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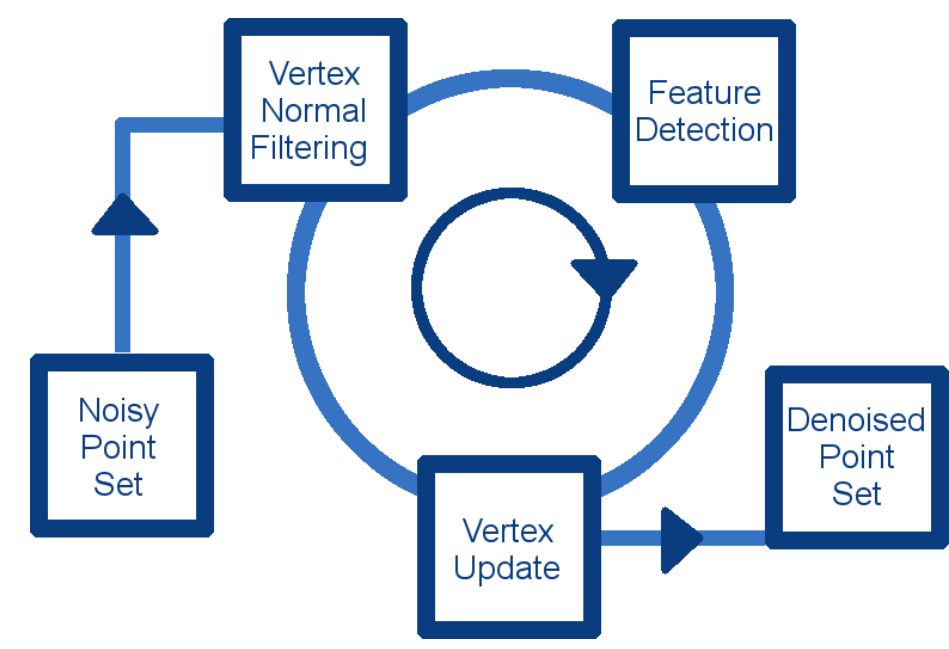


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# Analysis of NVT-based Point Set Denoising in Parameter Space

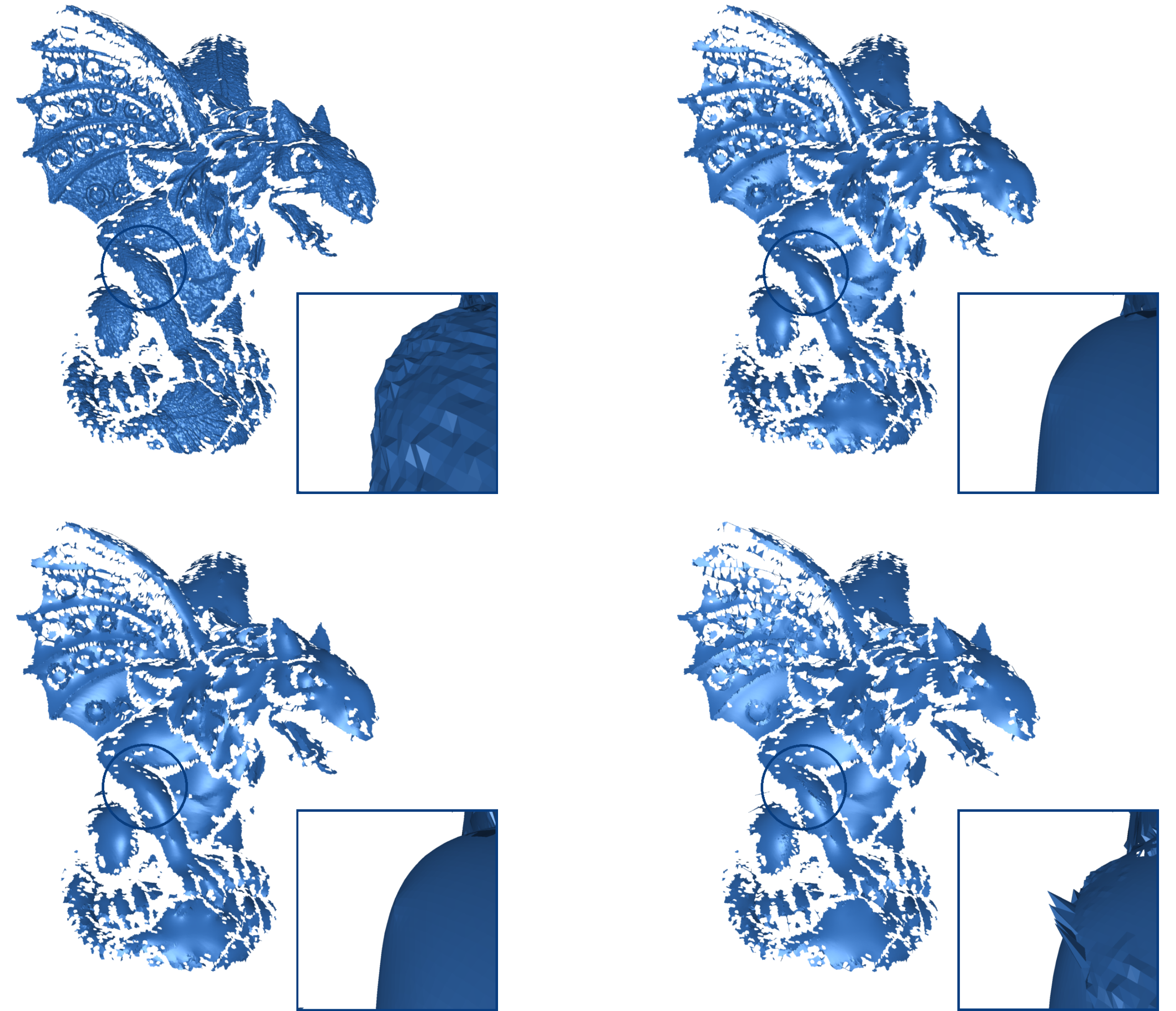
## Point Set Denoising

Our point set denoising [1] is an iterative, 3-phase algorithm for noisy point sets. Its parameters offer a variety of tuning opportunities. Used models are the gargoyle (real, noisy, irregular), the Chinese ball and rabbit (real, noisy, many features), the fan disk (sharp features, near-flat areas,  $\sigma_n = 0.28l_e$ ), the sphere ( $\sigma_n = 0.19l_e$ ) and the cube (sharp features,  $\sigma_n = 0.3l_e$ ), with the last 3 being synthetic and noisy. Standard values are  $k = 6$ ,  $\rho = 0.9$ ,  $\tau = 0.25$ ,  $\varepsilon = 2r$ ,  $p = 80$ ,  $d = 3$ , and  $\alpha = 0.1$ .



## Radius $r$

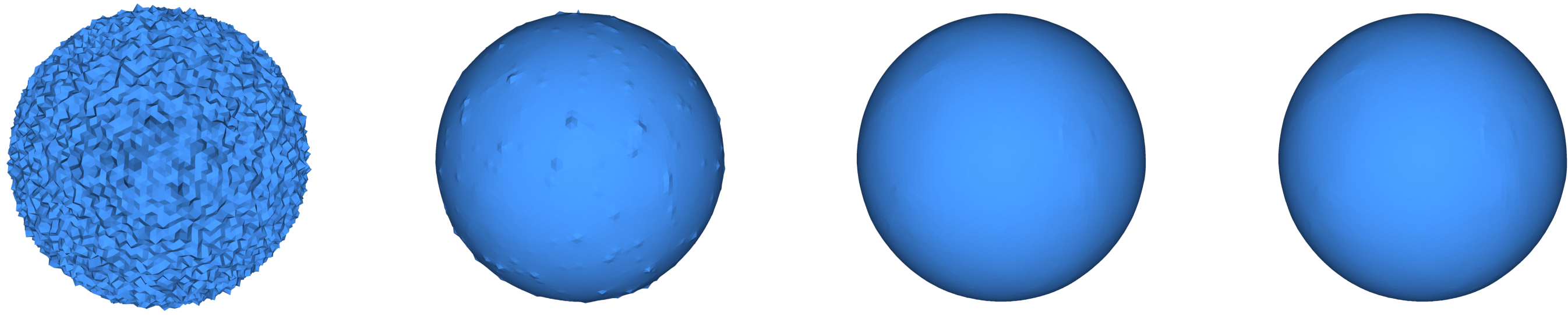
The radius  $r \in \mathbb{R}^+$  is twice the average distance of the kNN-neighborhood graph (standard  $k = 6$ ) of the point set.



The gargoyle model and denoising applied with  $k = 1, 6$ , and  $30$ .

## Distance Constraint $\varepsilon$

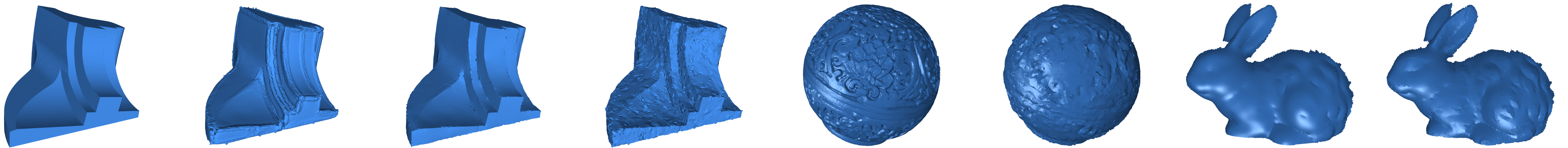
The parameter  $\varepsilon \in \mathbb{R}^+$  decides, whether a vertex update takes place utilizing a movement forecast and a comparison to the moved distance (according to the initial position).



The sphere model and denoising applied with  $\varepsilon \in \{0.05, 0.0876, 0.3\}$ .

## Dihedral Angle Threshold $\rho$

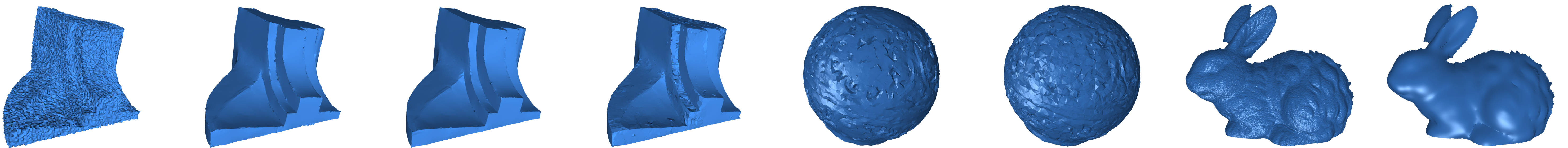
The threshold  $\rho \in [-1, 1]$  decides whether a neighborhood weight gets assigned value 0 or 1 w.r.t. normal similarity during its determination in phase 1 and 2.



The fan disk model, denoised versions with  $\rho \in \{0.3, 0.9, 0.99\}$ , the Chinese ball, denoised with  $\rho = 0.75$ , and the denoised rabbit with  $\rho = 0.95, 0.99$ .

## Eigenvalue Threshold $\tau$

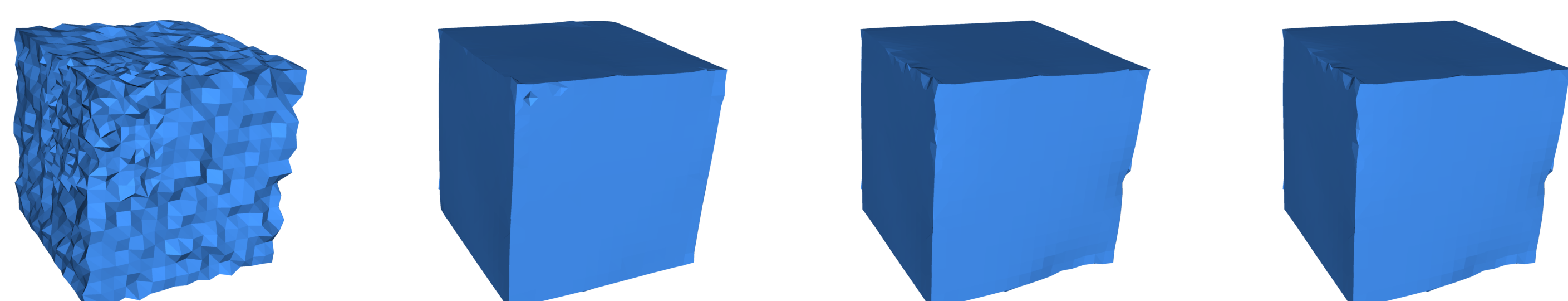
The value  $\tau \in [0, 1]$  decides whether eigenvalues of the tensors in phase 1 and 2 get assigned 0 or 1. Dominant ones get strengthened, the others weakened.



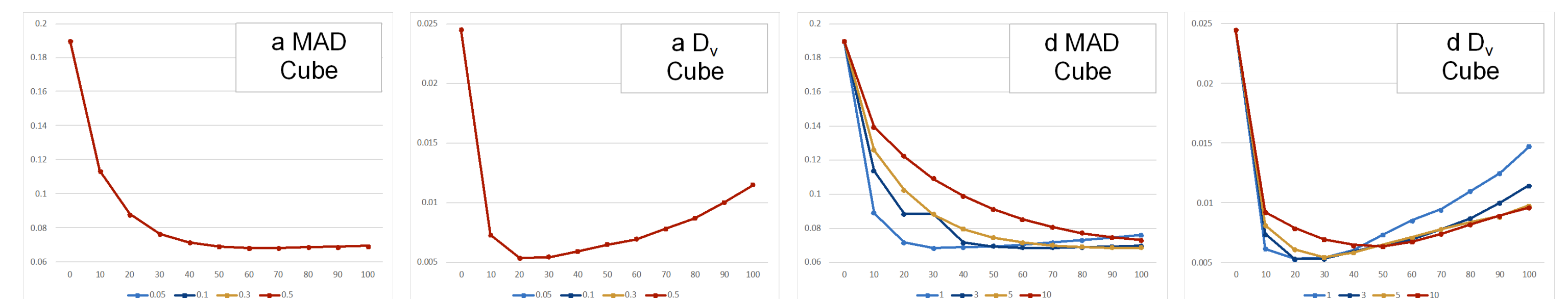
The noisy fan disk, denoised versions with  $\tau \in \{0.1, 0.35, 0.45\}$ , denoised Chinese ball with  $\tau = 0.1, 0.45$ , and the rabbit model, denoised with  $\tau = 0.25$ .

## Iterations $p$ - Smoothing Limiter $\alpha$ - Damping Factor $d$

Finally, we consider the number of iterations  $p \in \mathbb{N}$ , as the point set changes dynamically, the damping factor  $d \in \mathbb{N}$ , controlling the impact on the updated normal in phase 1, and the smoothing limiter  $\alpha \in \mathbb{R}^+$ , influencing the weights applied to flat points in phase 3. The convergence analysis is taken via the mean angular deviation (MAD) and an  $L_2$  vertex-based error metric ( $D_v$ ), see [1].



The cube model, denoised versions with  $(\rho = 0.95, \tau = 0.3)$ ,  $\alpha = 0.1$ ,  $d = 3$ , and the plotted error values.



## Future Work

- ▶ Examining cross correlations between parameters
- ▶ Automated model-based parameter selection

## References

- [1] S. K. Yadav, U. Reitebuch, M. Skrodzki, E. Zimmermann, and K. Polthier, 2018, 'Constraint-based point set denoising using normal voting tensor and restricted quadratic error metrics', Computers & Graphics. DOI: <https://doi.org/10.1016/j.cag.2018.05.014>.