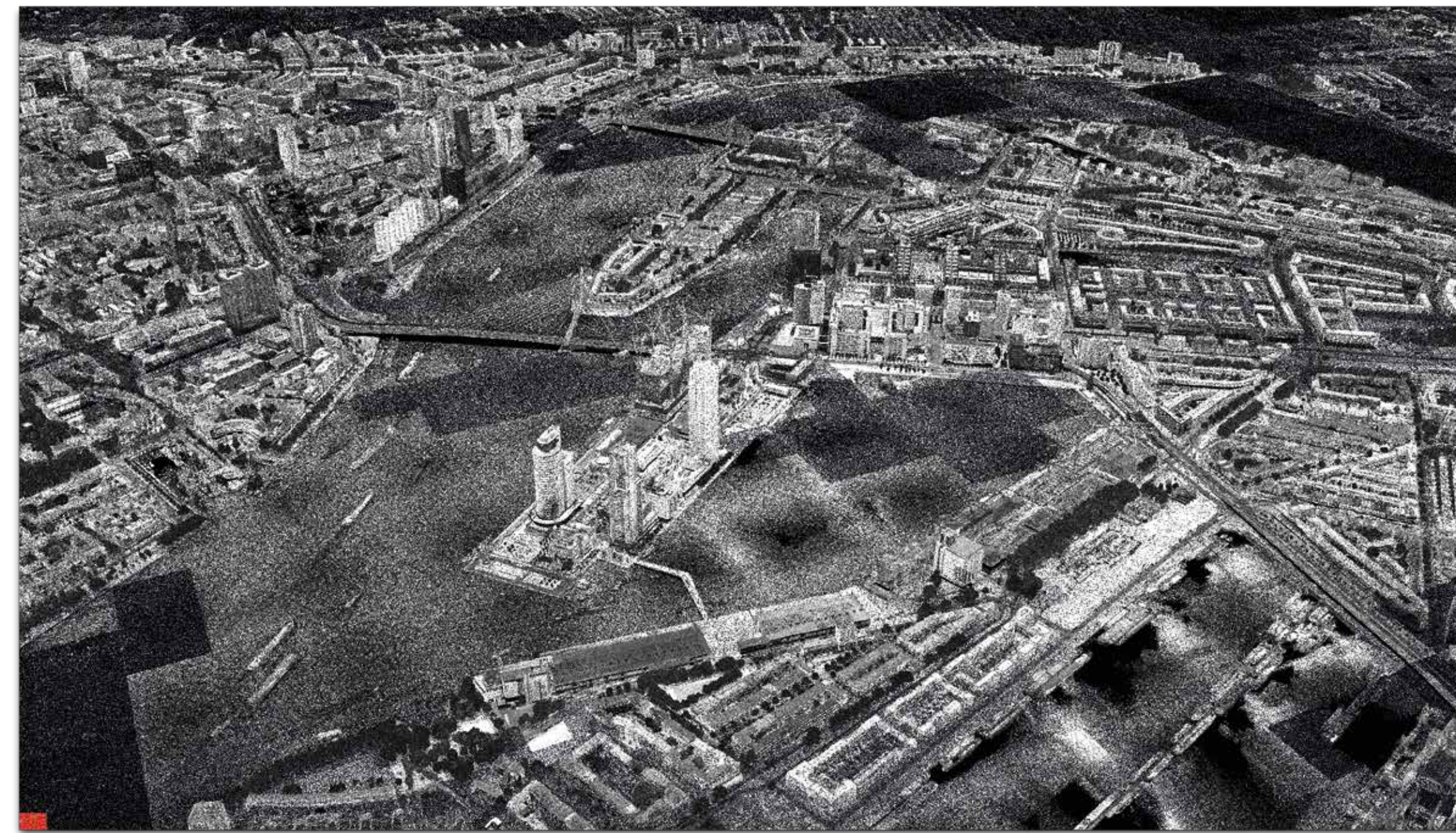


Feature-aware LiDAR point cloud simplification

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1. Introduction

LiDAR point clouds are highly detailed and cover large areas. This brings great advantages for applications such as flood modeling, crisis management and 3D city modeling. Unfortunately, and despite recent developments on this subject, current methods from practice are unable to fully take advantage of modern LiDAR datasets. First, because of their huge data volume they do not fit in a computer's internal memory. As a result, many of the conventional software tools have become very inefficient. And second, many existing methods use only 2.5D data-structures and algorithms. While this alleviates memory requirements and simplifies computation, it comes at the price of a significant loss of information, because valuable 3D information that is present in LiDAR point clouds is ignored.



LiDAR dataset from the municipality of Rotterdam

My research aims to develop efficient methods for point cloud processing and analysis that use truly 3D data-structures and algorithms based on the Medial Axis Transform (MAT).

Case study

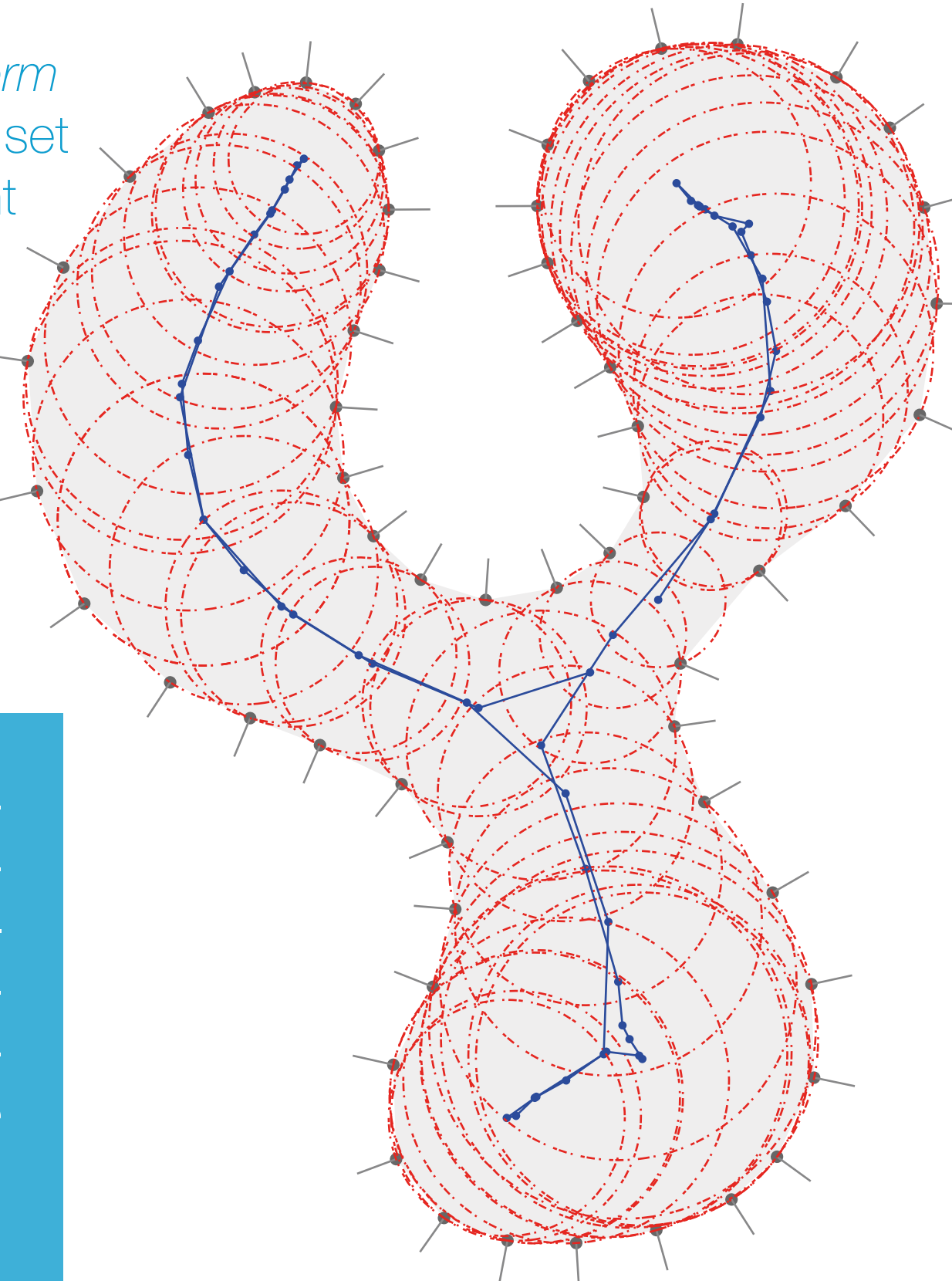
The Dutch Kadaster is currently working on 3D TOP10NL: a national topographic map in 3D based on the national LiDAR elevation model (AHN2). To keep processing times on a reasonable level, the AHN2 dataset must be thinned in a preprocessing phase. Currently, they employ a simple n^{th} point filter. Unfortunately, due to non-adaptiveness this easily results in the destruction of significant surface characteristics.

2. Shrinking balls

Ma et al. (2012) introduced the shrinking ball algorithm to approximate a point approximation of the MAT from an oriented input point cloud. For each sample point, we start with a very large tangent ball that is centered along the point's normal. An empty maximal tangent ball is found by iteratively reducing the ball's radius using nearest neighbor queries from its center point.

Compared to earlier algorithms (e.g. Amenta et al., 2001) it is simple, fast, robust in practice, and easy to parallelize. This makes it a good choice for approximating the MAT of large LiDAR point clouds.

The *Medial Axis Transform (MAT)* is defined as the set of maximal balls tangent to the object surface at two or more points. The centers of these balls form the Medial Axis, a medial skeletal structure.

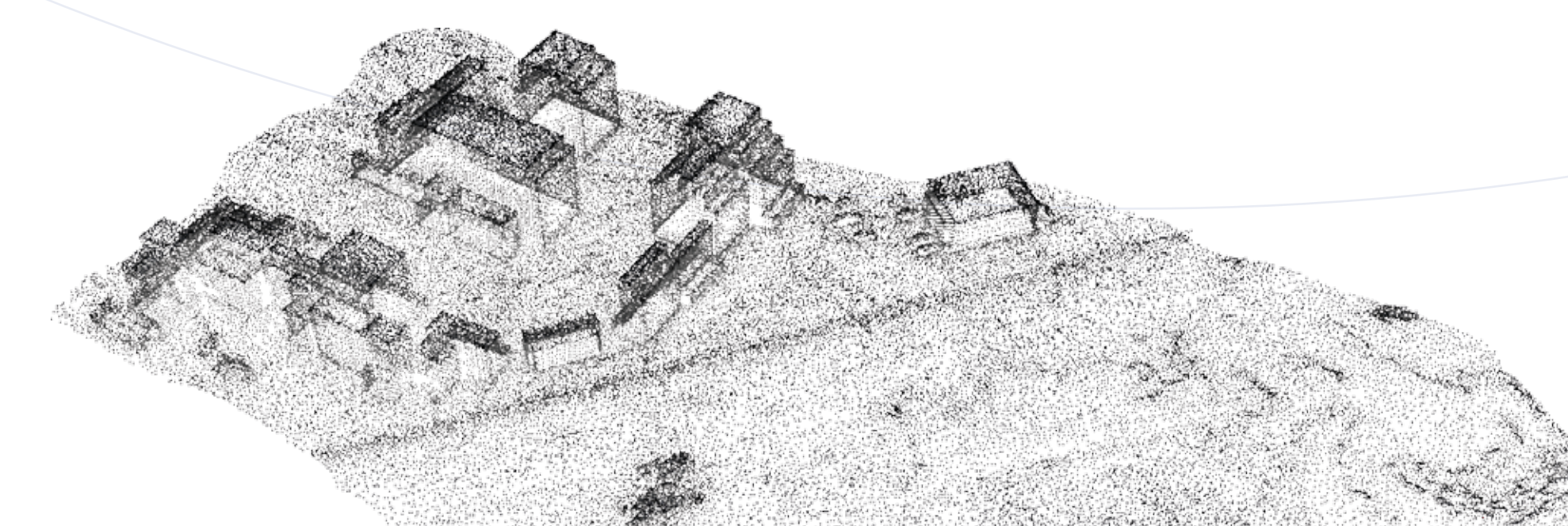


3. Simplification

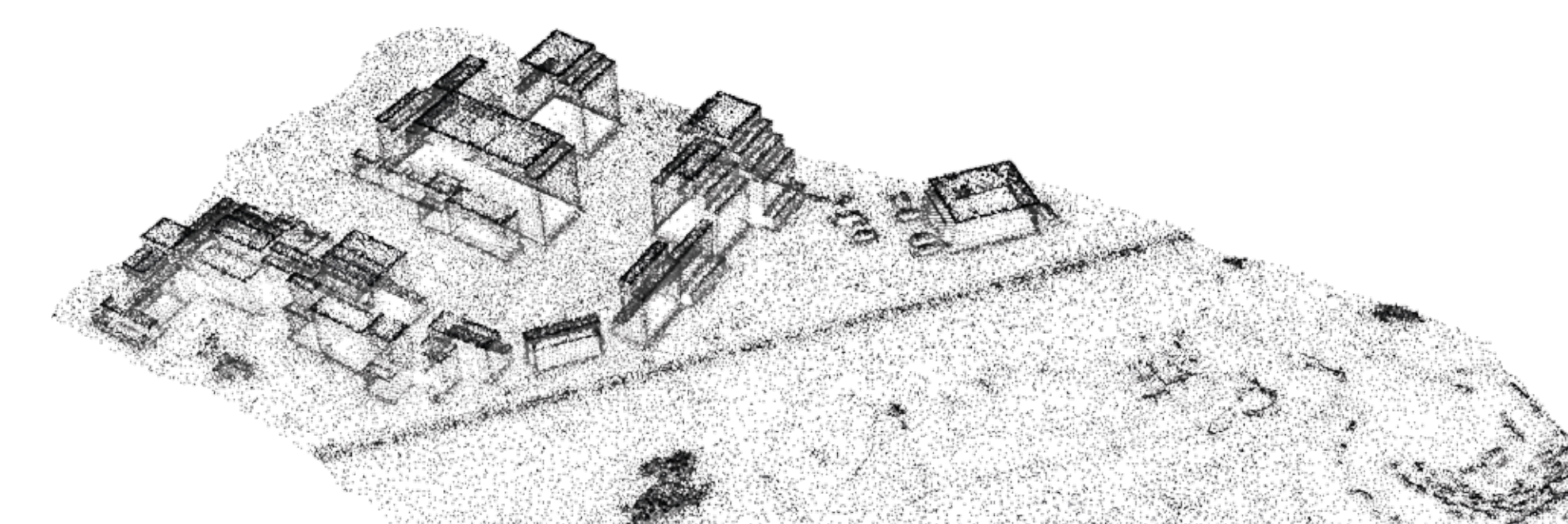
Point cloud simplification aims to lower the overall point count, while maintaining a sufficiently dense sampling of small features. As a result, the same overall surface shape can be adequately described with fewer samples, and less computational resources are needed for any subsequent processing.

I am investigating a point cloud simplification technique based on the *local feature size*. By relating the point density to the local feature size we can obtain a simplified point cloud with a sampling density that is adaptive to the geometry of the sampled objects.

Below the resulting simplified point clouds are shown for a point count reduction to approximately 11% of the original point count. For comparison a randomly thinned point cloud is also shown.



Local feature size simplification (linear)

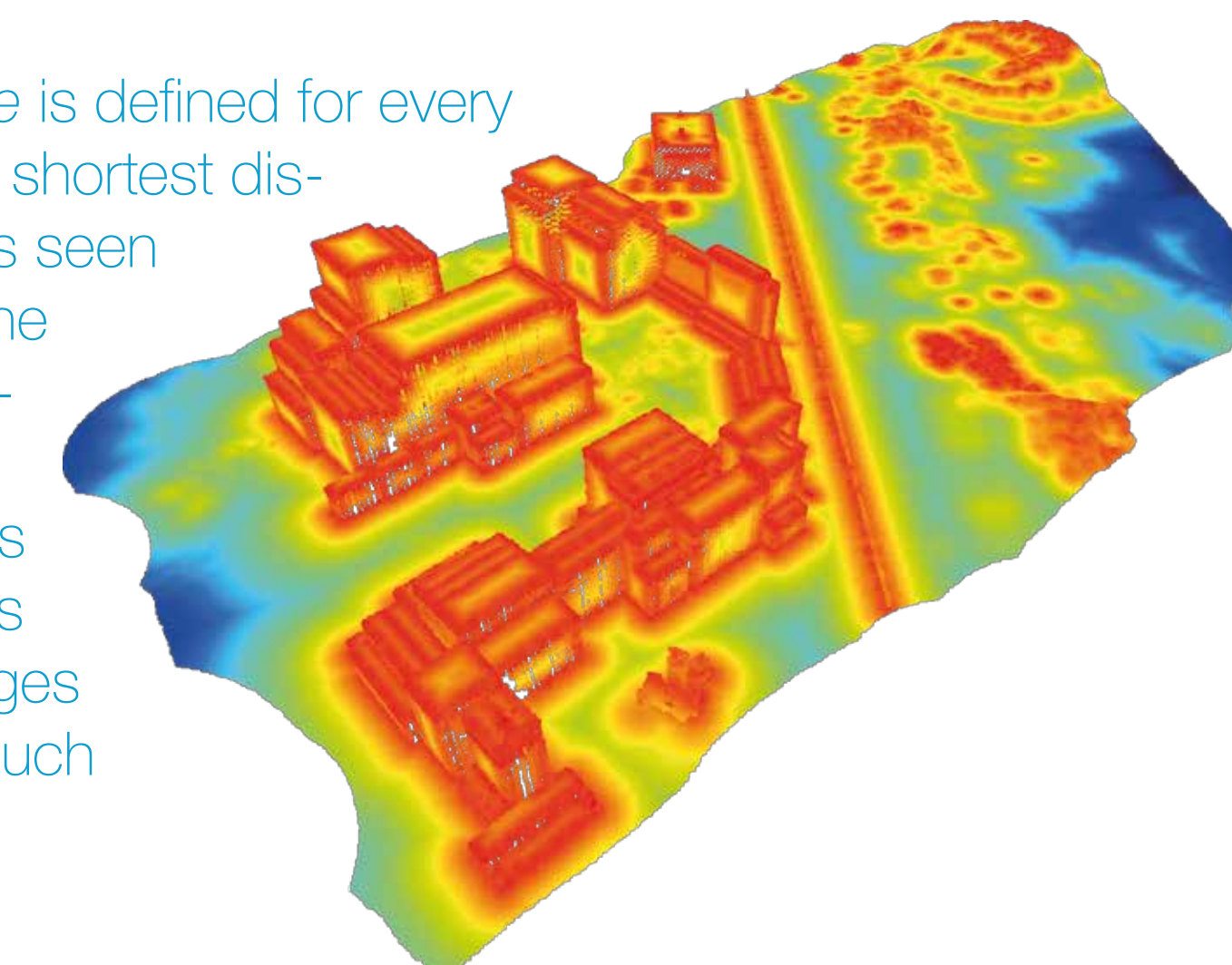


Local feature size simplification (quadratic)



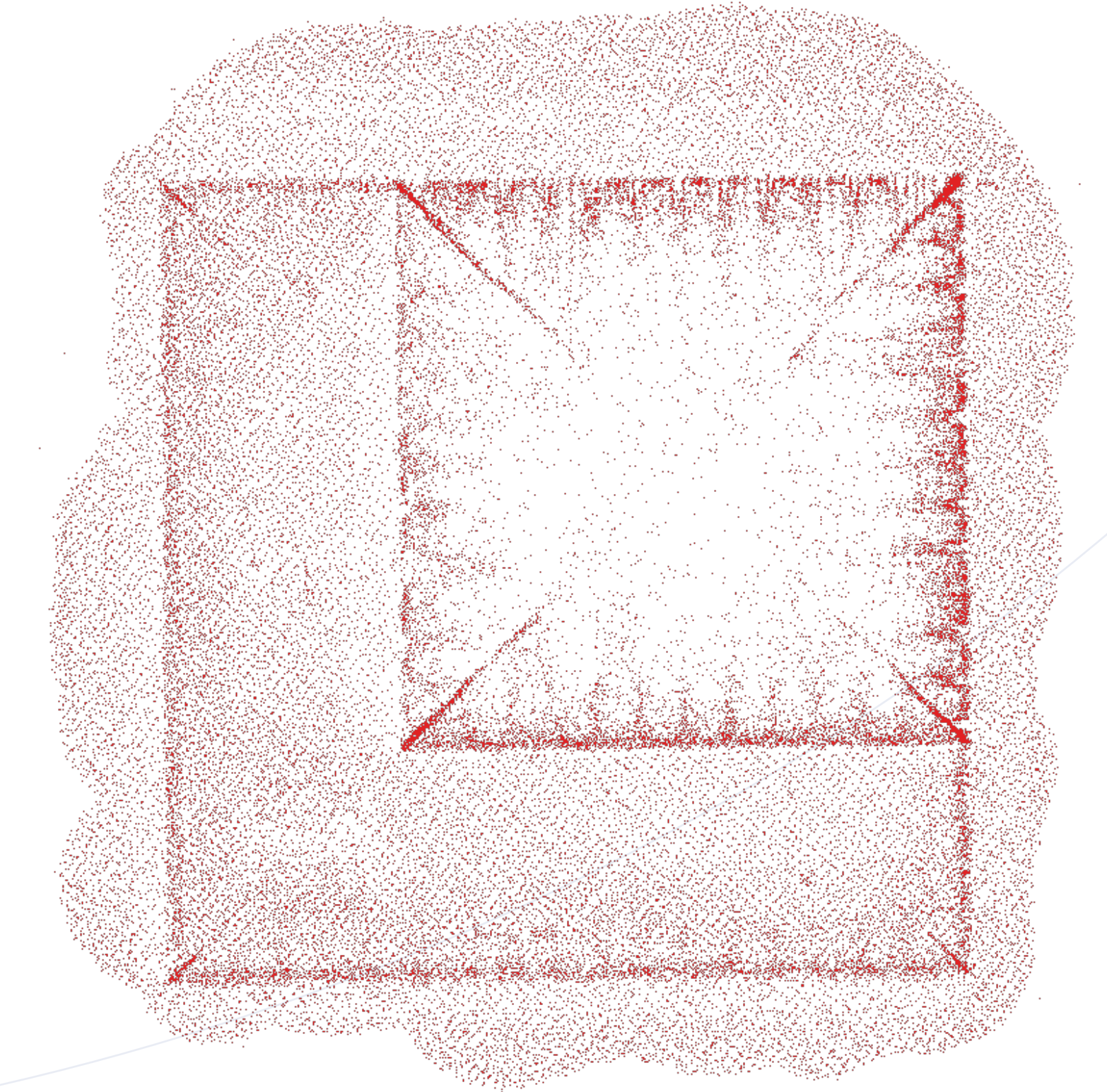
Random point thinning

The *local feature size* is defined for every surface point as the shortest distance to the MAT. As seen from the image on the right, a low local feature size (red color) typically corresponds to significant features such as building edges or small structures such as cars and fences.



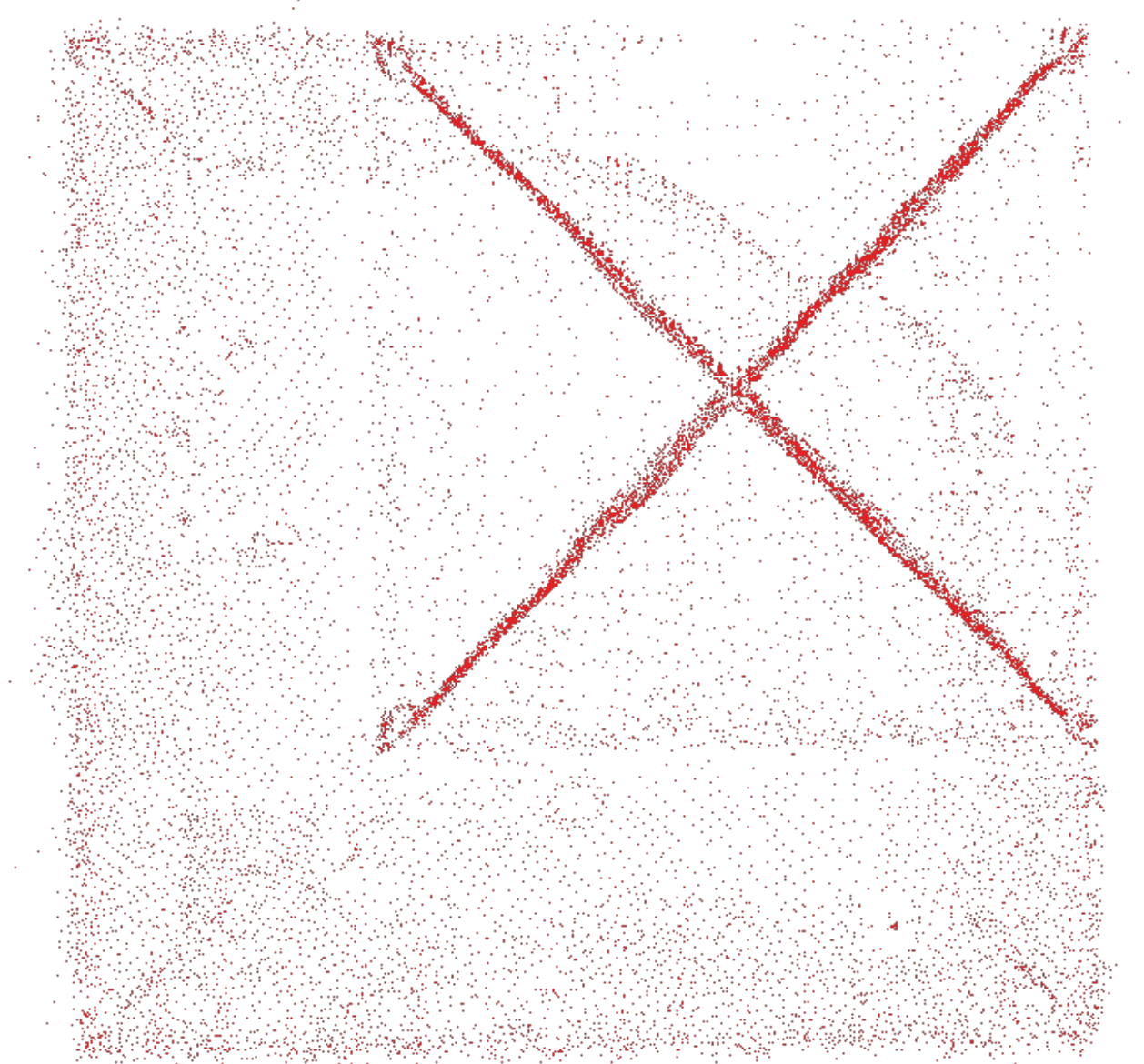
Handling noise

The MAT is notorious for its sensitivity to small perturbations in the object surface. Since LiDAR point clouds typically contain significant levels of noise, it is essential to deal with this problem. Therefore I extended the shrinking ball algorithm with additional termination criteria for the ball shrinking process of each point. As a result I obtain a denser and less noisy approximation of the MAT.



Original shrinking ball algorithm

Modified shrinking ball algorithm



Top view of a building extracted from the LiDAR dataset of the municipality of Rotterdam. On top, the MAT approximation obtained using the original shrinking ball algorithm. The bottom figure shows the MAT approximation obtained using the modified noise-aware version of the shrinking ball algorithm.

References

- Jaehwan Ma, Sang Won Bae, and Sunghye Choi. 3D medial axis point approximation using nearest neighbors and the normal field. *The Visual Computer*, 28(1):7–19, 2012
- Nina Amenta, Sunghye Choi, and Ravi Krishna Kolluri. The power crust. In *Proceedings of the sixth ACM symposium on Solid modeling and applications*, pages 249–266, 2001
- Tamal Dey, Joachim Giesen, and James Hudson. Decimating samples for mesh simplification. In *Proceedings of the 13th Canadian Conference on Computational Geometry*, pages 85–88, 2001