Visualization of Varying Hierarchies by Stable Layout of Voronoi Treemaps

Sebastian Hahn[1], Jonas Trümper[1], Dominik Moritz[2] and Jürgen Döllner[1]
Hasso-Plattner-Institute, Potsdam, Germany

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Abstract: Space-restricted techniques for visualizing hierarchies generally achieve high scalability and readability (e.g., tree maps, bundle views, sunburst). However, the visualization layout directly depends on the hierarchy, that is, small changes to the hierarchy can cause wide-ranging changes to the layout. For this reason, it is difficult to use these techniques to compare similar variants of a hierarchy because users are confronted with layouts that do not expose the expected similarity. Voronoi treemaps appear to be promising candidates to overcome this limitation. However, existing Voronoi treemap algorithms do not provide deterministic layouts or assume a fixed hierarchy. In this paper we present an extended layout algorithm for Voronoi treemaps that provides a high degree of layout similiarity for varying hierarchies, such as software-system hierarchies. The implementation uses a deterministic initial-distribution approach that reduces the variation in node positioning even if changes in the underlying hierarchy data occur. Compared to existing layout algorithms, our algorithm achieves lower error rates with respect to node areas in the case of weighted Voronoi diagrams, which we show in a comparative study.

1 INTRODUCTION

Space-restricted visualization of hierarchical data has been a well investigated research field for the last decades. Although most of the existing techniques perform well with respect to scalability, readability, and the aspect ratio of the items (i.e., the graphical representation of hierarchy nodes), the stability of the layout represents a major challenge. If the depiction of similar hierarchies (e.g., varying hierarchies) does not expose similar layouts, the usability is substantially restricted. Users need to analyze and correlate the visualization results to compare the hierarchy visualization and to detect changes.

Guerra-Gómez et al. (Guerra-Gómez et al., 2013) define five types of tree-comparison problems. In our case, we need to discern two comparison problems: The layout algorithm faces a type 3 problem ("positive and negative changes in leaf node values with aggregated values in the interior nodes and with changes in topology"); the user faces a type 1 problem ("positive and negative changes in leaf node values with aggregated values in the interior nodes [...] and no changes in topology"). That is, the layout algorithm has to deal with both topological as well as value changes and

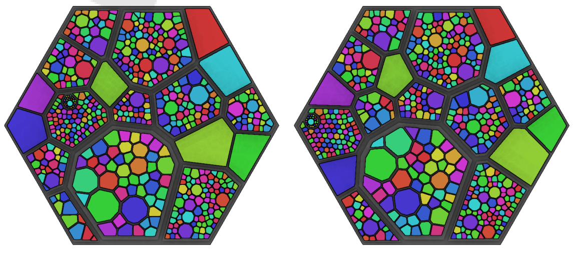
(a) (b)

Figure 1: Chromium Compositor project (approx. 500 files): Visualization of its hierarchy for two revisions. Despite a number of changes in 1 month (May 2013) – 314 files changed, 30 files added, and 18 files deleted – the layout is stable and we notice significant coherence between the two images (the nodes' unique ids are mapped to color).

shall produce a layout that exhibits only few topological changes but still represents value changes.

In other words, we refer to such a layout algorithm's 'tolerance' against changes in varying input hierarchy-data with respect to the arrangement and layout of resulting visual representations as *layout stability*. Layout stability is considered essential for effectively and efficiently performing visual analysis tasks such as comparing hierarchies and attributes of such hierarchies' nodes, and tracking changes to hi-

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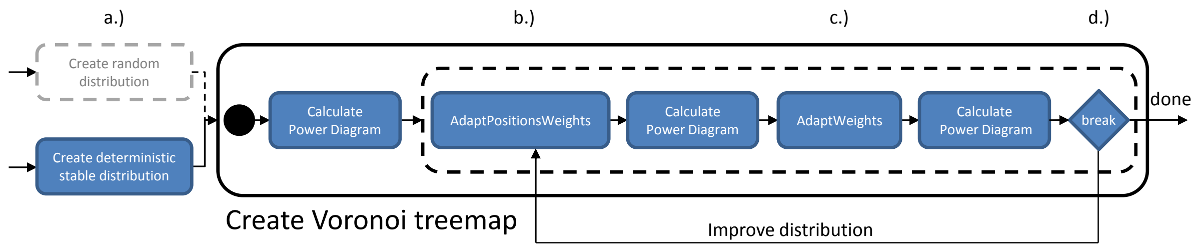


Figure 2: Process of computing a Voronoi treemap with weighted sites.

erarchies over time (Nocaj and Brandes, 2012b; Card et al., 2006; Hadlak et al., 2010). A key reason for this fact is that users explore visual representations and create their own mental maps (Kitchin, 1994). Such maps significantly aid their orientation in the visualized information space by providing a reference system similar to road maps in the physical world. As with navigation in the physical world, such map is useless if changes to the input data result in items not being placed as expected. Thus, users can only use their mental map if the context – the spatial position of hierarchy nodes – is more or less stable, i.e., within some small frame of placement error. Otherwise, a new mental map has to be constructed. For example, in software visualization, large sequences of versioned module hierarchies (e.g., source-code trees) demand for a degree of coherence in corresponding visual representations to facilitate comprehension of the underlying software evolution.

Voronoi treemaps appear to be promising candidates to increase layout stability for visualizing varying hierarchies. Due to the way Voronoi diagrams are constructed, changes in the input data (a point distribution) typically only induce locally constrained changes to the output. One of the main disadvantages of existing layout algorithms for Voronoi treemaps (Balzer et al., 2005; Nocaj and Brandes, 2012a) consists in using a random initial distribution, which can result in essentially different depictions of similar hierarchies. We present an approach for deterministically computing an initial point distribution as input for the Voronoi Treemap computation stage instead of the random initial distribution used by Nocaj and Brandes (see Fig. 2a). As the distribution algorithm is tolerant against changes in the input hierarchy, we ensure that hierarchy nodes are position-stable in the resulting layout, and achieve a high degree of layout stability for varying hierarchies. Further, our approach reduces the error of achieved target areas for weighted Voronoi treemaps. For it, we show three optimizations to the latest algorithm: (see Fig. 2b) a less restrictive but holding criteria for the prevention of empty cells, (see Fig. 2c) a different calculation for increasing and decreasing the cell sizes through the iterative process, and (see Fig. 2d) a more precise break condition. We show an application of our Voronoi treemap layout algorithm in the field of software visualization, exemplified for the case of a sub-module of the open-source web browser Chromium[1], the Chromium Compositor (cc) project (as shown in Fig. 1).

This paper is structured as follows. Section 2 gives a brief overview about related and previous work on layout stability, mental maps and treemaps, as well as techniques used for shape transformations. A theoretical model for *varying hierarchical data* is given in Section 3. Section 4 describes the workflow and proposed algorithms to render Voronoi treemaps layout stable with respect to varying hierarchical data. In Section 5 our improvements to the latest Voronoi treemap algorithm by Nocaj and Brandes (Nocaj and Brandes, 2012a) are shown to reduce the number of iterations and to increase precision of target-area sizes. The evaluation of our improvements to the Algorithm of Nocaj and Brandes is presented in Section 6. Finally, Section 7 concludes this paper and gives an outlook on possible future work.

2 RELATED WORK

Since the invention of Treemaps by Johnson and Shneiderman (Johnson and Shneiderman, 1991), space-restricted hierarchical visualization has been improved along the dimensions of item ordering, aspect-ratio, readability, and stability. While the original Slice'n dice treemap layout (Shneiderman, 1992) creates representations with good stability, its items can have imbalanced aspect ratios that aggravate overall readability and size comparison between items. Other layout techniques such as Squarified (Bruls et al., 2000) or Strip (Shneiderman and Wattenberg, 2001) focus on creating items with an aspect-ratio close to one, but are less layout stable (Sud et al., 2010).

[1] http://www.chromium.org, last accessed 07/25/2013

As outlined above, for our visual-analysis tasks, in particular the recognition of a hierarchies' nodes, the memorability of item positions is a primary goal. The InfoSky, presented by Andrews et al., uses a force-based node placement and additively weighted power diagrams for the visualization of hierarchically structured documents (Andrews et al., 2002). Kuhn et al. present a non-space-restricted approach that creates a so-called *software landscape* or *software map* by applying a mountain metaphor to create a consistent visualization (Kuhn et al., 2008). For it, a multidimensional scaling (*MDS*) algorithm creates a distribution of the hierarchy nodes in visual space. Afterwards, a hill shading based on the lines of code of each artifact is applied. This use of MDS leads to a high degree of consistency over several variants of a hierarchy but does not allow for visualizing the hierarchy's structure. To achieve higher layout stability, Tak and Cockburn present a rectangular-based treemap layout-algorithm – Hilbert and Moore treemaps (Tak and Cockburn, 2013) – that uses the space-filling property of Hilbert and Moore curves. By this, the approach prevents spatial discontinuity with respect to the items' siblings. Reusing an initial reference layout for subsequent layout computations based on Voronoi treemaps (Nocaj and Brandes, 2012b) also partially addresses this issue. It assumes, though, as input a single version of the *same* hierarchy (or sub-hierarchies thereof). Whenever this hierarchy changes, the reference layout becomes invalid and thereby unusable. To achieve layout stability in Voronoi treemaps, the use of deterministic algorithms for computing an initial point distribution instead of random ones is essential. Due to the fact that Voronoi treemaps can be used with arbitrary convex root polygons, generalizable polygon coordinates are needed. A common way to achieve this is the use of generalized barycentric polygon coordinates, or Wachspress coordinates (Wachspress, 1975). These coordinates, which are well defined for convex polygons, allow the description of a point inside the polygon with respect to a polygon's vertices. Floater et al. further present an algorithm using Wachspress coordinates to transform the coordinates of points from inside an initial polygon into a target polygon (Floater et al., 2006).

Our goal combines the above challenges: We want to create a visualization that allows for implicitly identifying *unchanged* and *changed* hierarchy nodes across multiple variants of a hierarchical dataset. That is, the stability property of our computed layout shall enable users to distinguish (un)changed nodes by their relatively (un)stable spatial position and, thereby, also the recognizability of structural patterns (groups of unchanged hierarchy nodes). By this, they are effectively able to identify trends in the visualization of those data, to compare depictions of different states.

3 VARYING HIERARCHICAL DATASETS

There exists a wide range of varying hierarchical datasets. To illustrate this diversity, we pick two examples, illustrating a set of change operations that induce the variation of the datasets, before we define a formal model of the datasets that we consider in this paper.

File-Systems on Hard disks Files on a hard disk are structured strongly hierarchical (excluding links) using folders. In addition to this parent-child-relationship meta information on files, e.g., the attributes size and modification date, exist. A folder's size is then the aggregation of the sizes of all files contained in such folder. Furthermore, a file system can be modified by editing files, and through it modifying their file size (operation *changeAttribute*), *deleting* files as well as folders, and *adding* new files or folders.

Tree of Life The tree of life shows a hierarchical structure of different organisms (the tree's leafs) grouped by species. As in the file-system example, attributes exist for the leafs. A typical attribute here is an organism's population. Analogous to the file system, these attributes change over time, too (*changeAttribute*). Organism or even species become extinct (*delete*) while others evolve (*add*).

A Formal Model We define a formal model for varying hierarchical dataset $H = (N, \mathbb{E})$, which contains a set of nodes $N = \{n_0, ..., n_i\}$ and a set of versioned edges $\mathbb{E} = \{E_0, ..., E_j\}$ as follows:

$$E = \{k_0, ..., k_l\} \quad k = (n_p, n_c) \tag{1}$$

k in E are considered as edges between nodes described by a tuple of nodes (a parent n_p and a child node n_c) with the following properties: (a) Only one tuple exists in E where $n_p = null$ and through this the child of that n_p is considered as root node. (b) Every child node has only one unique parent node. (c) There are no (transitive) cycles in E.

Hence, a tuple $T = (N, E_i \in \mathbb{E})$ defines one variant of our hierarchical dataset. We say that subsequent variants of such tuples are similar to each other, i.e., $\forall_{i \in [0, j-1]} : T_j \sim T_{j+1}$. We further define a function uid :

$N \times E \to \mathbb{N}$ that yields a unique identifier per path $\mathrm{p} : N \times E \to N \times ... \times N$ such that:

$$\forall_{n_i,n_j \in N, E \in \mathbb{E}} : \quad \mathrm{p}(n_i,E) \neq \mathrm{p}(n_j,E) \Leftrightarrow \mathrm{uid}(n_i,E) \neq \mathrm{uid}(n_j,E) \tag{2}$$

Here, $\mathrm{p}(n,E)$ returns the path from node n to the root node n_r defined by E. Note that each variant $E \in \mathbb{E}$ can define a different path p for a node $n \in N$. In other words, our data model considers nodes that are *moved* in H as *different* nodes and they will have more than one unique identifier uid. Last, there exists a set of functions $attr_i : N \times E \to \mathbb{R}$ returning numerical attributes per node $n \in N$ and versioned edges E.

4 A STABLE INITIAL DISTRIBUTION

Nocaj and Brandes construction of Voronoi cells is deterministic – except that they start with nondeterministic initial positions for the Voronoi sites. To achieve stability, we thus need to find a method that is able to create deterministic initial positions. That is, our approach has to fulfill the following requirements:

- The initial-distribution algorithm for the Voronoi sites has to be deterministic.
- If change operations such as *add* or *delete* occur to a parent node, they should not affect positions of its children already positioned in an earlier evolution step.
- The placement of sites relative to each other has to be stable, even if polygon's shape of their parent has changed.
- *changeAttribute* operations on nodes should only cause small changes in the resulting layout.

Voronoi treemaps allow for using arbitrary convex polygons as root item, within which any subsequent direct and indirect child items are contained. For each created shape that represents a child node, the algorithm can further be applied recursively to this node's children.

We start with a target polygon having a given number of vertices (*corners c*) that represent the root item in which a set of Voronoi sites (S) should be distributed. Next, we calculate a regular polygon with the same number of vertices (Fig. 3a). Given a set of nodes (S), which are assumed to have a uniquely identifier, we are able to define consistent Cartesian coordinates in a unit square for each node. In our case, we compute such unique identifier (uid) as a hash $<< x,y >>$ (an integer) from a node's path p. We then encode the first and last half of this hash with $x \in [0..1]$ and $y \in [0..1]$. Next, these two coordinates are transformed into the incircle of the regular polygon (Fig. 3b and 3c) by calculating polar coordinates (see Equations in (3)).

$$\begin{aligned} &c = numberOfPolygonVertices \\ &apothem = \cos\left(\frac{\pi}{c}\right) \\ &<<x,y>> = hash \\ &\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} 0.5 \\ 0.5 \end{pmatrix} \\ &r = apothem \cdot \sqrt{x'^2 + y'^2} \\ &\phi = \pm \arccos\left(\frac{x'}{r}\right) \end{aligned} \tag{3}$$

As a last step, we compute Wachspress coordinates (Wachspress, 1975) for the regular polygon and the sites distributed within. They then describe the sites position inside a convex polygon as weighted terms of the polygon's vertices. By using the vertices' weights, each point of the distributed sites is transformed into the target polygon (Fig. 3d) (Floater et al., 2006). Since it is guaranteed both that the target polygons in Voronoi treemaps are convex at any time, and that the incircle and Wachspress coordinates are well defined for convex polygons, the whole workflow effectively ensures that the distributed points are always placed inside the respective target polygon.

As an additional benefit, we do not need to recompute the Wachspress coordinates' weights of a polygon if the target polygon's vertices change their position slightly while polygons number of vertices remains constant. This can happen, e.g., when changes in the item's occur. It thereby allows for a fast recalculation of the target distribution. The Wachspress coordinates only need to be recomputed if the number of vertices of the target polygon increase or decrease.

5 OPTIMIZED LAYOUT COMPUTATION

After the initial distribution, the actual Voronoi treemap is computed (Fig. 2 b,c,d). Although the original algorithm (Nocaj and Brandes, 2012a) describes a rather fast way for computing Voronoi treemaps, we identified several optimizations for achieving more precise results with respect to the size of target area size of created Voronoi cells. These optimizations concern the functions used in the iterative positioning process (Fig. 2 b,c) as well as the break condition (Fig. 2 d) that decides weather a distribution is sufficiently precise.

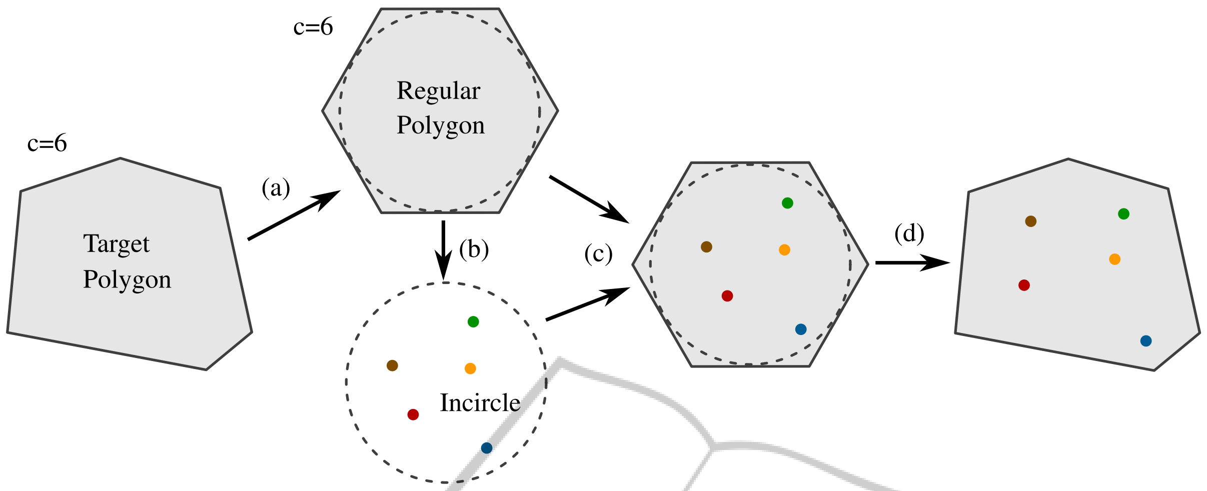


Figure 3: Workflow for computing a deterministic initial site distribution within a target polygon (left). (a) A regular polygon with the same number of vertices as the target polygon is created. (b) Sites are distributed by our deterministic approach into a unit circle and (c) transformed into the incircle of a regular polygon. (d) The regular polygon and the sites distributed within are transformed into the target polygon by using Wachspress coordinates.

5.1 Precision of Target-Area Size

As the initial positioning of the Voronoi sites does not necessarily reflect the targeted weights, Nocaj and Brandes propose an iterative optimization based on Lloyd's algorithm. Lloyd's algorithm, also known as Voronoi relaxation, in its original form is used to calculate Voronoi diagrams where the sites' location coincide with the centroids of its Voronoi cell(Du et al., 1999).

Nocaj and Brandes use power diagrams to iteratively adapt the sites' weights and positions during each iteration. For it, the *current areas* (current size of a cell) of the cells are iteratively adapted towards the *target areas* (cell size that should be achieved). That is, they loop through the functions `AdaptPositionsWeights` and `AdaptPositions` until a break condition is satisfied.

As pointed out by Nocaj and Brandes, empty cells have to be prevented during the iterative optimization of weights and positions: A centroid is required for optimizing a site's position, but cannot be computed for empty cells. Such a site's empty cell can emerge if the site is encircled by a circle defined by the weight of another site. Consequently, empty cells can be avoided by limiting the site's weights such that the constraint in Equation 4 is satisfied.

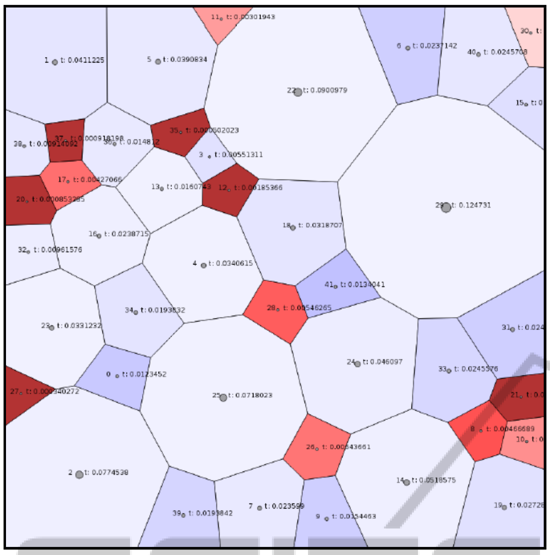
$$\forall s,t \in S, s \neq t : ||s-t|| > \max(\sqrt{w_s}, \sqrt{w_t}) \qquad (4)$$

However, Nocaj and Brandes propose a criterion that is too strong in several cases. They limit the new site's weight to the minimum of the distance of the cell that it belongs to and its maximum weight in Algorithm 1. This often results in many cells being too small and thus – counterintuitively – especially cells that should be very small are far too large.

We propose a weaker limit for a site's weight as follows: A site's weight in `AdaptPositionsWeights` is limited to the minimum distance to any other site, just like Nocaj and Brandes did in `AdaptWeights`. In most cases, this criterion is weaker, but it always satisfies the constraint in Equation 4. Our Algorithm 3 uses the same method to determine the distance to the nearest neighbor as proposed by Nocaj and Brandes in Algorithm 2. The distances can be calculated by means of a Voronoi diagram in $O(n \log n)$.

During our experiments, we noticed that the method of Nocaj and Brandes often results in *oscillating* site locations, weights, and areas during the iterative optimization. To overcome this problem f_{adapt} is limited to $1 \pm \rho$ if its first derivative (increasing/decreasing the weight) starts oscillating as described in Algorithm 4.
Note that even though the distance is described in Algorithm 3 and 4 as being the distance between two sites, it can also be computed as twice the distance to the cell from a site. It is not necessary to know which site is the nearest neighbor. Also note that most distances can be calculated as the squared distances which does not require calculating any square roots.

The effects of our optimizations are shown in Fig. 4 and are evaluated and discussed in detail in Section 6.


(a) Approach of Nocaj and Brandes

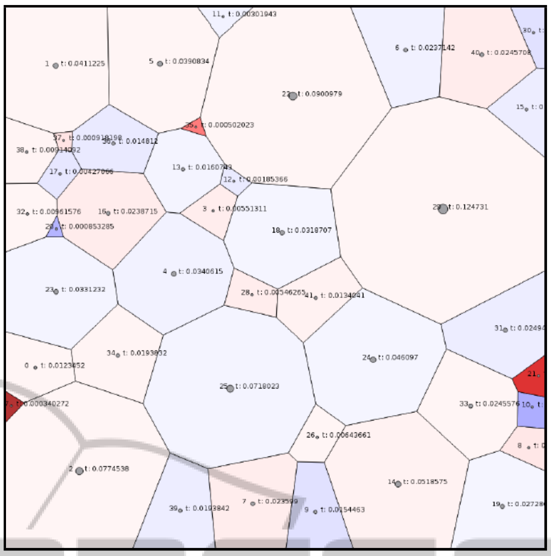

(b) Our Approach

Figure 4: Errors in target-area size shown by color (red = too big, white = correct, blue = too small), i.e., color encodes how much the actual size of a target area deviates from its expected size (given by the respective attribute value mapped to area size). Comparison between the results from the algorithm of Nocaj and Brandes (left) and our approach (right). In comparison to Nocaj and Brandes, our optimizations yield higher precision with respect to the error in target-area size .

Algorithm 1: `AdaptPositionsWeights` $(p, \mathcal{V}(S), S, W)$ used to adapt the positions and weights in an iterative optimization algorithm proposed by Nocaj and Brandes.

```
1 foreach site $s \in S$ do
2     $a \leftarrow centroid(\mathcal{V}_s)$
3     $distanceBorder \leftarrow min_{x \in \overline{\mathcal{V}_s}} ||x - s||$
4     $w_s \leftarrow (min(\sqrt{w_s}, distanceBorder))^2$
```

Algorithm 2: `AdaptWeights` $(p, \mathcal{V}(S), S, W)$ used to adapt the weights in an iterative optimization algorithm proposed by Nocaj and Brandes.

```
1 $NN \leftarrow Nearestneighbor(S)$
2 foreach site $s \in S$ do
3     $A_{current} \leftarrow A(\mathcal{V}_s)$;          // current area
4     $A_{target} \leftarrow A(\Omega) \cdot \frac{v(s)}{v(p)}$;          // target area
5     $f_{adapt} \leftarrow \frac{A_{target}}{A_{current}}$
6     $w_{new} \leftarrow \sqrt{w_s} \cdot f_{adapt}$
7     $w_{max} \leftarrow ||s - NN_S||$
8     $w_s \leftarrow (min(w_{new}, w_{max}))^2$
9     $w_s \leftarrow max(w_s, \varepsilon)$
```

5.2 Break Condition

The iterative optimization to calculate Voronoi diagrams where the cells have a target area requires a break condition (see Fig. 2d) that is satisfied when the iterative optimization has finished. Nocaj and Brandes propose to cancel the optimization process when the sum of *area errors* is below a certain threshold. They define the area error as the difference between the current area and target area of a Voronoi cell. Furthermore the maximum number of iterations is limited.

Unfortunately the area error often does not converge to zero and the minimum error that is reached in a reasonable number of iterations highly depends on the number of sites and the target areas of the Voronoi cells. Consequently, the threshold is often reached after only a few iterations or not reached at all and the maximum number of iterations is reached. In the first case more iterations would reduce the sum of area errors. In the second case fewer iterations would probably not imply a much higher sum of area errors.

Algorithm 3: Optimized version of `AdaptPositionsWeights` $(p, \mathcal{V}(S), S, W)$ with less-restrictive empty cell prevention.

```
1 foreach site $s \in S$ do
2     $a \leftarrow centroid(\mathcal{V}_s)$
3 $NN \leftarrow Nearestneighbor(S)$
4 foreach site $s \in S$ do
5     $w_{max} \leftarrow ||s - NN_S||$
6     $w_s \leftarrow (min(\sqrt{w_s}, w_{max}))^2$
```

Algorithm 4: Optimized version of `AdaptWeights`$(p, \mathcal{V}(S), S, W)$ that prevents "oscillation".

```
1  $fs \leftarrow$ initialize with zeros
2  $NN \leftarrow Nearestneighbor(S)$
3  foreach site $s \in S$ do
4      $A_{current} \leftarrow A(\mathcal{V}_s)$
5      $A_{target} \leftarrow A(\Omega) \cdot \frac{v(s)}{v(p)}$
6      $f_{adapt} \leftarrow \frac{A_{target}}{A_{current}}$
7      if $fs_s \neq 0$ and $\mathrm{sgn}(f_{adapt} - 1) \neq \mathrm{sgn}(fs_s - 1)$ then
8          $f_{adapt} \leftarrow \min(1 + \rho, max(f_{adapt}, 1 - \rho))$
9      $w_{new} \leftarrow \sqrt{w_s} \cdot f_{adapt}$
10     $w_{max} \leftarrow ||s - NN_S||$
11     $w_s \leftarrow (min(w_{new}, w_{max}))^2$
12     $w_s \leftarrow max(w_s, \varepsilon)$
13     $fs_s \leftarrow f_{adapt}$
```

We propose a threshold for the difference between the maximum area error (the maximum error of each individual cell, $|A_{target_s} - A_{current_s}|$) of different iterations which could be seen as the slope of the maximum area error. More formally, the optimization process if canceled when $e_{diff} < threshold$. e_{diff} is defined in Equation 5 where e_{-l} is the maximum error l iterations ago in a list L_e of l iterations, $e_{\lfloor \frac{l}{2} \rfloor}$ is the middle entry of L_e and e_0 is the maximum error in the current iteration.

$$e_{diff} = \max(e_{-l}, e_{\lfloor \frac{l}{2} \rfloor}) - e_0 \qquad (5)$$

A disadvantage of this method is that the area error of the resulting Voronoi diagram does not have an upper bound. However, we know that more iterations would probably not reduce the area error.

6 COMPARATIVE EVALUATION

To evaluate the optimizations of our approach (Alg_{OA}) (presented in Section 5) in comparison to the algorithms of Nocaj and Brandes (Alg_{NB}) (Nocaj and Brandes, 2012a), we tested both algorithms distributing different numbers of sites within the same parent polygon. For it, we computed distributions of 10, 50 and 250 sites with random polygon weights with 1000 iterations per distribution. To achieve comparable results we use the same seed to compute the weights for each run. The dependent variables of our study are: Time needed to compute the distribution within 1000 iterations, maximum error of the target sizes and the sum of target-size errors. Table 1 shows the evaluation setup with (in)dependent variables in detail.

Table 1: Dependent and independent variables for the comparative study (example for 10 sites).

Seed	Alg	Time	Max Err	Sum Err
s_1	Alg_{OA}	t_1	err_{max_1}	err_{sum_1}
s_1	Alg_{NB}	t_2	err_{max_2}	err_{sum_2}
s_2	Alg_{OA}	t_3	err_{max_3}	err_{sum_3}
s_2	Alg_{NB}	t_4	err_{max_4}	err_{sum_4}
...	...	...	...	...
s_n	Alg_{OA}	t_{2n-1}	$err_{max_{2n-1}}$	$err_{sum_{2n-1}}$
s_n	Alg_{NB}	t_{2n}	$err_{max_{2n}}$	$err_{sum_{2n}}$

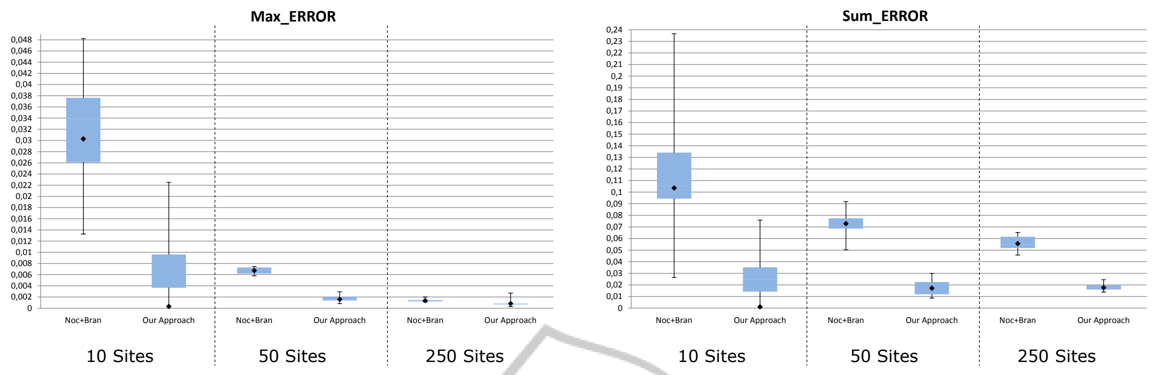
The mean computation time of Alg_{OA} compared to Alg_{NB} shows equal results with each number of sites (Table 2 shows the mean computation times in detail), our algorithms shows better error rates in both the maximum area error and the sum of area errors for every number of distributed sites (shown in Fig. 5 a,b). A paired t-test shows that our method significantly decreases both, the maximum area error (10 Sites: $p = 2 \cdot 10^{-6}$; 50 Sites: $p = 8 \cdot 10^{-8}$; 250 Sites: $p = 0,01$) as well as the sum of all area errors (10 Sites: $p = 4 \cdot 10^{-4}$; 50 Sites: $p = 2 \cdot 10^{-6}$; 250 Sites: $p = 8 \cdot 10^{-8}$).

Table 2: Mean computation times for the comparative evaluation. The computation times of our algorithm are equal compared to the ones of Nocaj and Brandes.

Number Of Sites	Alg	Mean Time
10	Alg_{OA}	355 *ms*
10	Alg_{NB}	353 *ms*
50	Alg_{OA}	1686 *ms*
50	Alg_{NB}	1701 *ms*
250	Alg_{OA}	8937 *ms*
250	Alg_{NB}	8914 *ms*

7 CONCLUSIONS AND FUTURE WORK

We have presented an extension to an existing layout algorithm for Voronoi treemaps by using a deterministic initial distribution for the Voronoi sites. Since the resulting layouts are stable with respect to varying input hierarchies and varying size of items, this enables the use of Voronoi treemaps for *comparing* hierarchy variants. Such data sets emerge, e.g., from versioned source-code trees of software systems. Fig. 6 shows an example of such a varying hierarchy, depicting the *cc* project from the *Chromium* Git repository (branch: master) over several revisions (annotated with



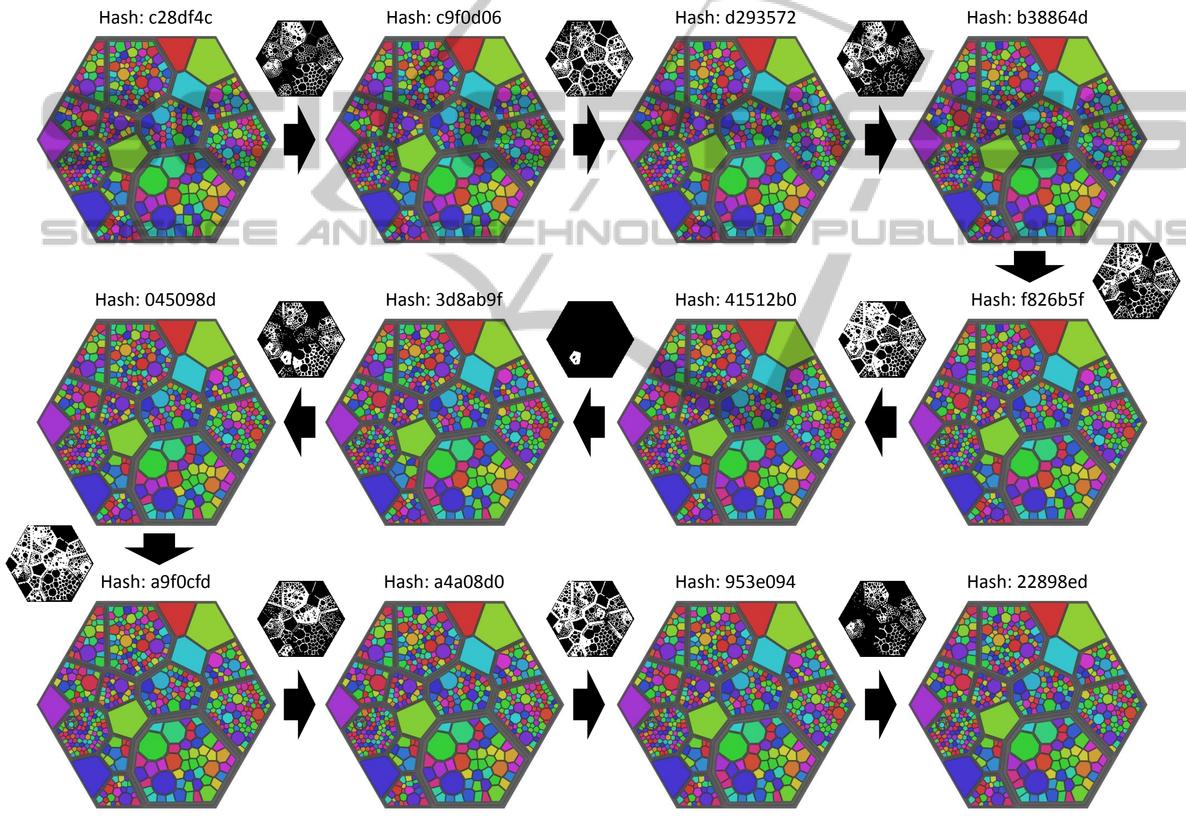


Figure 6: Visualization of the hierarchical folder structure (with about 500 nodes) of 12 revisions from the *cc* project of the *Chromium* Git repository (master). The area of the cells is mapped to the corresponding file size of the represented node. The nodes' unique identifier – created from the paths to the root node – is shown as color. For each adjacent layouts, which represent successive revisions, a difference mask is shown. Unchanged areas are represented by black pixels, while white pixels indicate differences between the two respective layouts. Although several changes (operations: *changeAttribute* in 169 files, 5 files *added*, 2 files *deleted*) are present in the input data, the resulting layouts are appears as stable and exhibit only few, local differences. Through it, the layout is memorable over all revisions.

the commit-hashes). Our comparison of target-error rates further show that we achieve a lower target-error rate than existing layout algorithms. We conclude that the resulting layout represents attributes of the input data more accurately than previous techniques.

As future work, we plan to apply keyframe animations to blend between the display of the hierarchy variants. We then plan to evaluate how well users can track existing hierarchy items in the visualization and whether the placement of items can be further optimized with respect to user expectations. Since computing layouts for large graphs is still too slow for interactive use, it would likely benefit by porting the layout algorithm to GPUs. Moreover, we want to add support for *move* and *rename* as possible change operations.

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