schöbel et al. [1] investigated voids in SiC particle reinforced aluminum (AlSic) during a heating cycle. In this application it is of high interest, how the voids decrease during heating and increase while cooling down. Figure 1 shows cross-sectional images of two adjacent time-steps of the cooling process from 400 °C (A)

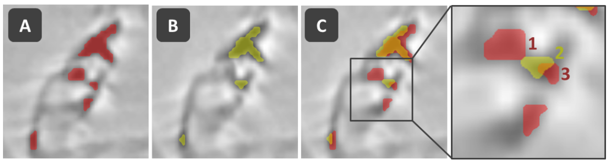

Figure 1: Voids in SiC particle reinforced aluminum (AlSic). (A and B) Cross-sectional images of two adjacent time-steps of the cooling process from (A) 400 °C down to (B) 300 °C. (C) Overlay of (A) and (B) with a zoom-in indicating that void 2 has to be assigned either to void 1 or to void 3.

down to 300 °C (B). The voids were extracted in their work by thresholding and colored in red (A) and yellow (B). Figure 1 (C) depicts an overlay of (A) and (B) as well as a zoom-in indicating that void 2 has to be assigned either to void 1 or 3. As void 2 touches void 1 and slightly overlaps with void 3, a distinct assignment to void 1 or 3 is not possible. To address this problem, we introduce the computation of a *Tracking Uncertainty* in our work. The Tracking Uncertainty is calculated for all potential features in a certain neighborhood and based on the features' volume overlap and volume ratio. As a result, the void tracking in Figure 1 (C) is fuzzy and void 2 is assigned to both voids 1 and 3, each with a specific Tracking Uncertainty. We refer to this tracking approach as *Fuzzy Feature Tracking*. To analyze the Fuzzy Feature Tracking results, novel visualization and interaction approaches are required.

In the following sections we present a visual analysis framework to explore 4D-XCT dataset series and to handle the different aspects of its spatial information as well as the evolution of this information throughout the series. We apply our approach to show results on two real-world in-situ applications. The first application area is the shrinkage of beech wood, where we focus on the voids between wood fibers during a drying-out process. In a second analysis we present results of a void formation in AlSiC alloys during a heating up and cooling down cycle.

2. Workflow and Task Analysis

When analyzing 4D-XCT dataset series, users currently have to search interesting features in 3D renderings or by scrolling through 2D slice images. The user needs to search for corresponding features in all other datasets manually, mostly in the same way he has found the interesting feature (e.g., by scrolling through slice images). Simple feature characteristics such as extents may be extracted with rulers or similar tools. This procedure is highly subjective and even for experienced domain specialists it is hard to find features of interest in all steps of the dataset series. Apart from the subjectivity, such a workflow is rather time-consuming and error prone. In this work, we aim to overcome these drawbacks by designing a visual analysis tool for interactive exploration of 4D-XCT dataset series. We collaborated in this project with various company partners and material scientists in application areas such as analysis of metal alloys and wood analysis. Together with these domain partners we defined a detailed list of requirements for our tool. Although the applications are quite different, the experts' requests converged in the following questions: How are feature properties distributed at a certain step in the dataset series? How many features are created, continuing, splitting, merging or dissipating at a specific step? Which features are involved in a split or merge event and where are they located? How does a feature evolve regarding its properties and in which events is it involved? Based on these demands, we derived the following main tasks:

- **T1:** Determine events (creation, continuation, split, merge, dissipation) from one step to the next.
- **T2:** Visualize spatial information including the extracted features for each step.
- **T3:** Visualize an overview of the events and the corresponding feature properties.
- **T4:** Visualize an overview of the events and how they connect features from one step to the next.

To solve these tasks, we implemented a visual analysis tool which integrates the following features:

Fuzzy Feature Tracking: Features are tracked from one step to the next (T1). To provide feature tracking information along the whole dataset series. If features are created, we determine continuing, splitting, merging or dissipating. As the events are not clearly distinguishable in all cases a Tracking Uncertainty is computed for each event.

Volume Player: Combining the need for visualizing spatial feature information (T2) and for providing an overview of events (T3), volume blending is applied on two subsequent steps in the dataset series, rendering smooth transitions between the steps.

3D Data View: 3D renderings of all steps arranged in a row show all determined features (T2). Individual features may be color-coded according to the assigned event type.

Event Explorer: The combination of an events overview and the feature properties is achieved in the Event Explorer (T3). The Event Explorer consists of a row of scatter plots, where each plot provides a snapshot of a single step in the series. Events may be plotted according to user-defined feature properties as well as their event type. All views are linked together, so a selection in the Event Explorer updates all other views and allows for a detailed exploration of the data. For example, a merged feature of interest may be filtered in the scatter plot. Then its origin as well as how it evolves may be traced along all steps in the series in the spatial domain as well as throughout the complete series.

Fuzzy Tracking Graph: The Fuzzy Tracking Graph visualizes the evolution of features combined with their events with respect to each other (T4). The uncertainty information per event is integrated using Fuzzy Feature Tracking and shows more than one assigned feature for an event. Therefore, the opacity of the vertices and edges of the Fuzzy Tracking Graph are adjusted according to the Tracking Uncertainty of the events.

3. Related Work

Regarding visual analysis of industrial XCT data, several approaches have been presented recently. Fritz et al. [2] presented a method to analyze graphite particles in ductile iron and steel fibers in reinforced sprayed concrete. Reh et al. [3] introduced an approach to explore pores in carbon fiber reinforced polymers. The FiberScout [4] allows domain experts to explore the characteristics of fiber reinforced polymers. All these techniques share the fact that they analyze a single condition of a specimen, but not a process the specimen is exposed to.

Regarding the analysis of dataset series (mainly time-series) a wide-spread variety of approaches have been presented. Aigner et al. [5] overview time-oriented visualizations from many application domains. In literature approaches such as ThemeRiver [6] or Stacked Graphs [7] cover research questions such as the evolution of thematic variations over time within a large collection of documents or the presentation of large datasets to a general audience. Waser et al. [8] presented World Lines for steering multiple simulation runs. In their approach tracks sharing a common time axis are shown in a tree. Bajaj et al. [9] presented the hypervolume visualization for informative visualization of scalar fields embedded in n-dimensional spaces. Liu et al. [10] presented an approach for data mining on time series in which automatic time series model identification and automatic outlier detection are employed. Additional related work is found concerning morphological data analysis of time series data [11, 12]. As all these approaches are not capable of analyzing 3D volumetric data these techniques are not applicable for 4D-XCT applications.

In the medical domain several papers report on 4D data analysis. Köhler et al. [13] published an approach for the extraction of vortex flow in the aorta and pulmonary artery incorporating line predicates. This technique evaluates time-resolved and spatial phase-contrast magnetic resonance imaging data (4D PC-MRI) and facilitates reliable measuring of 3D flow for qualitative and quantitative analysis of the patient-specific hemodynamics. A related method for pre-clinical cardiovascular research provides tools to interactively explore 4D blood-flow data and to depict essential blood-flow characteristics [14]. Both methods share the same imaging modality with temporal resolution varying from 14 to 21 time-steps with about 50 ms difference between each time-step. In the field of industrial XCT yet no 4D-XCT visual analysis techniques have been proposed so far.

As we apply and test our methods on the data of different real world applications such as AlSic alloys and beech wood, we consider feature extraction as being out of scope for this work and refer the reader to the segmentation algorithms used in the corresponding papers [1, 15].

Feature Tracking: Based on the extracted features, an essential pre-processing stage is the tracking of features along the dataset series. Altendorfer [16] tracks voids in the AlSiC alloys dataset series. After registering the volumetric datasets and a subsequent segmentation of the voids overlaid void contours are visualized. As this tracking is not automatic, it is insufficient for our domain experts' needs. For automatic tracking of features two general approaches are considered as most relevant for this work: One approach is to track features based on voxel data. For instance, Silver et al. [17] track 3D features in computational fluid dynamics datasets. The spatial overlap of the features is calculated with boolean difference operations of the voxel data. The second approach is to calculate feature properties such as size and position of each feature and perform the tracking based on the extracted properties. Samtaney et al. [18] introduced such a tracking method. In which features in 2D and 3D computational fluid dynamics simulations are calculated. The features are then tracked by finding potential correspondences in adjacent time-steps and by subsequently comparing their feature properties. As the voxel-based approach is more memory- and time-consuming, we decided to use feature properties for our Fuzzy Feature Tracking and extend it with the calculation of the Tracking Uncertainty.

Tracking Graph Visualization: After tracking features in the dataset series the tracking result needs to be visualized in an intuitive way. Besides coloring of tracked features along time-steps [17], a directed acyclic graph is a common representation to show the evolution of a feature over time [18, 17]. For visualizing such graphs an appropriate graph layout using a single spatial dimension to indicate time or evolution is called *tracking graph*. Each feature is represented by a track. Tracks may start, continue, merge, split or end with respect to the corresponding feature events creation, continuation, split, merge and dissipation. We are using a tracking graph in this work as well. When visualizing a tracking graph the main challenge is found in minimizing the edge crossings between the different steps. Widanagamaachchi et al. [19] used tracking graphs in a system for the exploration of combustion simulations. They implemented a median heuristic approach to solve their edge crossing minimization problem. As their solution showed reasonable results even for large graphs, a median heuristic [20] was used as well minimizing the edge crossings in our Fuzzy Tracking Graph.

Uncertainty Visualization: To communicate information on the calculated Tracking Uncertainty, an adequate technique for uncertainty visualization is needed. In the domain of industrial X-ray computed tomography several approaches have been recently published with regard to uncertainty visualization. Heinzl et al. [21] presented a workflow for the analysis of multi-material components in terms of probability and uncertainty. With MObjects [3] an approach was introduced for the visualization of mean objects aggregating internal structures in carbon fiber reinforced polymers. Amirkhanov et al. [22] focused in their work on fuzzy metrology of real-world components. As the component surface is not explicit in an XCT scan due to artifacts and noise, a certain positional uncertainty in the data is given. Uncertainty is encoded by varying the thickness of reference shapes, as well as by using boxplots as extension to tolerance widgets. In a different domain Collins et al. [23] have presented a system to support decision-making of automated speech-recognition results, encoding uncertainty in graphs. Typically such systems present a best-guess result to the user although deviating results may be correct. In this solution, the authors visualize the recognized sentence as well as alternative words in a lattice graph. Each recognized word is represented by a vertex showing the word in the label. Uncertainty is encoded here by the vertex position, fill hue and a border transparency. For our Fuzzy Tracking Graph visualization we applied the idea of encoding uncertainty on the vertices. Con-

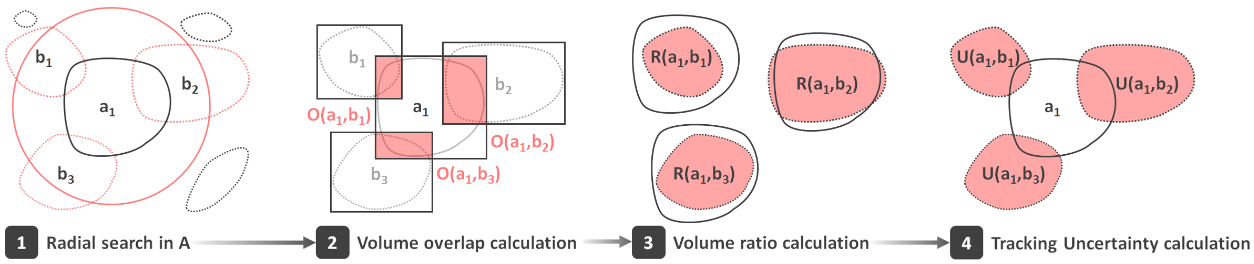

Figure 2: Fuzzy Feature Tracking to find probable corresponding features for A in B. (1) Radial search at the centroid position of a_i in B. (2) Volume overlap calculation for each probable feature in B based on bounding boxes. (3) Volume ratio calculation for each probable feature in B. (4) Tracking Uncertainty calculation for each correspondence from a_1 to the probable features b_1, b_2 and b_3 in B.

sidering the graph layout with minimized edge crossings in our Fuzzy Tracking Graph, we omit the uncertainty encoding by changing the vertex position. But we color vertices and edges according to their event type and encode the Tracking Uncertainty by varying the opacity.

4. Preprocessing

Specimens may change their size during the 4D-XCT scans of a process (e.g., an alloy specimen expanding under thermal load) and in consequence also features may change or move. To compensate on these changes, the datasets need to be registered with each other. In general, registration techniques may be split into rigid techniques requiring affine transformations between fixed and moving image [24] and non-rigid techniques which also deal with local feature deformations [25]. For the dataset series analyzed in this work, the underlying processes are global processes and thus the specimens and features are expected to show uniform movement in all directions. In addition, the intervals between the steps in our dataset series are short. So movements of specimens and their features are either limited or do not exist at all. Thus, a rigid registration is sufficient for our application scenarios. We apply mutual information based registration as presented by Mattes et al. [25] to account for deviations of greyvalues in the XCT scans of our dataset series. If the process to be analyzed leads to deforming structures or features moving or expanding in one direction, i.e., in the case of tensile tests, the registration component needs to be replaced with deformable registration techniques. After registration, the features are extracted using thresholding methods [15, 1]. A connected-components filter using a 26-connectivity labels the features uniquely. Thus, the extracted features consist of sets of labeled voxels within a regular volumetric grid. Finally, the properties of interest, such as feature volume, extent, and centroid are calculated for all features in a dataset. These preprocessing steps are executed for all datasets in the series.

5. Fuzzy Feature Tracking

One of the main tasks in this work is to track features within a 4D-XCT dataset series. For each feature all probable correspondences need to be determined and one of the five events creation, continuation, split, merge and dissipation needs to be assigned. We thus calculate for each correspondence between two features a simple Tracking Uncertainty based on the individual feature properties. The Tracking Uncertainty makes use of the volume overlap as well as the volume ratio of a feature and its correspondences: Two features with the same volume at the same position have a low Tracking Uncertainty, whereas two features with different sizes at diverse positions lead to a high Tracking Uncertainty. Figure 2 illustrates the proposed determination of correspondences for a feature a_1 in 2D: Consider A and B as two adjacent steps in the dataset series. Let a_i be a feature in dataset A with a number of n_A features and b_j be a feature in dataset B containing n_B features. For each feature a_i in A a corresponding feature b_j in B has to be found and an event assigned. For each feature all corresponding features are stored in a list of *correspondences*. Solid lines show features in A whereas the dotted lines highlight features in B. The following steps are processed in sequence:

Radial search: A radial search with radius r is performed at the center of a_i in dataset A, where r is user-defined. Found corresponding features for a_i are stored in *correspondences*.

Volume overlap calculation: As our algorithm is based on feature properties and in order to reduce calculation times, the volume overlap $O(a_i, b_j)$ is calculated using bounding boxes. The result is normalized to 1.

Volume ratio calculation: The volume ratio $R(a_i, b_j)$ of two features a_i and b_j is calculated dividing the smaller volume of the features a_i and b_j by the larger one.

Tracking Uncertainty calculation: Based on the volume overlap $O(a_i, b_j)$ and ratio $R(a_i, b_j)$ a Tracking Uncertainty $U(a_i, b_j)$ is calculated.

$$U(a_i, b_j) = 1 - (O(a_i, b_j)w_o + R(a_i, b_j)w_r). \qquad (1)$$

As the material behavior of how features may change their size in the dataset series is dependent on the used materials and application scenarios, $O(a_i, b_j)$ and $R(a_i, b_j)$ can be weighted with the user-defined weights w_o and w_r, where $w_o + w_r = 1$. Following this sequence we have identified the probable correspondences for all features from A to B. For the following event assignment, we also need to identify the correspondences from B to A and repeat the steps above in the other direction. Having all correspondences from A to B and from B to A, we go through the correspondences and assign the event types (see Algorithm 1 regarding event assignment).

Creation: A creation event is assumed, if a feature is present

in B without a corresponding feature in A. This is valid for a feature b_j if $b_j.correspondences().size() = 0$. In this case, a *creation* event is assigned.
Continuation: Features which are present in A and which have a correspondence in B *continue* from one step to the next. Here we decide between two options. If only one corresponding feature b_j for a_i exists, so $a_i.correspondences().size() = 1$ is valid, we assign the continuation event. If $a_i.correspondences().size() > 1$, either a split event or a continuation event is possible. As a feature may change its size or position from A to B, we introduce two user-defined thresholds t_O and t_R to consider these changes. If $t_O \leq O(a_i, b_j)$ and $t_R \leq R(a_i, b_j)$ is valid, a continuation event is assigned, otherwise a split event is used.
Split: A feature in A can *split* into two or more features in B. This is valid if $a_i.correspondences().size() > 1$, $t_O > O(a_i, b_j)$ and $t_R > R(a_i, b_j)$.
Merge: Two or more features from A *merge* to a feature in B if $b_i.correspondences().size() > 1$, $t_O > O(a_i, b_j)$ and $t_R > R(a_i, b_j)$ is valid.
Dissipation: A feature disappeared, if it is present in A and no correspondence is found in B. So if $a_i.correspondences().size() = 0$, we assign a *dissipation* event.
For the datasets used in this work, all calculations are performed in 3D. We apply the Fuzzy Feature Tracking on each step of the dataset series and its adjacent one. The found correspondences over the whole series are the basis of our visual analysis system described in the following Section.

6. Visual Analysis of 4D-XCT Data

Our tool features multiple linked-views to fulfill the tasks as identified in section 2. Each of the individual views emphasizes a certain aspect of the dataset series. Figure 4 shows the graphical user interface of the implemented tool. The tool is implemented in our custom analysis framework using ITK, VTK and Qt toolkits. The Fuzzy Feature Tracking results are calculated for all dataset series within several seconds on an Intel Dual Xeon E5-2667 workstation allowing for interactive analysis.
Volume Player: The Volume Player shows control elements to traverse the different steps of a dataset series (see Figure 4 (A)). In a list steps of interest may be selected. When playing the selected sequence, the corresponding volumetric datasets are shown in a 3D renderer. As this may lead to coarse transitions in the rendering, we integrated volume blending to enable smooth transitions. Volume blending may be applied on both raw data and labeled data showing selected features and is facilitated by setting linear transition functions for two adjacent steps $t(n)$ and $t(n + 1)$. The opacity for $t(n)$ is decreased over

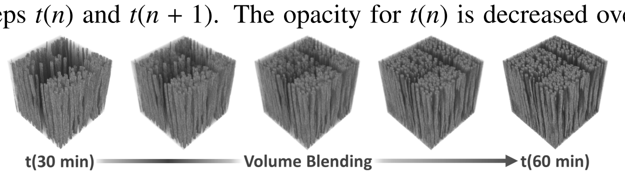

Figure 3: Five volume blending steps between the two steps $t(30\ min)$ and $t(60\ min)$ of the wood dry-out process dataset series.

```
Data: Datasets A, B with features and correspondences
Result: Assigned events
forall Features a_i in A do
    if a_i.correspondences().size() = 0 then
        SetEvent(Dissipation);
    else if a_i.correspondences().size() = 1 then
        SetEvent(Continuation);
    else if a_i.correspondences().size() > 1 then
        forall Features b_j in a_i.correspondences() do
            if t_O ≤ O(a_i, b_j) and t_R ≤ R(a_i, b_j) then
                SetEvent(Continuation);
            else
                SetEvent(Split);
            end
        end
    end
end
forall Features b_j in B do
    if b_j.correspondences().size() = 0 then
        SetEvent(Creation);
    else if b_j.correspondences().size() = 1 then
        SetEvent(Continuation);
    else if b_j.correspondences().size() > 1 then
        forall Features a_i in b_j.correspondences() do
            if t_O ≤ O(a_i, b_j) and t_R ≤ R(a_i, b_j) then
                SetEvent(Continuation);
            else
                SetEvent(Merge);
            end
        end
    end
end
```

Algorithm 1: Algorithm for assigning events.

time whereas the opacity for $t(n+1)$ is increased. This approach leads to a smooth transition between $t(n)$ and $t(n + 1)$. Figure 3 shows an example of the wood dry-out process, namely five volume blending transitions between the two steps $t(30\ min)$ and $t(60\ min)$.
3D Data View: The 3D Data View depicts a series of labeled data as 3D renderings in a row mimicking a film strip view of the series (see Figure 4 (B)). In 3D renderings for each timestep, the spatial information for all individual features is shown. For the interaction with the data, rotation, translation and zooming functions are available. The interactions are connected along all renderers. For the visualization transfer-functions are used. As event types were assigned to all features in the Fuzzy Feature Tracking, we color the features according to the assigned event types. Shading is disabled in the renderers, as it would deteriorate the perception of small features. If a selection in the Event Explorer is done, the 3D Data View is updated. Unselected features are either shown in gray color with low opacity as context information or completely hidden.
Event Explorer: To show a global overview of events and feature properties, a row of scatter plots is used in the Event Explorer (one for each step in the dataset series see Figure 4 (C)). In the scatters plot the events assigned to features in the Fuzzy

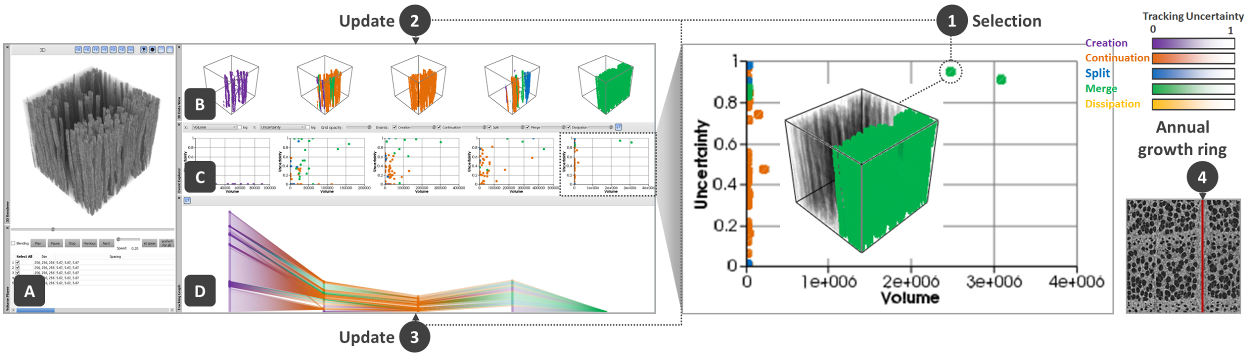

Figure 4: 4D-XCT visual analysis tool consisting of four linked-views: (A) Volume Player. (B) 3D Data View. (C) Event Explorer. (D) Fuzzy Tracking Graph. (1) A selection in the Event Explorer leads to an update (2 and 3) of the 3D Data View and the Fuzzy Tracking Graph.

Feature Tracking are visualized as colored points. Each event type is set to a color. The scatter plots may be tailored to the user's preferences and the analysis task. The axes show user-defined feature properties, e.g., feature volume or Tracking Uncertainty, and may be switched to log scale if needed. In the applications shown in Section 7 the number of features vary from 6 to 195 per step but also higher numbers of events are supported. As this number may be higher for other applications, filtering event types is possible to avoid visual clutter of too many points in the plots. Furthermore, the opacity of the plotted points is adjustable, separately for each event type. Regarding interaction techniques, selecting, panning and zooming into the plots facilitate a detailed analysis of interesting clusters. Finally the tool allows a selection of events. As all views are linked, a selection of an event (see Figure 4 (1)) leads to an update of the 3D Data Views and the Fuzzy Tracking Graph (see Figure 4 (2 and 3)).

Fuzzy Tracking Graph: The Event Explorer shows an overview regarding the events assigned to features in the Fuzzy Feature Tracking. The Fuzzy Tracking Graph (see Figure 4 (D)) expands this overview with the evolution of the features being tracked and connected over the whole dataset series. One or more events may be selected in the Event Explorer (see Figure 5(1)). Based on the selection, all corresponding features in the subsequent and adjacent steps are used to build the graph. In the initial graph layout, all vertices of corresponding features are grouped regarding their step and stacked in Y direction. The steps are arranged in discrete *layers* along the spatial dimension in X direction to indicate their evolution. We refer to the vertex position in a layer as *rank* of the vertex. As the vertices have no specific rank order in Y direction, edges may cross and thus deteriorate visual perception of how events are connected (see Figure 5(2)). For this reason we employ edge-crossing minimization based on mean heuristics by Gansner et al. [20] (see Figure 5 (3)). In their approach vertex positions in each layer are permuted to minimize edge crossings in the graph. Spline control points for the edges as their algorithm is for graphs where edges can connect vertices in ranks that are not adjacent. Regarding our data we added a further constraint: Features may not skip a step and therefore edges can only connect vertices from adjacent ranks. For that reason we omitted spline control points. In the final step, we encode the event types and the Tracking Uncertainty (see Figure 5 (4)). We use the colors of the event types as in the other views for coloring the vertices and the edges of the graph. If an edge connects events with different event types, a color gradient is used. The Tracking Uncertainty is visualized through the opacity of the vertices and edges.

7. Results and Evaluation

We apply our proposed tool on two real world applications which are wood shrinkage analysis during dryout and an AlSiC alloy under thermal load.

Wood Shrinkage Analysis: Taylor et al. [15] observed the shrinkage behavior of European beech wood at the micro-scale. Wood consists of wood fibers. When drying out, voids in-between the fibers grow and merge through the cell walls of the fibers. The key aspect of the wood dry-out analysis is to track how these voids grow and merge over time. Therefore the dry-out process of wet wood was investigated in-situ with XCT. The XCT measurements were performed on a GE phoenix|xray nanotom with a 180 kV X-ray tube. The X-ray source current was set to 275 μA and, the voltage to 50 kV, and the integration time of the detector to 125 ms. 700 projections were acquired for each scan. The resulting datasets was 256 x 256 x 256 voxels in size using a voxelsize of 5.67 $(\mu m)^3$. The full series consists of 25 volumetric datasets. The relative humidity in the sample chamber was between 21 % and 19 % at a temperature between 21.8 ° C and 22.6 ° C. A 3 x 3 median filter was used for smoothing the data. The datasets scanned after 15, 20, 25, 30 and 60 minutes of the dry-out process show the most significant changes of the voids between the wood fibers. The voids and were extracted with the automatic thresholding algorithm as proposed by Otsu [26]. Figure 4 shows the results of our analysis. In the last step of the Event Explorer, two merge events with a high volume were observed. Thus we selected both one after the other. Figure 4 shows the updated Fuzzy Tracking Graphs which give an overview, of how the voids were created and merged over time. The maximum of 92 events in step 1 led to 92 stacked nodes in the Fuzzy Tracking Graph and thus to visual clutter. The tracking results are however trace-

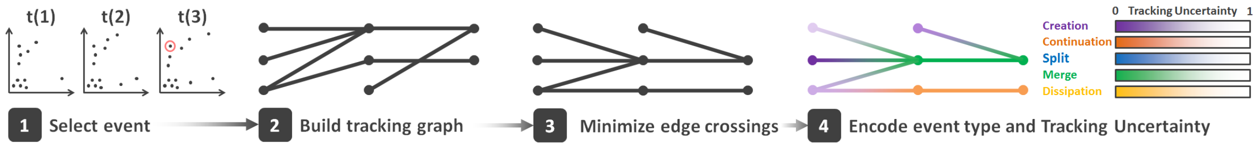

Figure 5: Calculation and visualization of the Fuzzy Tracking Graph: After an (1) event selection in the Event Explorer, (2) a tracking graph is built and the (3) edge crossings are minimized. Then (4) event types and Tracking Uncertainty are encoded.

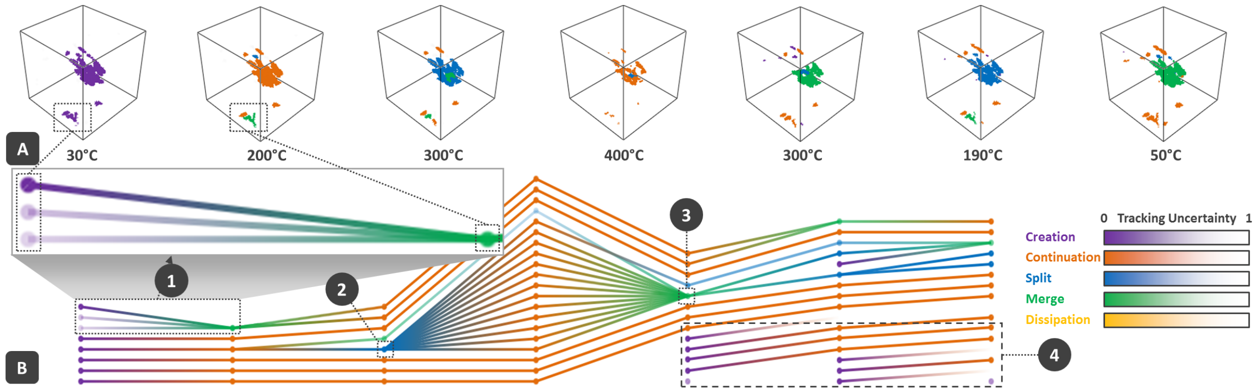

Figure 6: Results of the AlSiC dataset series: (A) 3D Data View of a void during a heating and cooling cycle (30 ° C → 200 ° C → 300 ° C → 400 ° C → 300 ° C → 190 ° C → 50 ° C). (B) Fuzzy Tracking Graph showing two areas (1 and 4) with encoded Tracking Uncertainty. (2 and 3) Highlighting of an interesting split (2) and merge (3) event for the sequence (300 ° C → 400 ° C → 300 ° C).

able because of the used coloring of event types. The varying Tracking Uncertainty can be explained as follows: Voids only originate in-between an uniform arrangement of wood fibers and thus many of them have nearly the same size before merging with others. Furthermore a high number of voids appear within small regions. Our result shows how the voids grow in the dataset series. During the dry-out process the large features merge from many smaller voids between the wood fibers as expected. Our domain experts further found using our tool that voids do not to merge across the barrier of an annual growth ring of the tree (see Figure 4 (1,4)).

AlSiC Alloys under Thermal Load: Schöbel et al. [1] investigated a heating cycle of SiC particle reinforced aluminum (AlSic). This material is of high industrial interest as it offers the high thermal conductivity of a metal with the low thermal expansion of a ceramic. Especially micro-voids in this material system and their evolution are of interest for the domain specialists. For the scan series, the material was analyzed under thermal load with synchrotron tomography at the ESFR ID15A beam-line in Grenoble. The specimen was heated up from 30 ° C to 400 ° C and cooled down to 50 ° C. As a result a dataset series covering the thermal cycle 30 ° C → 200 ° C → 300 ° C → 400 ° C → 300 ° C → 190 ° C → 50 ° C was acquired. The resulting scans show an extent of 400 x 400 x 400 voxels at an isotropic voxel size of 1.4 $(\mu m)^3$. We focussed on a region-of-interest with a size of 61 x 61 x 61 voxels showing a representative void area for our analysis. During this thermal cycle the volume fraction of micro-voids change. Voids decrease during heating and increase while cooling down. As these voids influence the thermal expansion of the material, their changes in size are of high interest. As the whole process of how the void splits and merges is of high interest for our domain experts, we did not filter the data by selecting specific events. Figure 6 (A) shows the 3D Data View with all seven steps. The features are colored according to their assigned event type. Figure 6 (B) shows the Fuzzy Tracking Graph of the whole dataset series. Two areas (see Figure 6 (1 and 4)) with encoded Tracking Uncertainty are highlighted. In the first step three features (see Figure 6 (1)) were created and assumed to merge in the second step, each with a different Tracking Uncertainty. Figure 6 (4) shows how new micro-voids are created and no continuing features in the adjacent steps are found. Regarding the application domain, Figures 6 (2 and 3) show an interesting split (2) and merge (3) event during the heating and cooling cycle from 300 ° C up to 400 ° C and down to 300 ° C. Selecting individual events in the Event Explorer was not necessary, as the number of micro-voids in the dataset series was low, showing between 6 and 20 events in a step. Especially the split event in Figure 6 (2) during heating and the merge event in Figure 6 (3) while cooling down show exactly which micro-voids are involved in this process and thus fully answers the questions of the domain experts.

8. Conclusions and Future Work

We have presented a visual analysis framework for the exploration of 4D-XCT dataset series. Based on a detailed task analysis, our tool was designed to address the different aspects of spatial data exploration and exploration of the dataset series itself. We extract individual features together with their properties track and visualize them between the steps of the dataset series. We assign each feature a corresponding event, i.e., creation, continuation, split, merge and dissipation and compute a Tracking Uncertainty between adjacent steps. For the visualization and analysis of this data, we introduced a 3D Data View mimicking a filmstrip view of 3D renderings for each dataset showing the spatial feature information. An Event Explorer shows the global overview of the dataset series in the form of scatter plots, one for each step. A Fuzzy Tracking Graph extends this concept to investigate the events' evolution throughout the series. We encode the Tracking Uncertainty by modulating the opacity of the nodes and edges. With the presented tool, an interactive analysis is facilitated by selecting events of interest in the Event Explorer which leads to an update of the 3D Data View and the Fuzzy Tracking Graph. As all our views are linked, event selections highlight corresponding features in the 3D Data View. We finally demonstrated our tool on the two real world applications of wood shrinkage analysis and AlSiC alloys under thermal load. For future work we will focus on further visual encodings for the Tracking Uncertainty as well as strategies to avoid visual clutter in the Fuzzy Tracking Graph. In addition we aim to analyze further in-situ applications such as tensile tests of fiber reinforced composites with our tool.

Limitations. Fuzzy Feature Tracking is designed to work with the data subjected to linear transformations. If changes between adjacent stages are very significant, this leads to the decreased precision. Visualization capacities of the Tracking Graph are limited in this respect and, during the visualization of large amount of features, the cluttering appears.

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