Robotics Final stage2

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⚠️Important Notice⚠️:

- Due to my poor computational resource, every time I tried to do localization and mapping on my UTM (M1 mac ubuntu VM) is stuck and terminated. I tried enormous of the effort to solve this but failed. So, I just used my local ros2-humble-mac, so it works quite well except for open3d package, which is not supported for the apple silicon. This is why I used the plyfile library instead of the open3d. So, you might need to install plyfile by command `pip install plyfile.` only when if you want to save the map. I am very sorry about this uncomfortable decision. And I manually implemented the voxelization by numpy because I can't use the Open3d Voxelization. So, please understand that the ply file may or may not be different from the type that generated from the open3d.
- Note: you can change the saveply file to utilize the open3d and also reduce the burden to install plyfile library. But as my limitation of the VM, I can't test it.

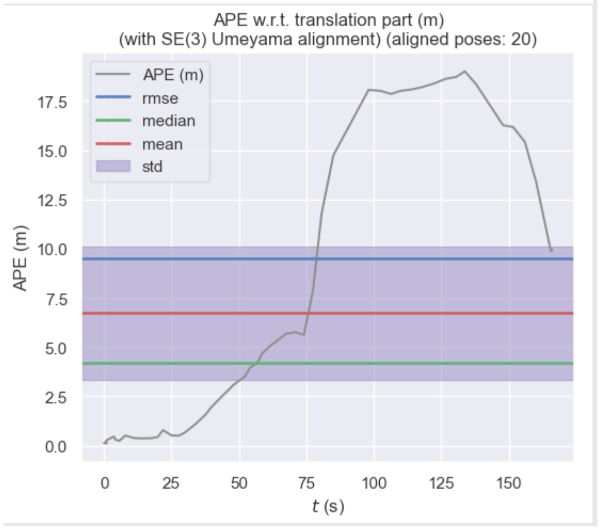
```
def saveply(self, filename='map.ply'):
        save_points = self.view_points if self.map_save else self.map_points
        vertex = np.array([(p[0], p[1], p[2]) for p in save_points],
                    dtype=[('x', 'f4'), ('y', 'f4'), ('z', 'f4')])
        el = PlyElement.describe(vertex, 'vertex')
        PlyData([el], text=True).write(filename)
```

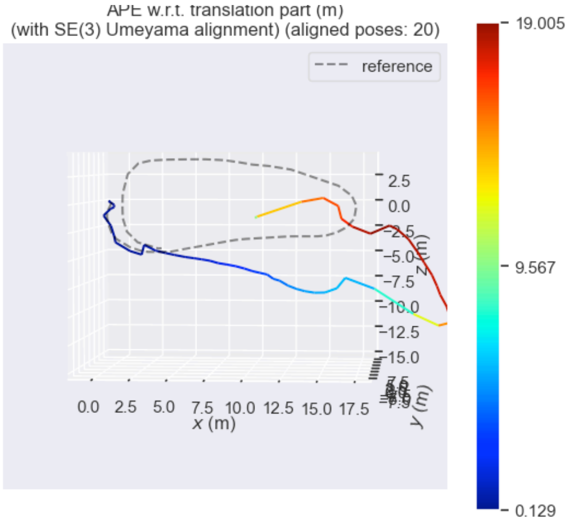
- into

```
def saveply(self, filename='map.ply'):
        save_points = self.view_points if self.map_save else self.map_points
        point_cloud = o3d.geometry.PointCloud()
        point_cloud.points = o3d.utility.Vector3dVector(save_points)
        o3d.io.write_point_cloud(filename, point_cloud)
```

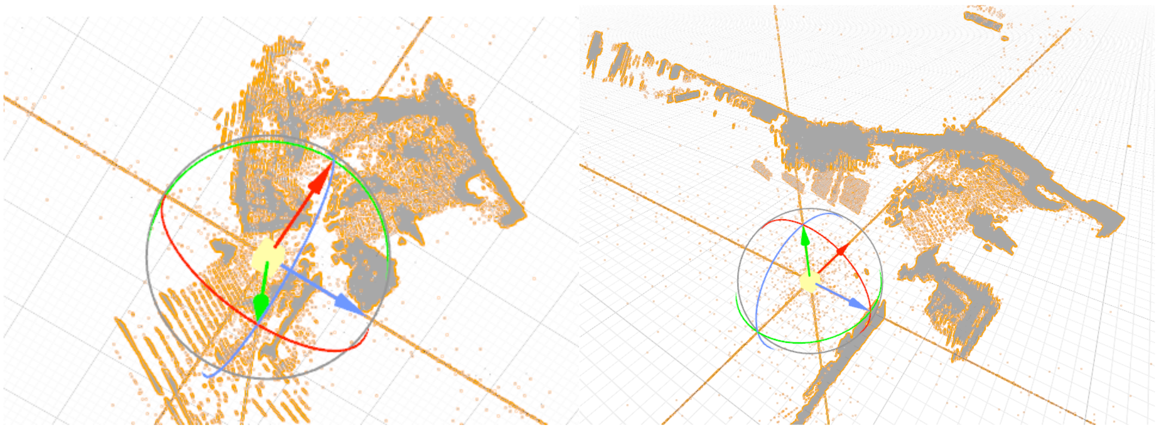
-

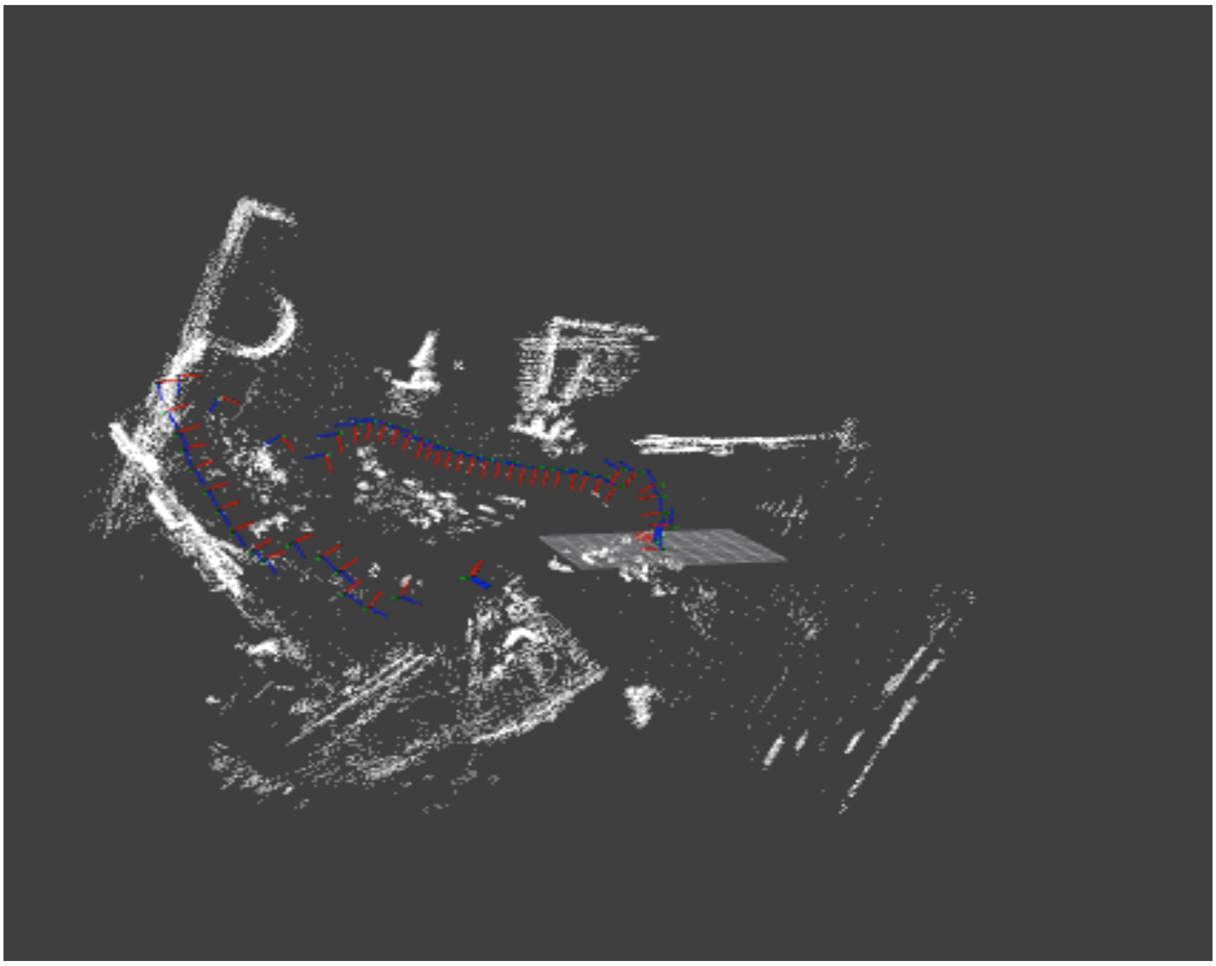
1. Analysis (bag play speed : 0.05 which is 20x slower than the normal)





These are my results of the stage2 db3 files were applied by the algorithm that I've used in the stage1. As you can see here, At first, it is naturally APE, error is 0 because the origin is the initialized point. But as you can see here as time goes, the error increases proportionally. This is because the error of the target (map_points) records cumulatively where the error of the real and estimate also cumulative. In this sense, we can expect the time proportionally increased error.


This is my result from the ply viewer mac. Again, in my VM, it eventually terminate while ICP in run-time, and also my m1 mac local doesn't support open3d conda environment, so I just attach this image by the local ply viewer.



In here, as you can see many duplicated points are in the dense area. This might cause crucial error while doing ICP because it will eventually use the total size of the points of maps when finding correspondences. As we assumed the points with only one to one correspondence might tightly fit in the ICP, if not the majority can have duplicated target points which is not we wanted when we consider the speed and accuracy. Also, this is somehow noisy data. So that, we need to remove those of the noise points.

For the questions of the handout, I think it is not necessary to maintain all the points data. As I explained earlier, it maybe harm to the either speed or accuracy of the ICP, because of the duplicated target data. Also, maintaining enormous data (140MB for example) in all seconds are quite memory consuming. Instead, one thing we only need is just maintaining one point in such grid by the voxelization might help to improve those possible hazards.

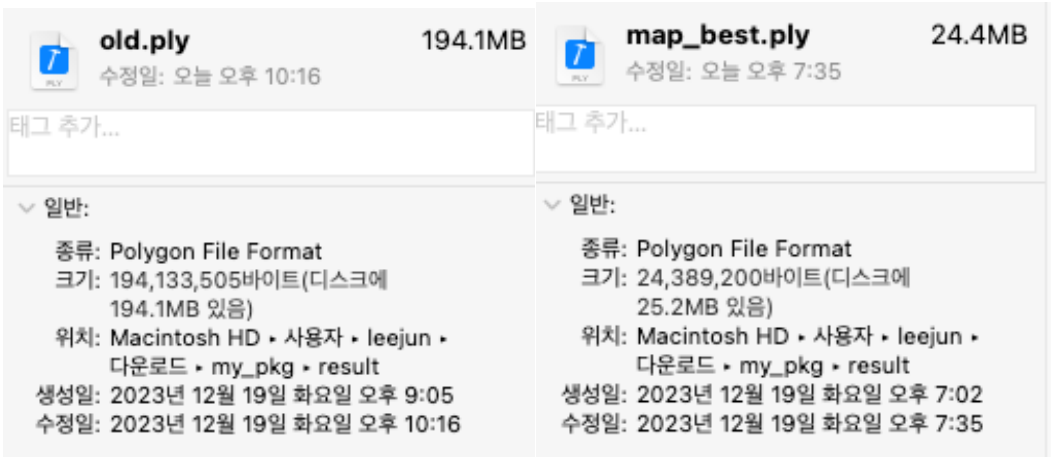
2. Evaluation

- **Memory efficiency**: (The bag play speed is equally 0.05, 20x slower)
- ⚠️ (Note that my code is updated version for the optimization on the pose accuracy. So,

the voxelized mapping will not show as the result below. You can save the map using the parameter self.map_save = True, but in this case due to the lagging program in my computer the pose accuracy is not correct as the below estimation. So, the default I set is False)

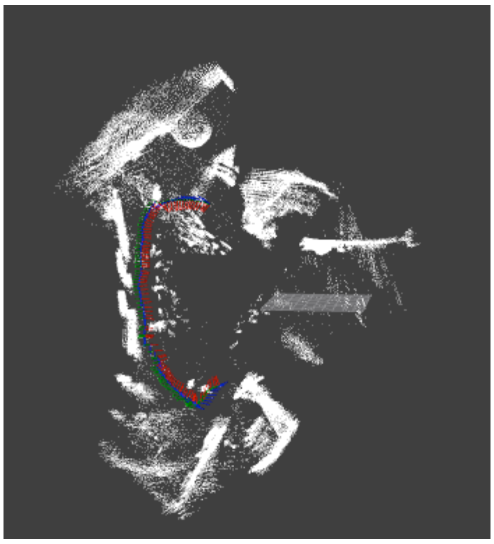
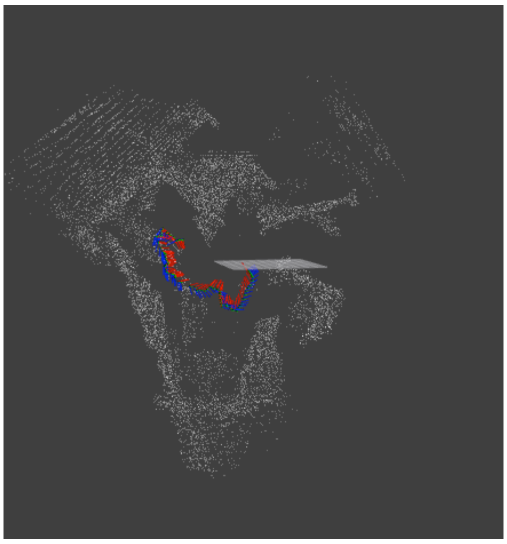
-

[Suggestion] Voxelization until it can get the meaningful result in localization mapping.
 Even though bag play file lagged in the baseline, so that the point cloud doesn't perceive all of the data in the baseline, there were significant improvement of the memory size by the proposed method which perceives n times data then the baseline.
The base line, which is the exactly same code of the Stage 1's memory consumption is following.
Only 73 times perceived of the all publishes.


old.ply 194.1MB
수정일: 오늘 오후 10:16
태그 추가...
일반:
종류: Polygon File Format
크기: 194,133,505바이트(디스크에 194.1MB 있음)
위치: Macintosh HD ▸ 사용자 ▸ leejun ▸ 다운로드 ▸ my_pkg ▸ result
생성일: 2023년 12월 19일 화요일 오후 9:05
수정일: 2023년 12월 19일 화요일 오후 10:16

map_best.ply 24.4MB
수정일: 오늘 오후 7:35
태그 추가...
일반:
종류: Polygon File Format
크기: 24,389,200바이트(디스크에 25.2MB 있음)
위치: Macintosh HD ▸ 사용자 ▸ leejun ▸ 다운로드 ▸ my_pkg ▸ result
생성일: 2023년 12월 19일 화요일 오후 7:02
수정일: 2023년 12월 19일 화요일 오후 7:35

The first one is the old version which is base line, and the second one is the voxelized version with d = 0.1. Please note that the map_best.ply file got the 399 published points which is significantly larger than the those of the baseline. With just a simple math we can calculate the difference of the ply storage in the same published points.
399 // 73 * 194.1 // 24.4 = 39 this means that about 39x can reduce the memory size!
(Note that the voxel size is the appropriate one that it is compatible for the remaining metrics)
Then there might be one more question that what about voxel grid size up to get more down-sampled one? The answer is, there is no linear reduction due to the existence of the noise. Think about the lonely point in the space. Then no matter the voxel size is, the remaining number after down sampling steal same as 1. So, in this manner, if the points were not overlapped in the certain voxel grid, it might not be reduced so that It means the linear reduction is not expected.
In my calculation of the real data in the stage2, the voxel size 2x goes to the about 4 or 5x reducing in some certain period, which is in the significantly dense voxel d limitation. If not, the reduction is not as much as n times of the voxel size increased.

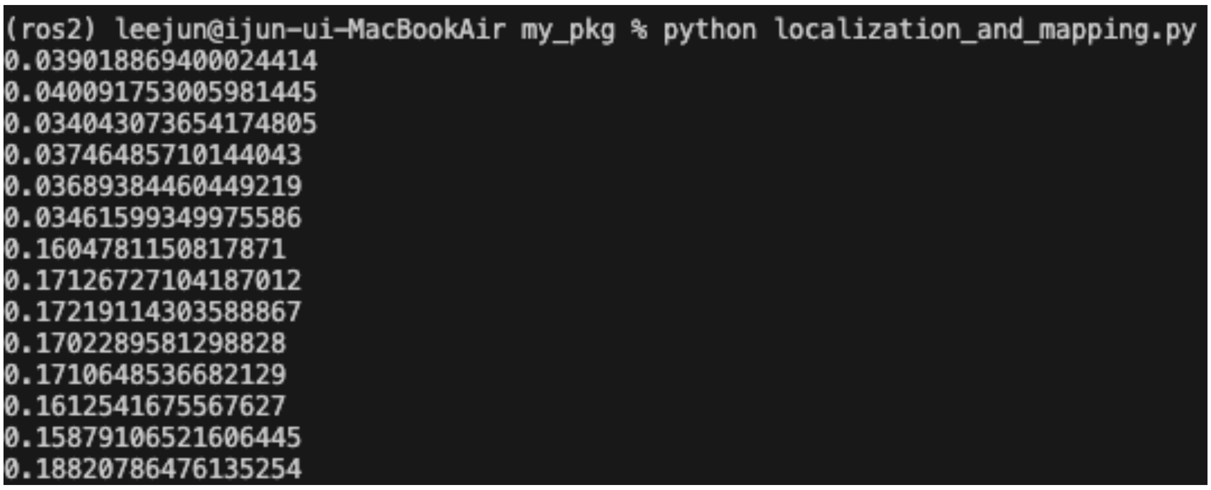



The left one is non voxelized and the right one is voxelized version.

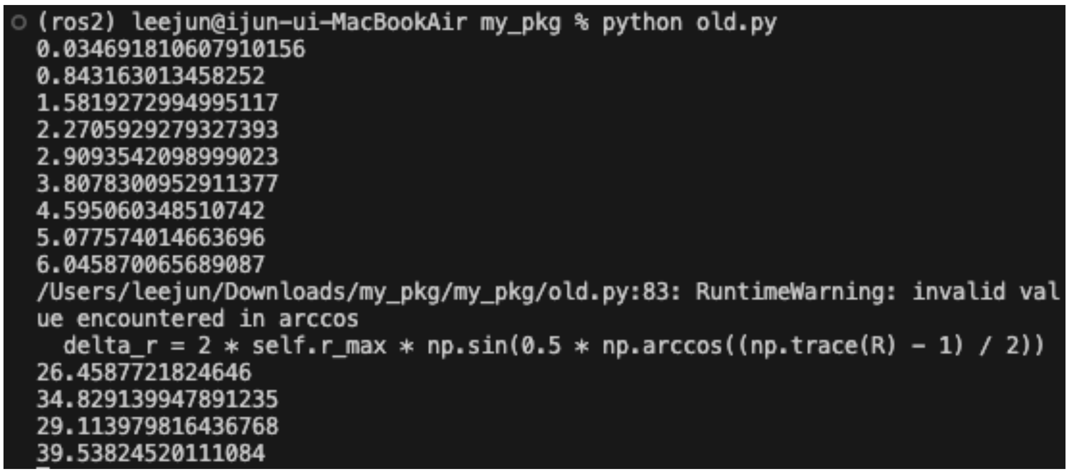
This much improvement directly from the idea that pointing the representative points in each section. In real time case, as the points from the depth image is quite dense so that even if the correspondence points and the target points exactly match after the ICP, the result of the updating the map points will accept both. Which is truly memory consuming. Also, the ICP algorithm doesn't match each point 100%, so that the correspondences will locate the nearby the target, but it may assume other points in terms of the map points. So, to prevent these problems, by representing one points as voxel, we can reduce the significant memory consumption.

	Baseline	Voxel (d = 0.1)	Voxel (d = 0.3)
Storage[MB]	194.1	24.4	12.1

- **Computation Speed**:
- (The bag play speed is equally 0.05, 20x slower, image is improve baseline order)
- [Suggestion] The y axis is fixed so that apply only x,z axis SVD using orthogonal projection.

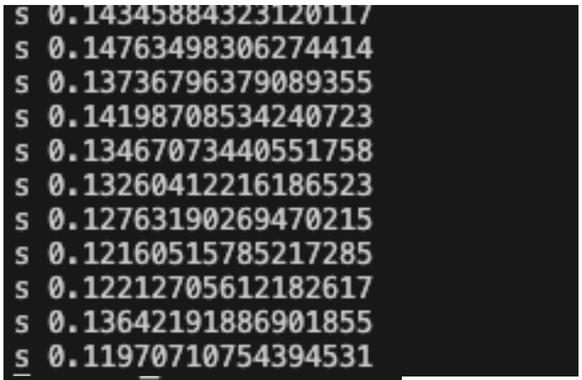


```
(ros2) leejun@ijun-ui-MacBookAir my_pkg % python localization_and_mapping.py
0.039018869400024414
0.040091753005981445
0.034043073654174805
0.03746485710144043
0.03689384460449219
0.03461599349975586
0.1604781150817871
0.17126727104187012
0.17219114303588867
0.1702289581298828
0.1710648536682129
0.1612541675567627
0.15879106521606445
0.18820786476135254
```

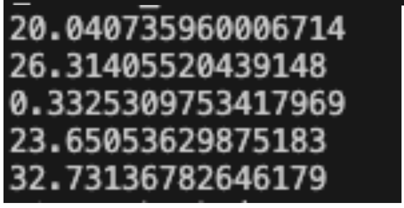


```
○ (ros2) leejun@ijun-ui-MacBookAir my_pkg % python old.py
  0.034691810607910156
  0.843163013458252
  1.5819272994995117
  2.2705929279327393
  2.9093542098999023
  3.8078300952911377
  4.595060348510742
  5.077574014663696
  6.045870065689087
  /Users/leejun/Downloads/my_pkg/my_pkg/old.py:83: RuntimeWarning: invalid val
  ue encountered in arccos
    delta_r = 2 * self.r_max * np.sin(0.5 * np.arccos((np.trace(R) - 1) / 2))
  26.4587721824646
  34.829139947891235
  29.113979816436768
  39.53824520111084
```

These are the computational time that includes the all of the following steps include compute_icp().



```
s 0.14345884323120117
s 0.14763498306274414
s 0.13736796379089355
s 0.14198708534240723
s 0.13467073440551758
s 0.13260412216186523
s 0.12763190269470215
s 0.12160515785217285
s 0.12212705612182617
s 0.13642191886901855
s 0.11970710754394531
```



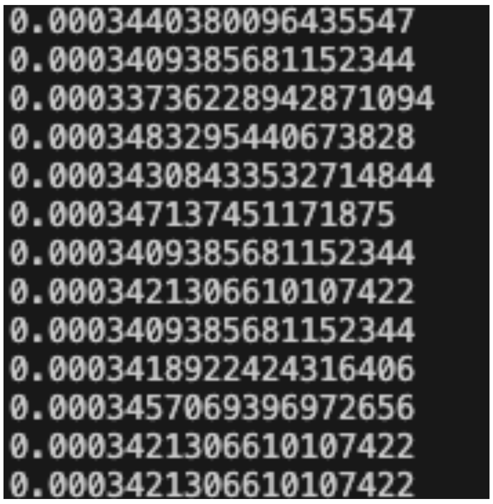
```
20.040735960006714
26.31405520439148
0.3325309753417969
23.65053629875183
32.73136782646179
```

These are the computational time that only includes the compute_icp().

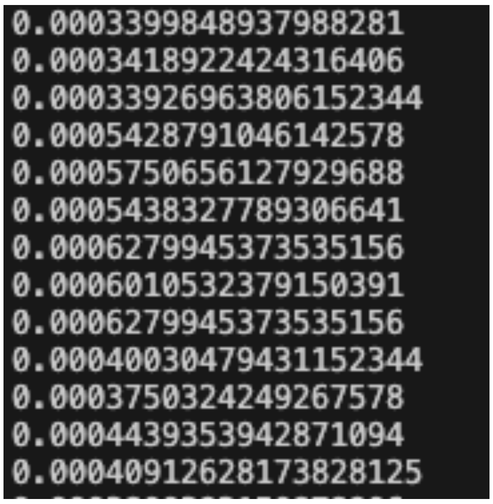
The overall improvement is like net, so the memory consumption decrease affects the speed of the computation. Because of the managing memory significantly decreased, the overall speed increased by reducing I/O burden. But what about the speed except the managing the memory?

The second two images demonstrate this. The overall speed of the new version of the localization and mapping remains the same as 0.12 but the old version of the ICP takes about 20 seconds which is about 17x slower than the improved version.

Someone might argue that it might be the reason of the target and source size difference by the voxelization, so that I fixed the size of source and target as 500 and again computed only the one iteration at the SVD and these are the results. **Which delete the effect of the voxelization. And below is the result.**



```
0.0003440380096435547
0.0003409385681152344
0.00033736228942871094
0.0003483295440673828
0.00034308433532714844
0.000347137451171875
0.0003409385681152344
0.0003421306610107422
0.0003409385681152344
0.0003418922424316406
0.0003457069396972656
0.0003421306610107422
0.0003421306610107422
```



```
0.0003399848937988281
0.0003418922424316406
0.00033926963806152344
0.0005428791046142578
0.0005750656127929688
0.0005438327789306641
0.0006279945373535156
0.0006010532379150391
0.0006279945373535156
0.00040030479431152344
0.0003750324249267578
0.0004439353942871094
0.00040912628173828125
```

The left one I baseline and the right one is my suggestion. As you can see here the lowest time is quite similar but the the baseline version which use the 3x3 matrix, the highest time consumed is 0.0062 around 1.8x slower than my suggestion. This is because the reduction of the degree of freedom of the matrix to compute in ICP-SVD.

	Overall	**Compute_ICP()**	**SVD (same target and source) Which delete the effect of the voxelization**
Baseline(s)	0.17	0.13	0.00034
Suggest(s)	33.7	18.8	0.00047
Bag speed	0.05(20x slower) because I want to see full computation without bothering		

As you can see above, the algorithm of the voxelization make amazing time reduction. But as you can see here the computing ICP by SVD in the same condition where the computing number of target and source points are same, the improvement seems quite good because it keeps doing this for 300times in for loop. This small improvement also very important in terms of the overall speed reduction.

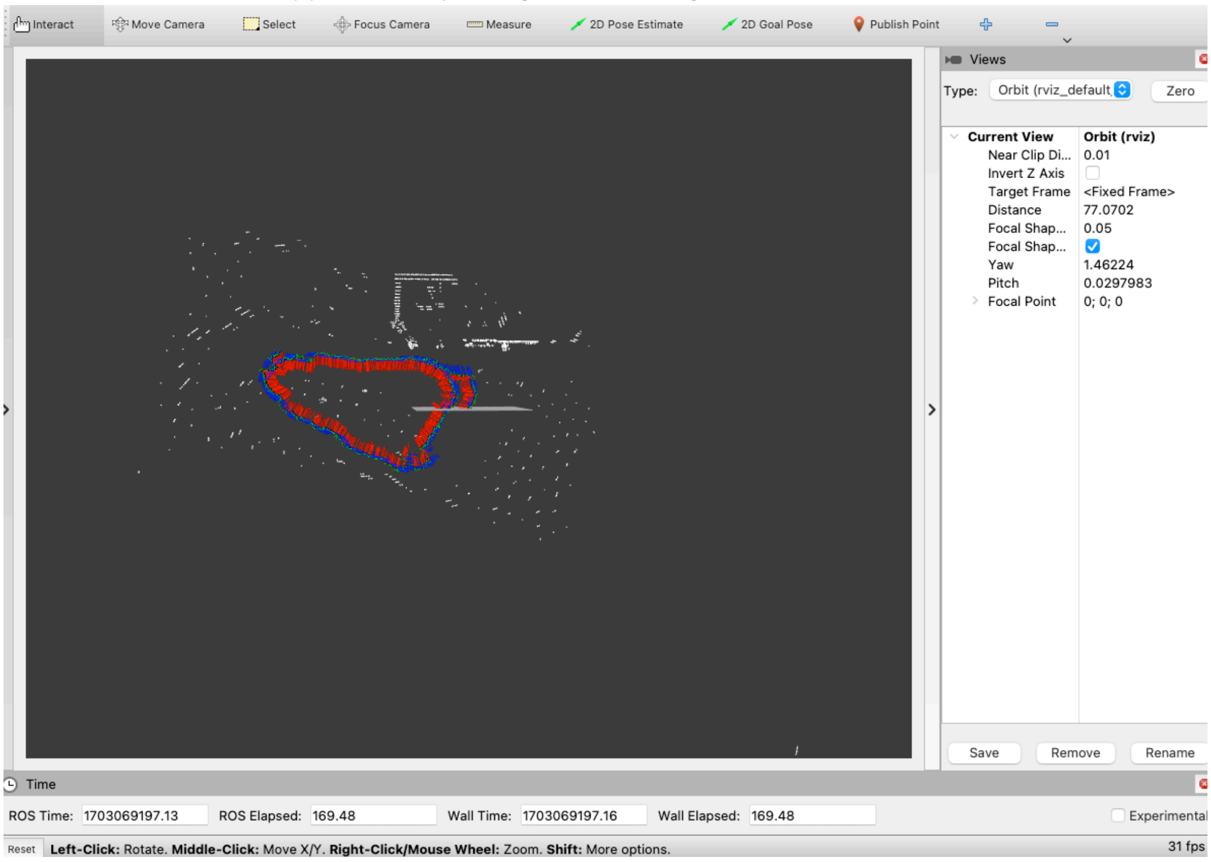
- **Pose accuracy**:

- (The bag play speed for my updated code is equally 1 normal speed)
- ⚠Important Notice⚠: I don't know why, but in my case without the align parameter goes well, but in the case of the align it seems awkward. Maybe caused by the axis setting, but anyhow, I did the command by following:

  evo_ape tum /Users/leejun/Downloads/my_pkg/result/stage2_gt_pose.txt /Users/leejun/Downloads/my_pkg/my_pkg/odometry_data.txt -p

  As far as I know, *without alignment* might be more difficult and my code did well in this bad situation.

  Please set self.map_save = False when you evaluate the accuracy.
- [Suggestion] The y axis is fixed so that apply only x,z axis SVD using orthogonal projection(2d). And also, the added data to the target (map points) is only the data which cannot find the correspondence. Let me say this strategy as **golden data strategy**. Which means the source data which the distance between the correspondence exceeds the threshold. With that, I applied the updating threshold algorithm from the **KissICP**.



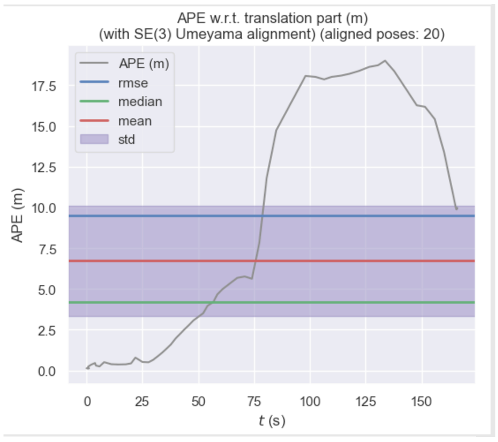
Type: Orbit (rviz_default) Zero

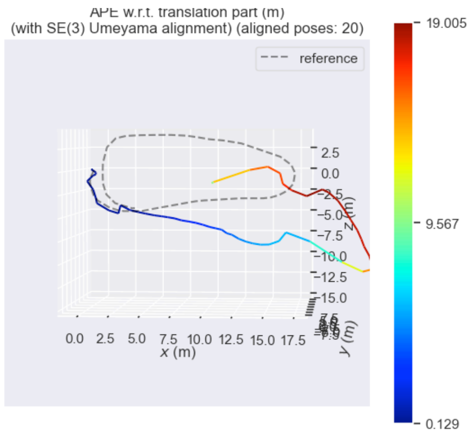
Current View	Orbit (rviz)
Near Clip Di...	0.01
Invert Z Axis	☐
Target Frame	<Fixed Frame>
Distance	77.0702
Focal Shap...	0.05
Focal Shap...	✓
Yaw	1.46224
Pitch	0.0297983
Focal Point	0; 0; 0

ROS Time: 1703069197.13 ROS Elapsed: 169.48 Wall Time: 1703069197.16 Wall Elapsed: 169.48

Left-Click: Rotate. **Middle-Click:** Move X/Y. **Right-Click/Mouse Wheel:** Zoom. **Shift:** More options. 31 fps

-
- Like this image, the only updating target points are missed correspondence points from source point. Which is the outlier. Then we can get abstract and accurate map as the image represents. (Please understand map will seems to be weird, because I only concentrate to the pose accuracy and speed. If you add the save points function, then it will show the whole point cloud but somehow slower and accuracy can decrease by the absence of the interpolate frame.)

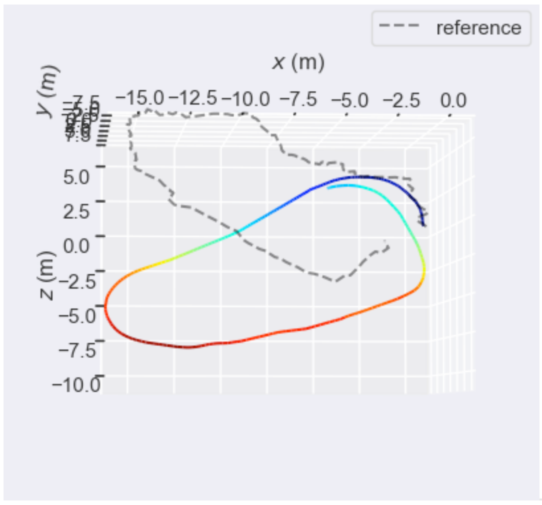


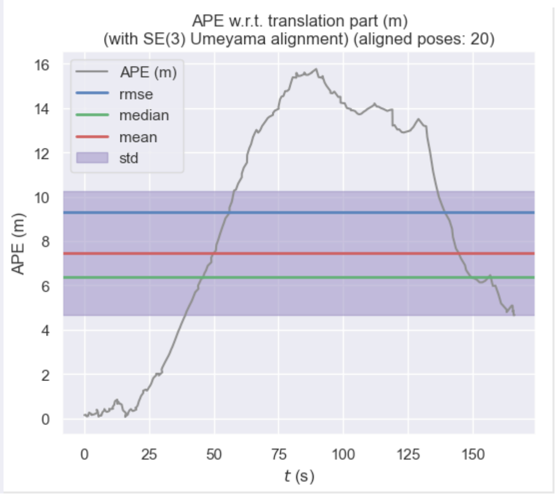


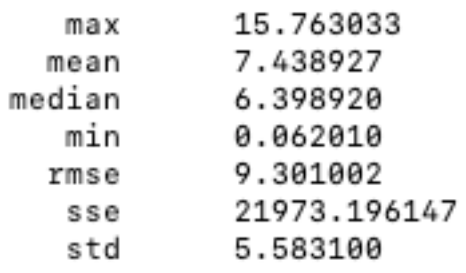
```
   max          19.004812
  mean          6.721188
median          4.207689
   min          0.128867
  rmse          9.527270
   sse          6626.127886
   std          6.752371
```

These are my **baseline** best result which performs the best among the baseline test by manually changing the bag speed. And this is the speed of 0.05 which is 20x slower than the normal.

But in my algorithm, it seems very accurate when compare by the baseline even if the bag play running speed is 20x faster than the baseline, which is just normal speed.

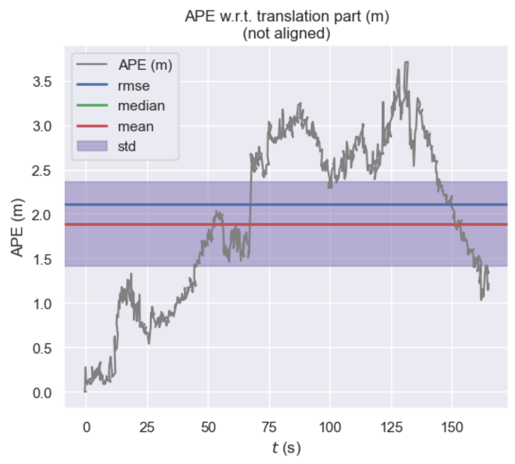


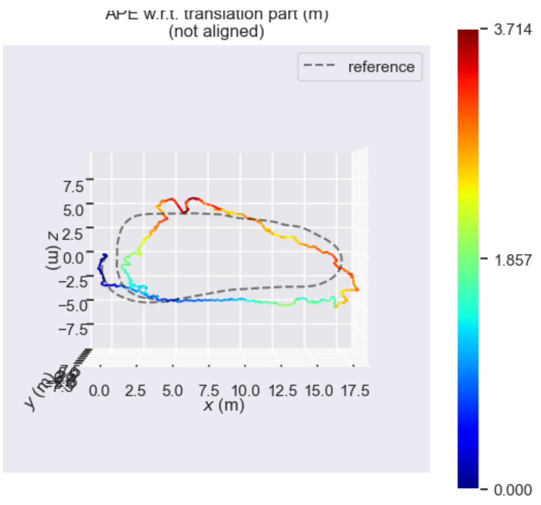


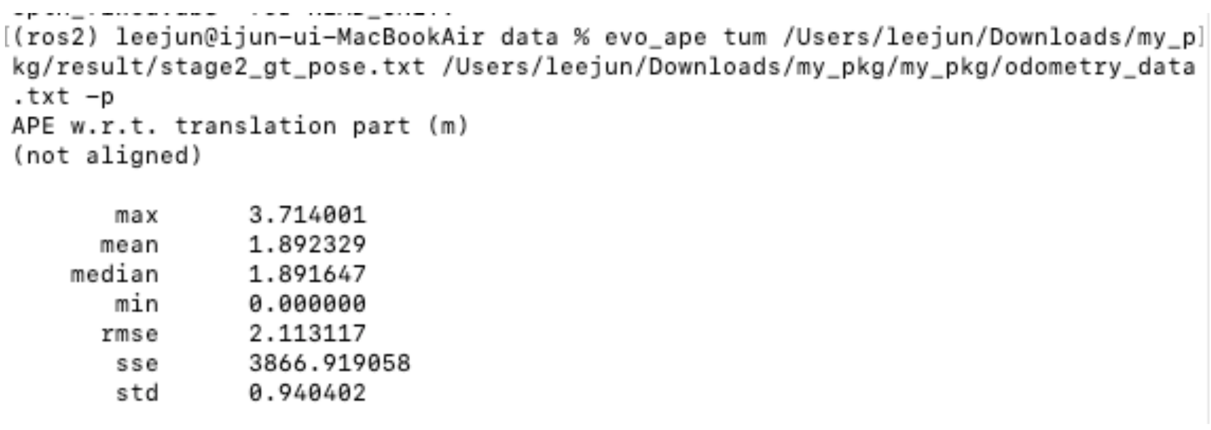


```
    max       15.763033
   mean       7.438927
 median       6.398920
    min       0.062010
   rmse       9.301002
    sse       21973.196147
    std       5.583100
```

This is the result before applying the **golden data.** Which means that it only applies the transformation of the xz plane only. As you can see here, the accuracy is not that good because if the data that is added to the map points, if it is not accurate data, the error is cumulatively increased.





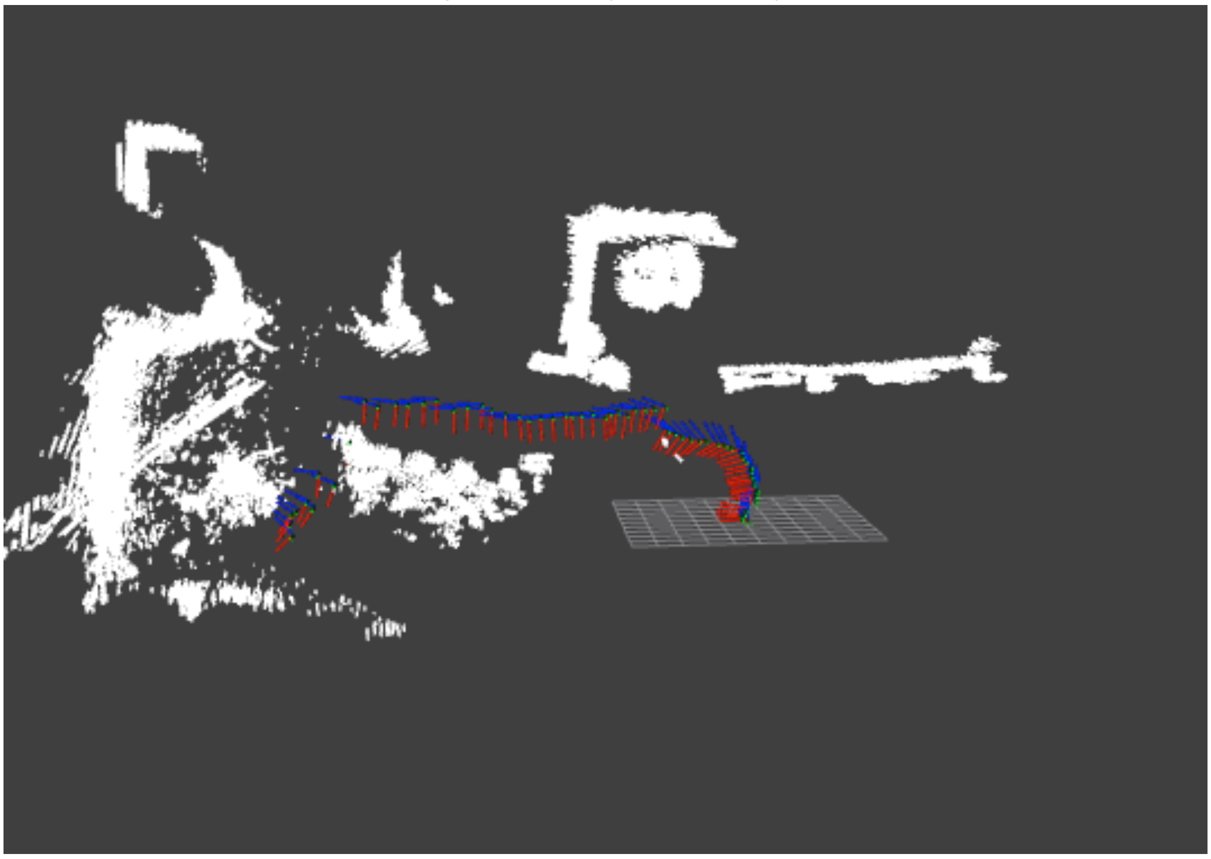


```
[(ros2) leejun@ijun-ui-MacBookAir data % evo_ape tum /Users/leejun/Downloads/my_p]
kg/result/stage2_gt_pose.txt /Users/leejun/Downloads/my_pkg/my_pkg/odometry_data
.txt -p
APE w.r.t. translation part (m)
(not aligned)

       max      3.714001
      mean      1.892329
    median      1.891647
       min      0.000000
      rmse      2.113117
       sse      3866.919058
       std      0.940402
```

This is the result of without alignment when apply evo-ape and after applying **golden data strategy**. Which is the final code. As you can see this image, the overall accuracy is very high.

This good improvement directly come from the making golden data. Most of the errors come from the complex added data which is having an error. But if we make the golden data which is not likely to change because it treated as the default. So, by doing this, the first captured space, which is likely to most accurate data among all received data. (You can imagine the accuracy of the first few depth map from the bag play.) In ICP will be treated these as default so there might not be any confusion by the false data.



This is the version that includes the map, but here as the I/O time consumes, the buffer by the bag play is not going well as the self.map_save = False version, which is the default, because of the lacking behind computation compared by self.map_save = False which doesn't require further I/O operation and voxelization. So, the result here as you can see, it is worse than the optimized version above.

	baseline	Only XZ plane projection	XZ plane projection, golden data strategy (Final)
Mean Error (m)	6.72	7.43	1.89
RMSE	9.52	9.3	2.11
Bag play rate	0.05	1	1

The reason of the accuracy improvement is that we set the movement in only XZ plane which reduces the computation amount and increase the speed and accuracy as well by reducing the Y axis computation. But the better improvement comes from the golden data strategy, which saves the outlier of the source points (where np.array(distances) > self.thres), because it reduces duplicated and cumulative error by permitting only one point as true value among multiple points from each receiving point clouds. This is similar with the case of the ML. If you give one input and multiple different outputs, then the ML model cannot no which output to choose. But by my golden data strategy, we can give them only one corresponding output and then it is easy and accurate to calculate. So, in these reasons, I can get better result.