Points Cloud and 3D Modeling
TP3

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Question 1

If you use a too small / too big radius, what is the effect on the normal estimation? Use screenshots to support your claims.

Solution

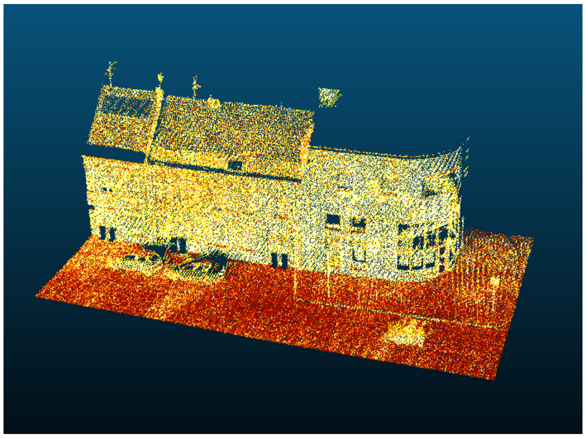
We can distinguish the normals in figure 1 to be red. We can observe on the left plot that we **underestimate** the normals of the points when we choose a very small radius (in this case it was 50 centimeters) due to the small neighborhood we consider to compute them. Whereas on the right plot, we can see that we **overestimate** the normals because we consider a larger neighborhood, the radius of this last is 2 meters.

Question 02

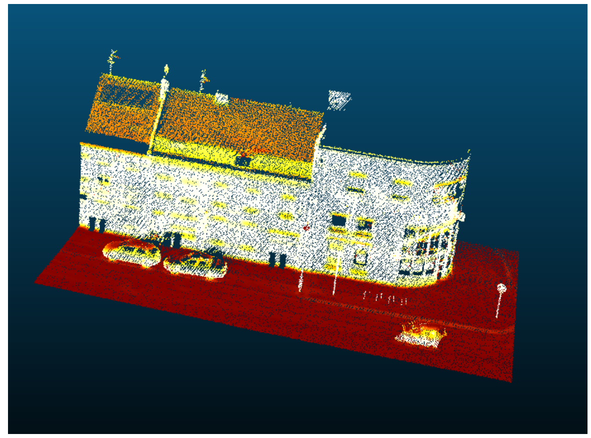
How would you choose the neighborhood scale for a good normal estimation?

Solution

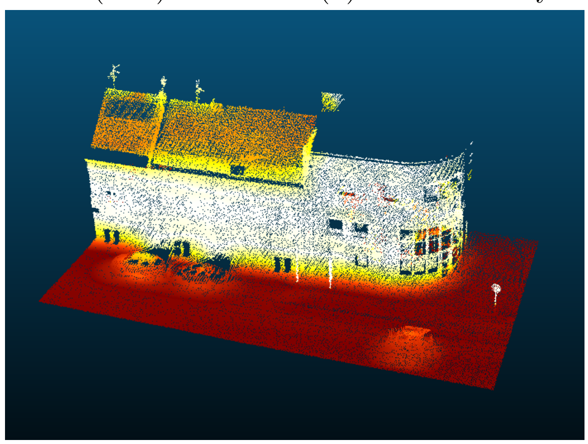
A good approach to estimate normals is to consider a flat area that would allow us not to underestimate them nor to overestimate them. A good example is to take the center of the car roof and compute the radius to the extreme points (it should be of the order of half a meter). An approach to overestimate is to take the flat road (which would give a radius of 3 or 4 meters). Finally an approach to underestimate the normals is to take the lamp post and take the radius if the lamp-cover (which would result in 5 centimeters or less).



(a) Too small radius (5cm).



(b) auto radius by CloudCompare (38 cm)



(c) Too large radius (2 m)

Figure 1: Comparison of normal estimation when using a too small or a too big raidus

Question 3

Show a screenshot of your normals converted as "Dip" scalar field in CloudCompare with radius = 0.50m.

Solution

Our implementation allows us to have the same result as the one we compute using CloudCompare.

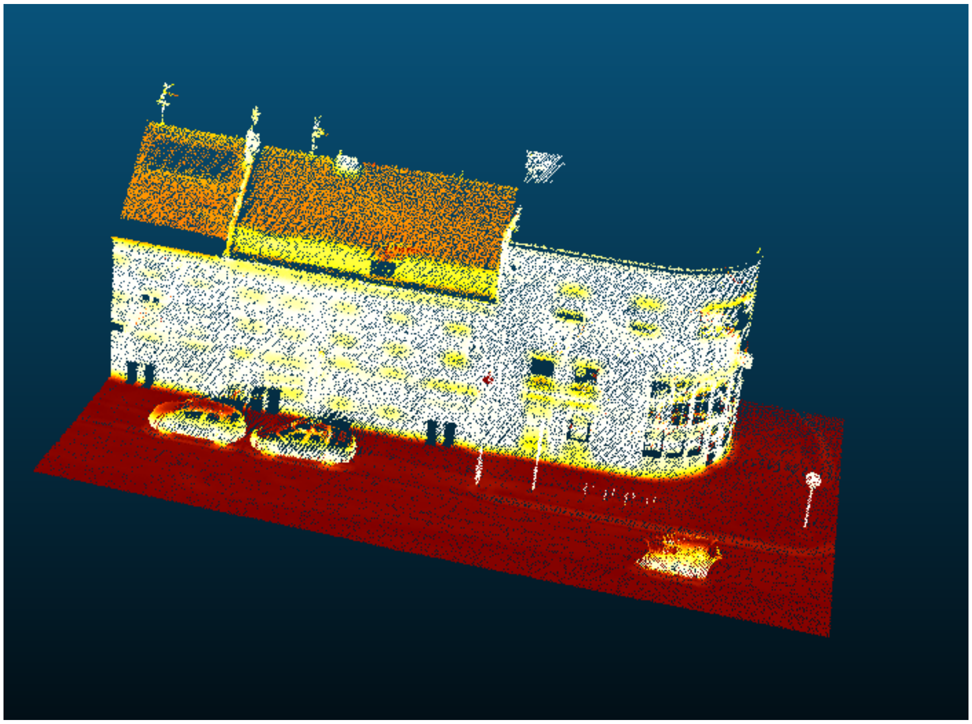


Figure 2: Our normals computation

Question 4

Change the neighborhood definition of your normal by using k nearest neighbors instead of a radius. Show a screenshot of your normals converted as "Dip" scalar field in CloudCompare with k = 30. What are the differences with the radius method and why?

Solution

The main difference remains in the way we define the neighborhood. When we use the radius method, to find the neighbors of a given point, we choose all the points that are on the radius of the circle having that point as its origin (so we don't have a fixed number of fixed). Whereas when we consider K-nearest neighbors, for a given point, we choose the k nearest points to it (so we will have a fixed number of neighbors). Using the radius method for estimating the normals is better because the radius is a measure that we can estimate to better estimate the normals, however, to estimate the k in the KNN, it's a bit not as easy as the radius. In this case, having $k = 30$ seems to be good (We also tried with $k = 10$ and we had also a good estimate of the normals). We will tend to underestimate the normals using KNN with a small k and overestimate them using a large k.

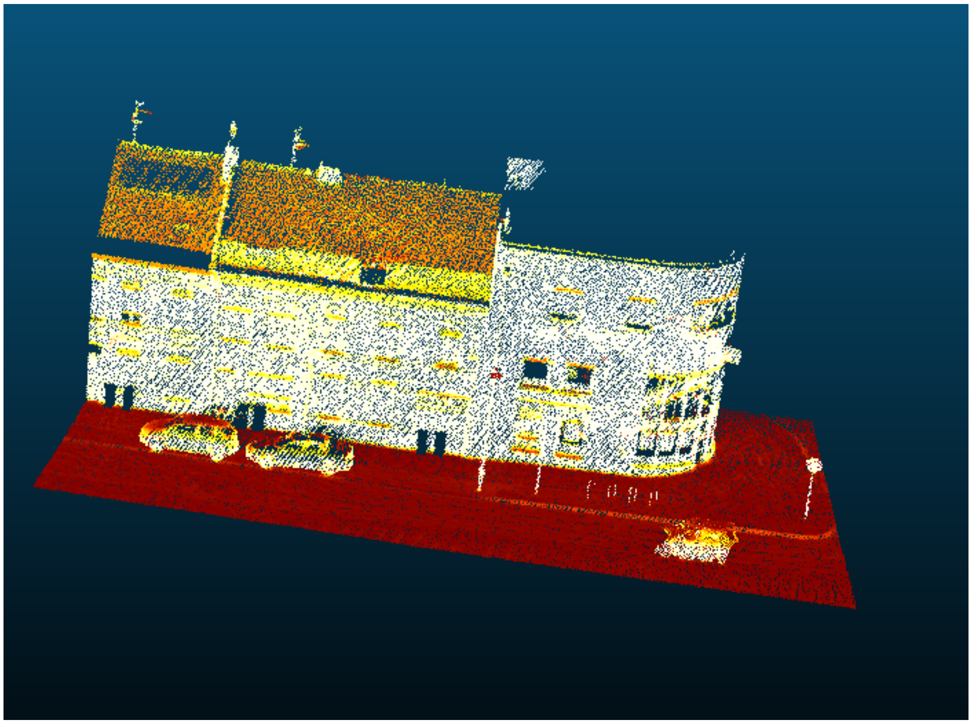


Figure 3: Our normals computation using KNN with k = 30

Bonus Question

Show screenshots of the 4 features as scalar fields of the point cloud. Can you explain briefly the names of the 3 last features considering their definition with eigenvalues?

Solution

Figures below show the different descriptors that have been computed.

Figure 4b shows the linearity field, which, as its name suggests, has high values for linear parts of the point cloud, which in our case is the whole point cloud. We know that

$$linearity = 1 - \frac{\lambda_2}{\lambda_1}$$

If we remember the meaning of the eigenvalues in the PCA, that is, the eigenvalues are sorted by order of explained variance, we can understand that a point cloud being linear would mean that the ratio $\frac{\lambda_2}{\lambda_1}$ would tend towards 0 since, λ_1 would be very large compared to λ_2.

Figure 4c shows the planarity field, and we can draw the same conclusions as for the linearity field. Again, with the same reasoning, we have

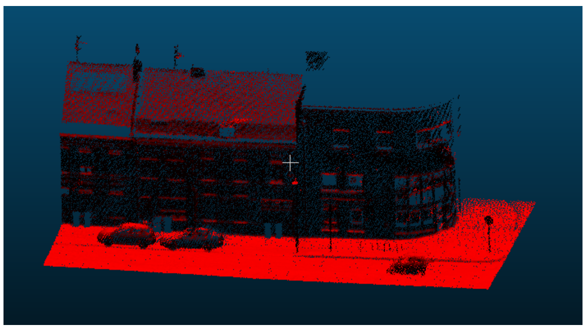
$$planarity = \frac{\lambda_2 - \lambda_3}{\lambda_1}$$

Planarity would mean that λ_3 would be very small compared to the other values.

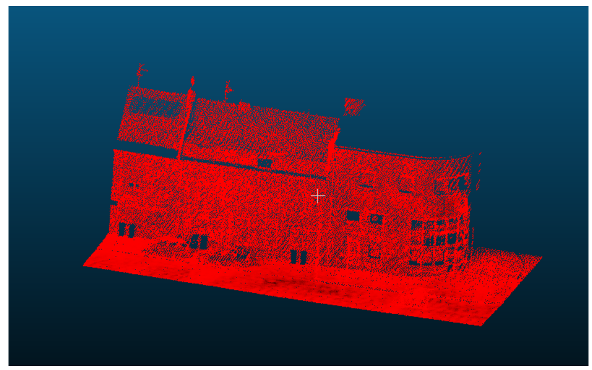
Figure 4d shows the sphericity field, which is equal to 0 everywhere, since the point cloud does not contain a spherical element.

$$sphericity = \frac{\lambda_3}{\lambda_1}$$

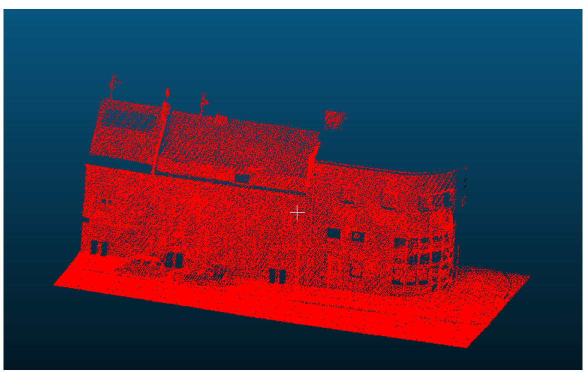
, which means that λ_3 should be big enough in comparison to λ_1 to create a meaningful sphere.



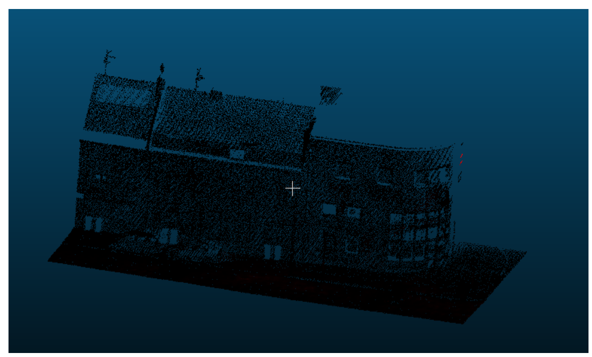
(a) Verticality field



(b) Linearity field



(c) Planarity field



(d) Sphericity field

Figure 4: Features of verticality, linearity, planarity, and sphericity.