NPM3D - TP3: Neighborhood descriptors

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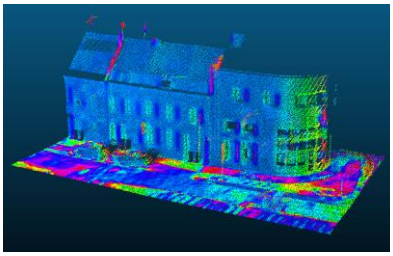
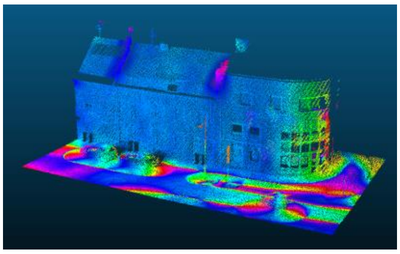
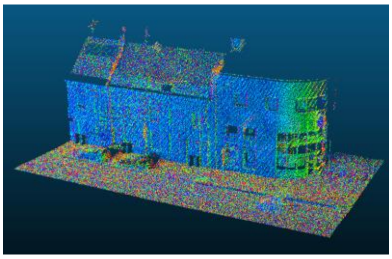
A. CloudCompare normals

Question 1:

Normals computed with 0.5m radius (left), 2m radius (middle) and 0.1m radius (right)

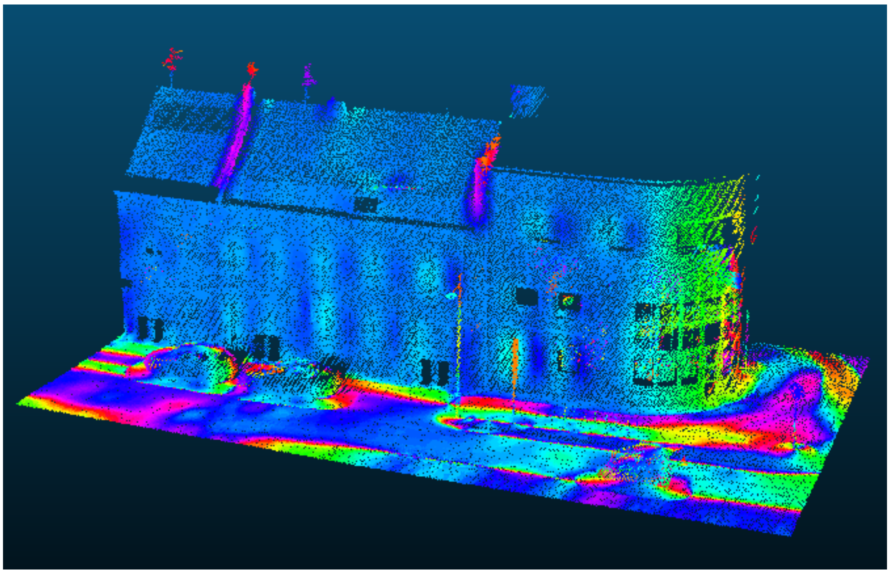
As I increase the radius, the normals lose their locality property, as they cover a larger surface. As I decrease the radius, the normals become too local, and vary significantly from point to point.

Question 2:

For a good normal estimation, I would start from a low radius, visualize the normals as previously done, and iteratively increase it until I observe some continuity in the normals over the space. In this case, 1m gives a decent compromise between continuity and locality (cf next question). In a more automated way, I could think of choosing a radius function of the average spacing between points.

B. Local PCA

Question 3:

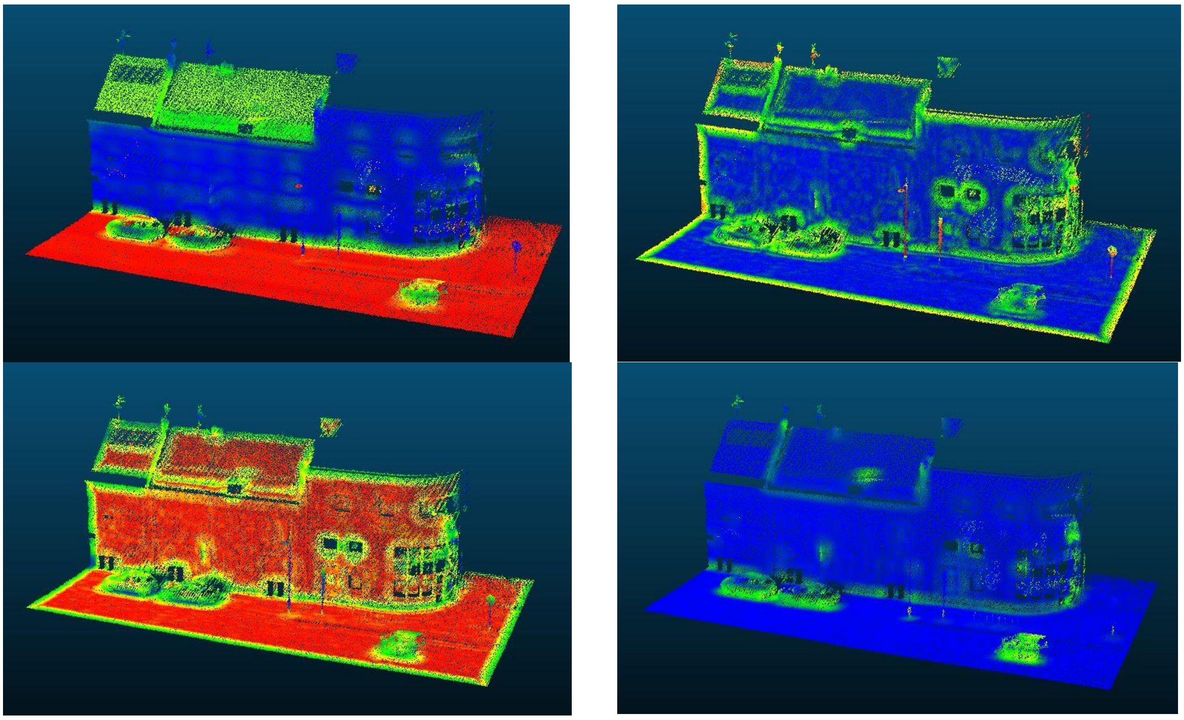


My Normals, computed with radius 1

Question 4:

In order to evaluate the quality of my normal estimation using eigenvectors, as eigenvectors are normalized, I can visualize the vector field e_3.n. On the planes, it is expected to be very low (as the variance of the neighborhood in the normal direction is expected to be low).

Question 5:



Features: Verticality (top left), Linearity (top right), Planarity (bottom left), Sphericity (bottom right)

Intuitively, I can explain the last 3 features as followed:

• Linearity: is high if $\lambda_2 << \lambda_1$, which corresponds to the case of points in a line (perfect line [1,0,0]).

• Planarity: is high if $\lambda_3/\lambda_1 << \lambda_2/\lambda_1$, which corresponds to a plane (perfect plane [0.5, 0.5, 0]).

• Sphericity: is high if $\lambda_3 = \lambda_2$, which corresponds to a sphere (perfect sphere [1/3, 1/3, 1/3]).

C. Mini-Challenge : point classification

I tried to add additional features: inspired by *Onboard Contextual Classification of 3-D Point Clouds with Learned High-order Markov Random Fields* (Munoz et al, 2009) *and Relevance assessment of full-waveform lidar data for urban area classification* (Weinmann et al, 2013), I added additional spectral features: omnivariance, anisotropy, eigenentropy, the sum of eigenvalues, change of curvature and cosinus and sinus of angles between normal/tangent and horizontal/vertical plane. This enabled to improve the cross-validation results from 63.5% mean accuracy over 5 folds to 70.5%, and to have a test average IoU of 33.85% (30.7% being the baseline). Increasing the number of points (500 to 5000 per class) easily enables to slightly improve the results (up to 73% mean cross validation accuracy, and 34.91% test mean average IoU). I also tried changing the classifier and using XGBoost with a small grid search hyperparameter tuning but this did not improve much the cross-validation results.