3D Point Cloud and Modeling (NPM3D)
TP 3: Neighborhood descriptors

Borachhun YOU

Question 1

If the radius of the spherical neighborhood is too small, few neighboring points are associated with each point, and the noise of the position of the point results in noise on the computed normals. The left image of figure 1 can be seen as an example.

If the radius is too big, the considered neighborhood covers a large space of points, resulting in lost of local information. For example, in the right image of figure 1, the edges of the windows have the same direction as the wall because the neighbors of the point on the edge of the window consists mainly of points on the wall.

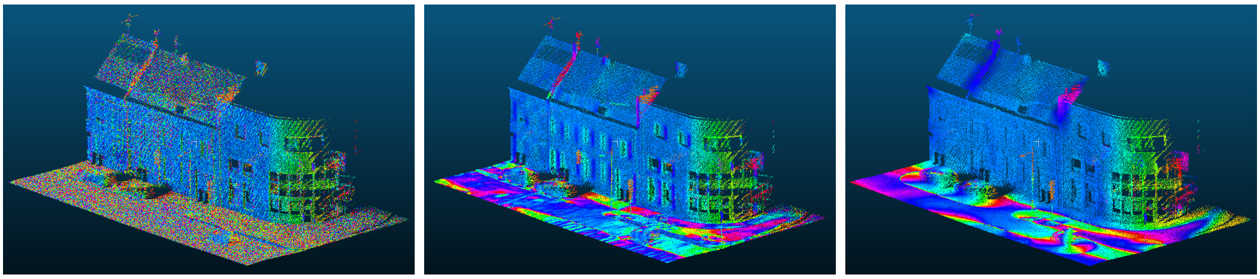

Figure 1: Normals computed on `Lille_street_small.ply` with CloudCompare with neighborhood radius of 0.1m (left), 0.5m (middle) and 2m (right)

Question 2

The neighborhood scale can be chosen based on how detailed we want the estimation to be. If we want to obtain small details, for example the edges of the windows in `Lille_street_small.ply`, we can use a small radius (the case of 0.5m in question 1). If small details are not important and can be omitted, then we can use larger radius for a less noisy result. In addition, the optimal value of the objective function of the optimization problem of plane approximation of the neighborhood can also be compared for different radii.

Question 3

If we consider a group of points describing a small part of a 3D surface, the eigenvector associated with the smallest eigenvalue is expected to be the normal of the surface.

Figure 2 shows the normals computed with the function `compute_local_PCA` with a neighborhood radius of 0.5m and converted as “Dip” scalar field. The result looks almost identical to the one obtained with CloudCompare in figure 1 (the middle image).

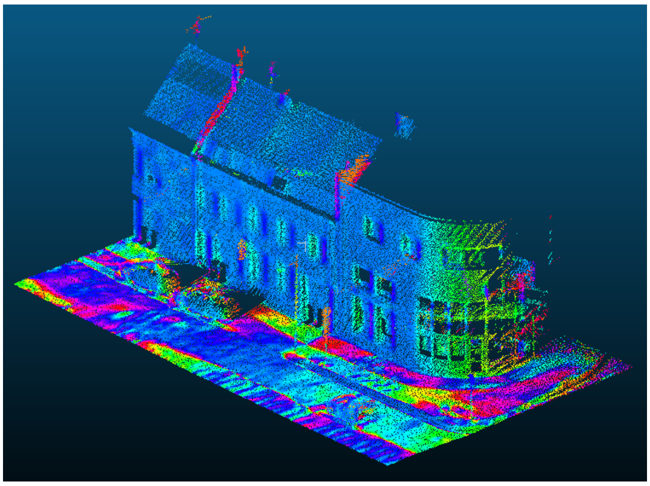

Figure 2: Normals with neighborhood radius of 0.5m

Question 4

Figure 3 shows the normals computed with the function `compute_local_PCA` with 30 nearest neighbors and converted as "Dip" scalar field. It can be seen that this result is noisier, especially on the ground, compared to figure 2 which uses the spherical neighborhood method. This is mainly due to the high density of points of the cloud. The 0.5m-radius spheres manage to capture more neighboring points than the fixed number of nearest neighbors method, making the result less noisy.

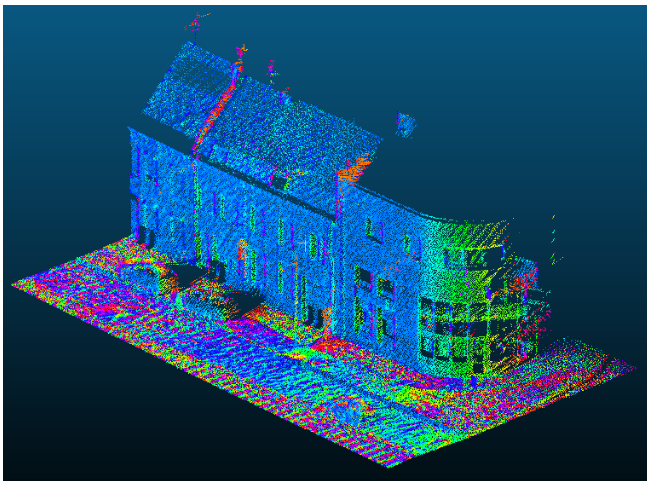

Figure 3: Normals with 30 nearest neighbors

Bonus Question

We consider the eigenvalue naming convention: $\lambda_1 \geq \lambda_2 \geq \lambda_3$.

With linearity, if $\lambda_1 \gg \lambda_2, \lambda_3$, the value is close to 1. This translates to points spreading out in one direction much more than the other orthogonal directions.

With planarity, if $\lambda_1 \approx \lambda_2$ and $\lambda_1, \lambda_2 \gg \lambda_3$, the value is close to 1. This translates to points spreading out in two orthogonal directions at approximately the same ratio but much less for the other orthogonal direction.

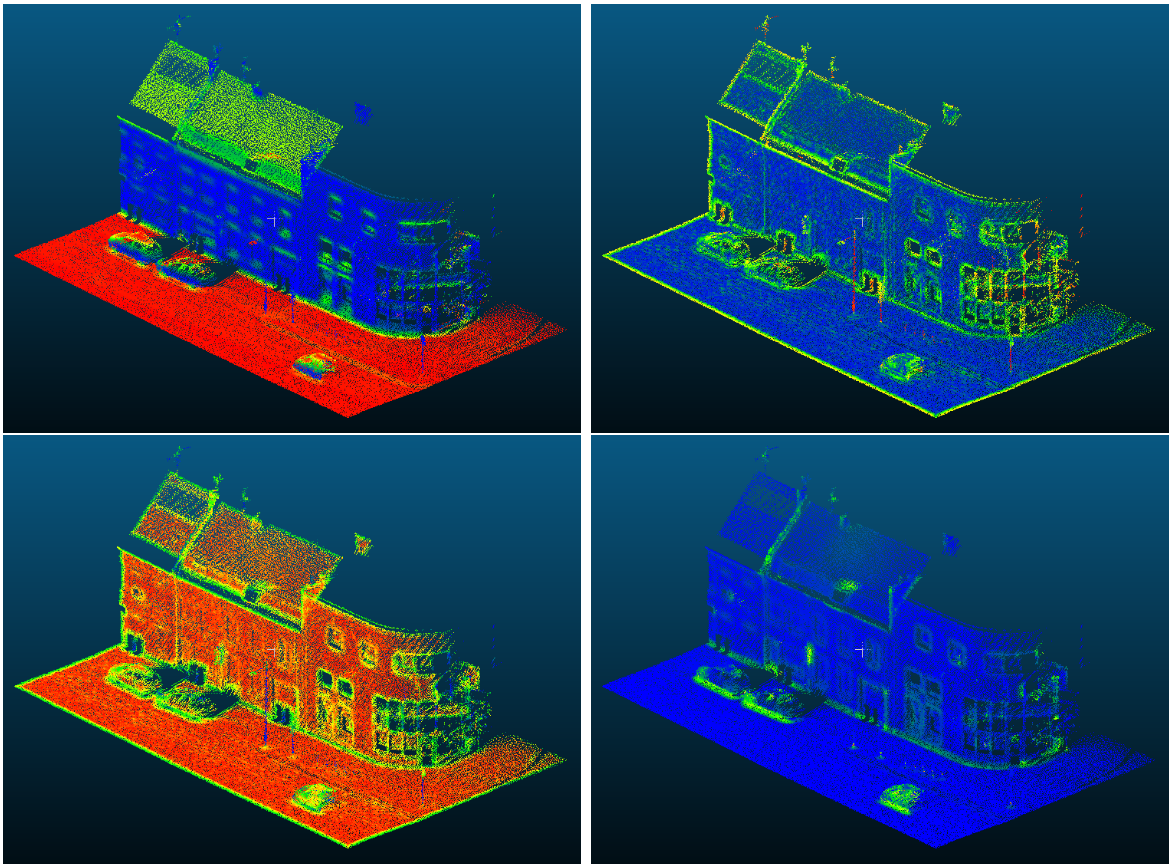

Figure 4: Four different features of the point cloud: verticality (top left), linearity (top right), planarity (bottom left) and sphericity (bottom right)

With sphericity, the value is close to 1 if $\lambda_1 \approx \lambda_3$, which also means that $\lambda_1 \approx \lambda_2 \approx \lambda_3$. This translates to points spreading out in the three orthogonal directions at approximately the same ratio.