TEL AVIV UNIVERSITY אוניברסיטת תל-אביב

THE IBY AND ALADAR FLEISCHMAN
FACULTY OF ENGINEERING

הפקולטה להנדסה
על שם איבי ואלדר פליישמן

Project 1

Mapping and perception for an autonomous robot/ 0510-7591

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Abstract:

In this assignment we will be analyzing and creating an occupancy map using the kitty data set recording: 2011_09_26_drive_0095.

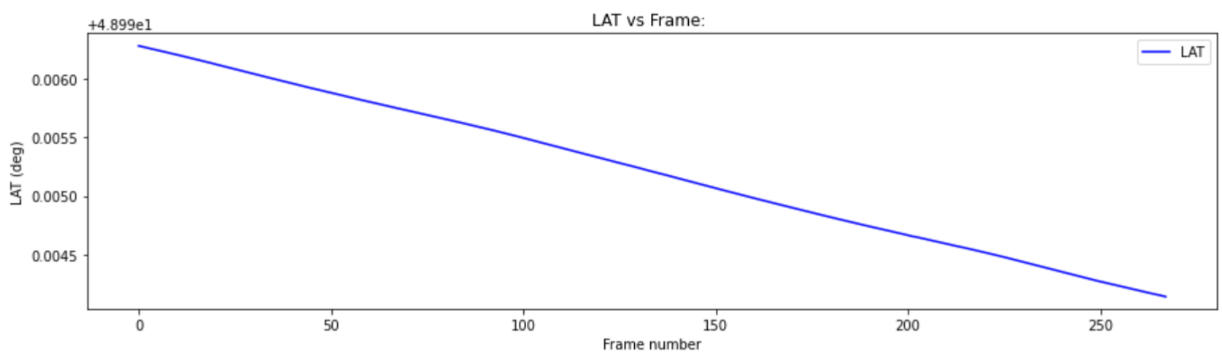
The data set contained:
256 frames of-
Lidar records compatible to each frame - velodyne points(m)
lat: latitude of the oxts-unit (deg)
lon: longitude of the oxts-unit (deg)
alt: altitude of the oxts-unit (m)
roll: roll angle (rad), 0 = level, positive = left side up, range: -pi .. +pi
pitch: pitch angle (rad), 0 = level, positive = front down, range: -pi/2 .. +pi/2
yaw: heading (rad), 0 = east, positive = counter clockwise, range: -pi .. +pi

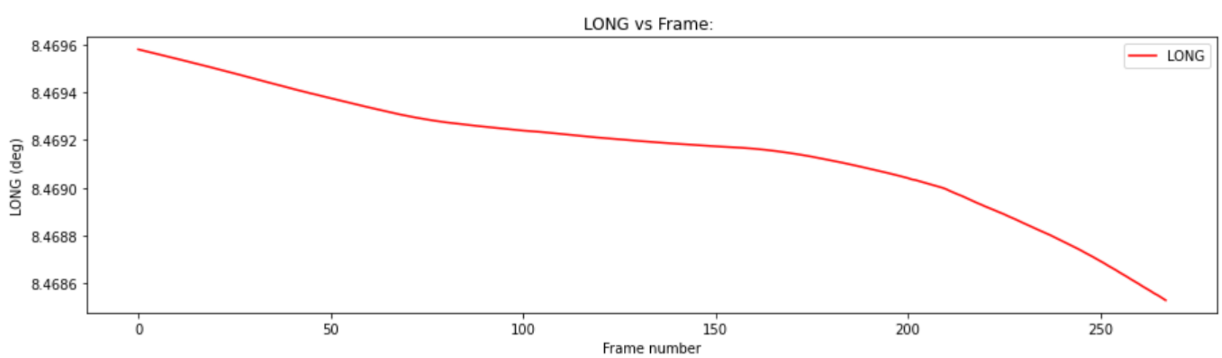
We will be creating a probabilistic occupancy grid map using the inverse range sensor module checking different parameters for Hit/Miss prob and Threshold
We will then corrupt the imu data and attempt to correct our occupancy grid map using the icp algorithm.

Solutions:

1.1.
In this recording the car drove south on a straight street pivoting to the left and then to the right. On the sides of the street there were houses, cars parked ,trees on the sidewalk and bike riders that passed on the cars left. Apart from the riders the street was clear from passing cars.
as can be seen lat and lon are decreasing going south west and the alt decreases then goes up a small amount as can be seen in the next figures:

1.2.





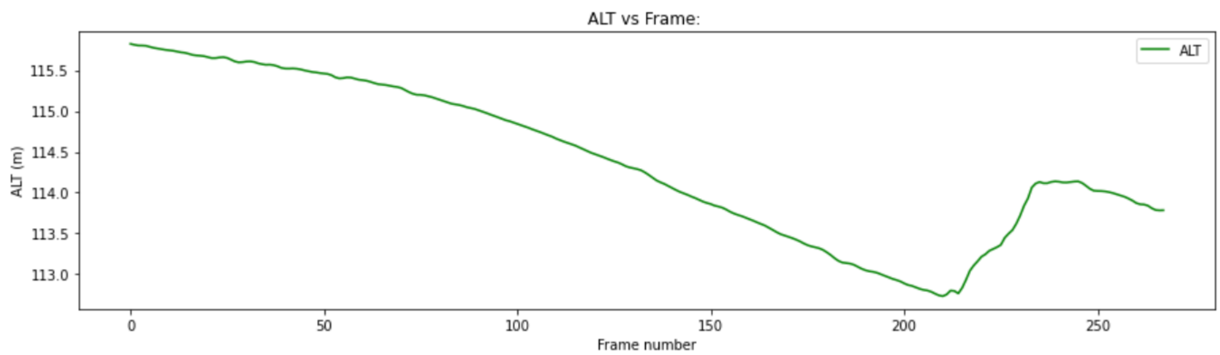
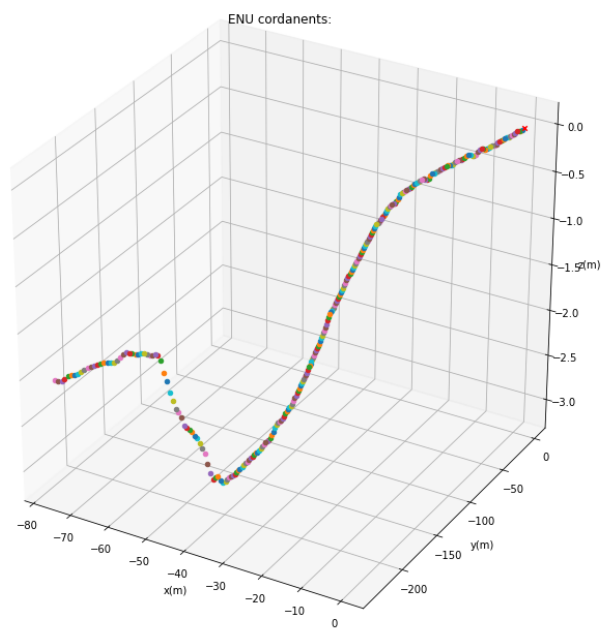
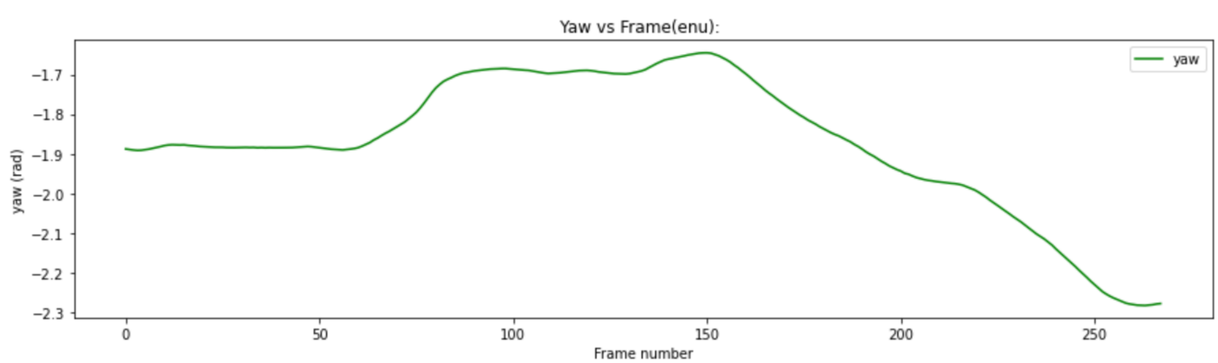


Figure 1

Translating to enu:





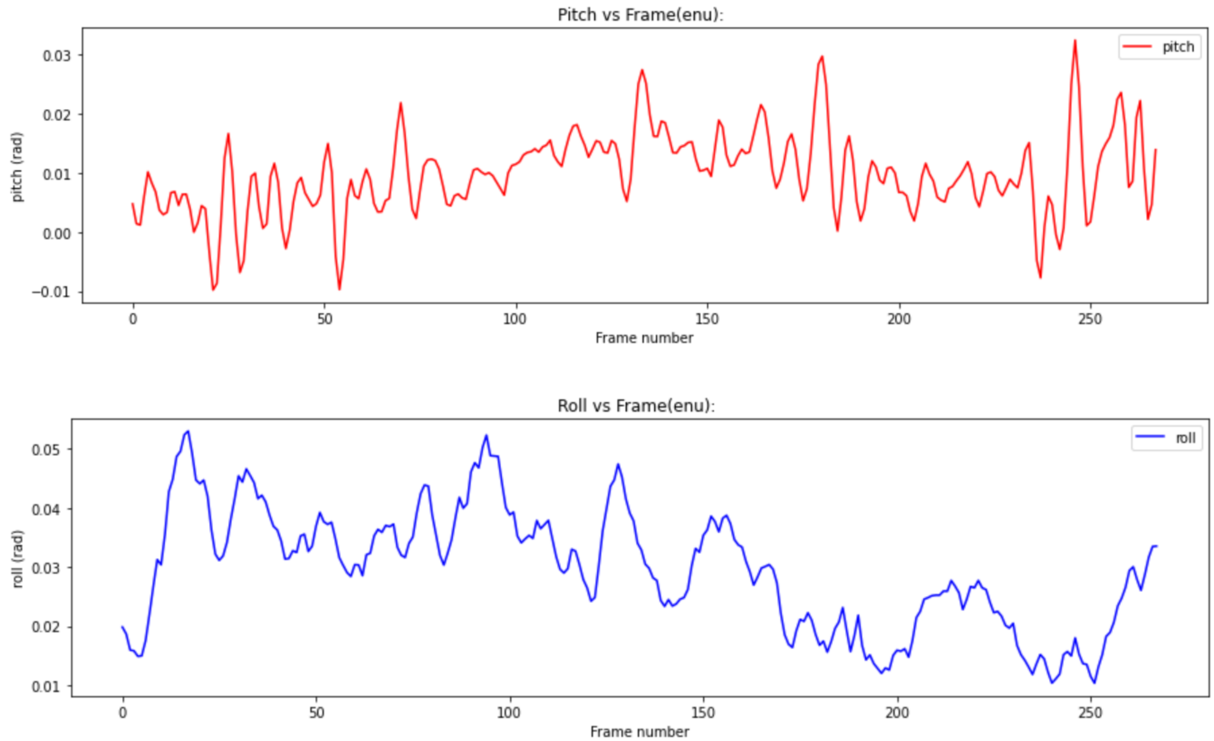


Figure 2

Yaw is negative and decreases indicating driving ssw(with a curve in the middle) pitch is positive hence we are declining and also matches xyz coordinates.
roll stays the same.

Translating to NED:

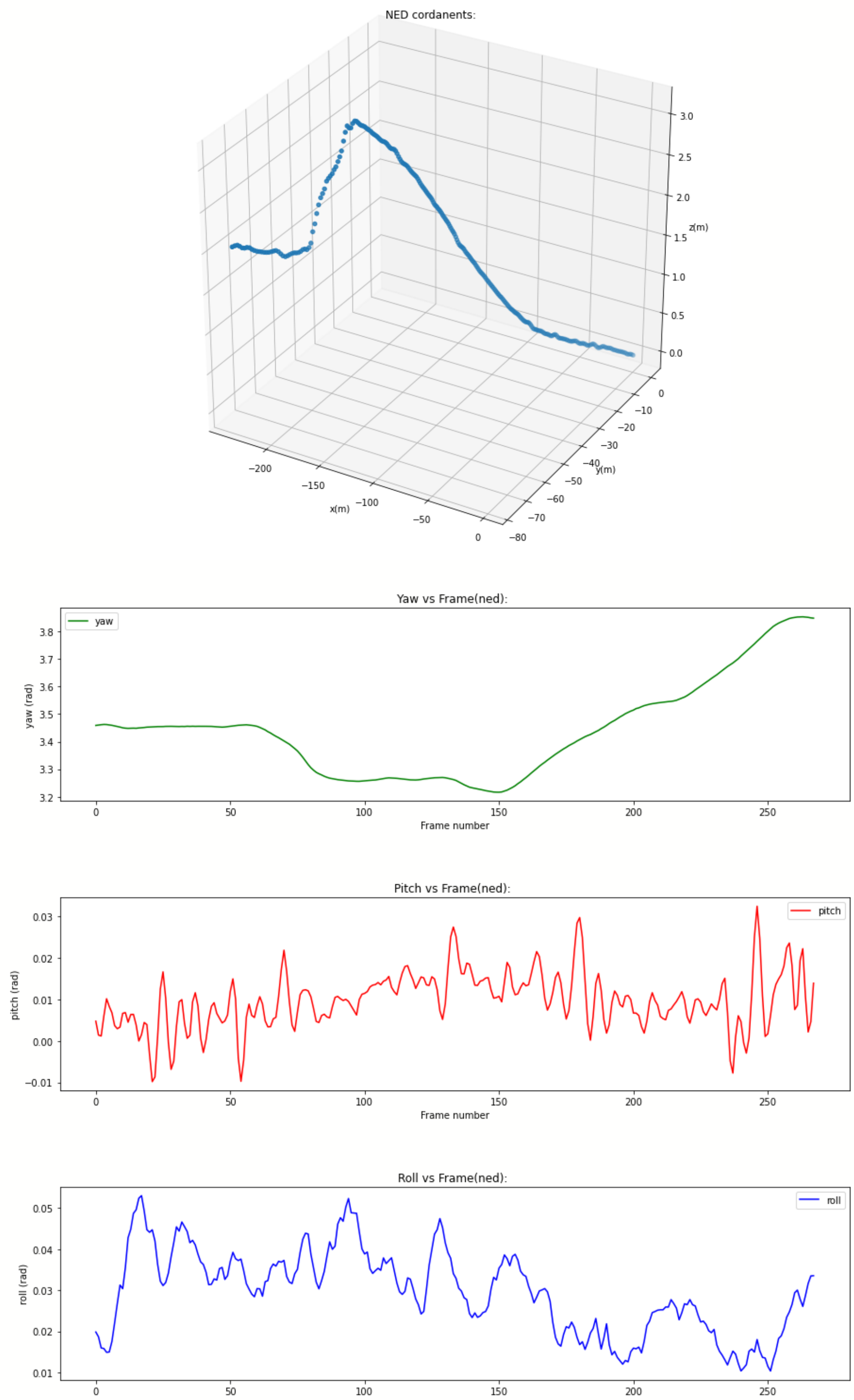


Figure 3

Here we can see that the yaw is the opposite then it was in enu and shifted by 90 deg the yaw increase and is positive indicating were turning ssw and this matches the xyz behavior.
the pitch increases indicating we are heading down in ned coordinate (z increases indicating the car is descending)

1.3. Google maps trajectory of the recorded data:

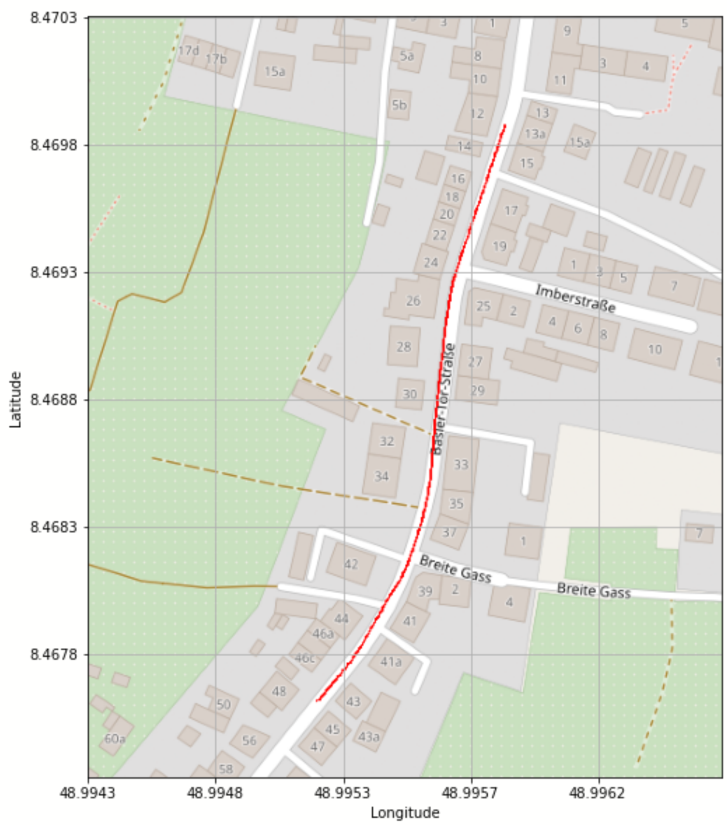


Figure 4

starting from the top of the red line we can see that were driving straight then turning left and then turning right this matches the photos
In addition we can see the gps recordings are pretty accurate so we can assume the gps signal reception was good.

2.1 probabilistic occupancy map:

Figure of final occupancy grid including all recorded data:
Hit/Miss prob 0.7/0.4 Threshold 0.8

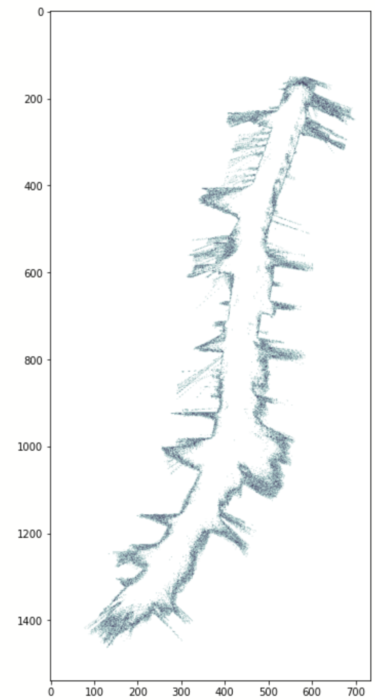


Figure 5:final occupancy grid (0.2m)

As we can see we get a very similar result as in the google maps layout we have a curve in the middle and we are traveling ssw the end block of the road are marked occupied because the scans were cut off and were left with the last scan containing false occupied cells of the ground. In addition you can see the impact of the riders on the left side of the road leaving uncertain areas of occupancy

2.2. Animation: scene image (RGB) • Left: Instantaneous 2.5D point cloud (BEV) • Right: Probabilistic Occupancy map

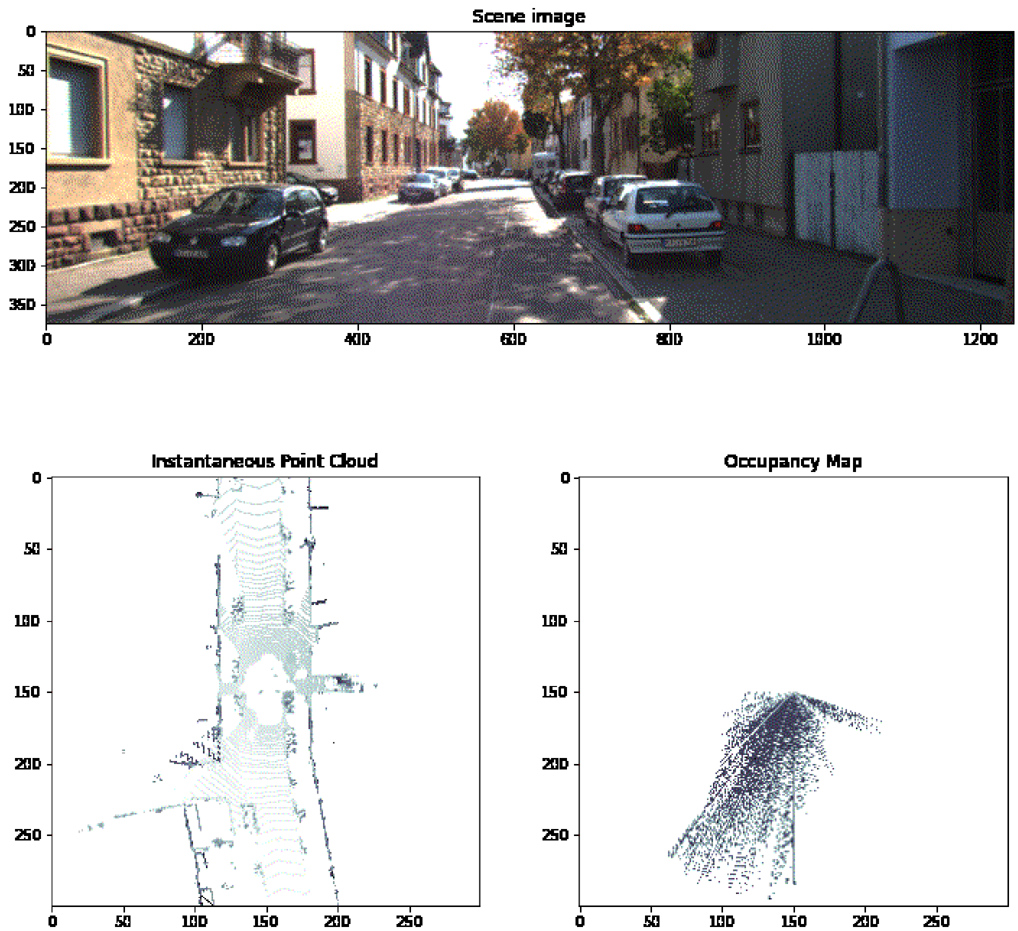


Figure 6: animation of occupancy map (0.2m)

2.3. changed parameters:

-Threshold 0.6 Hit/Miss prob 0.6/0.4:

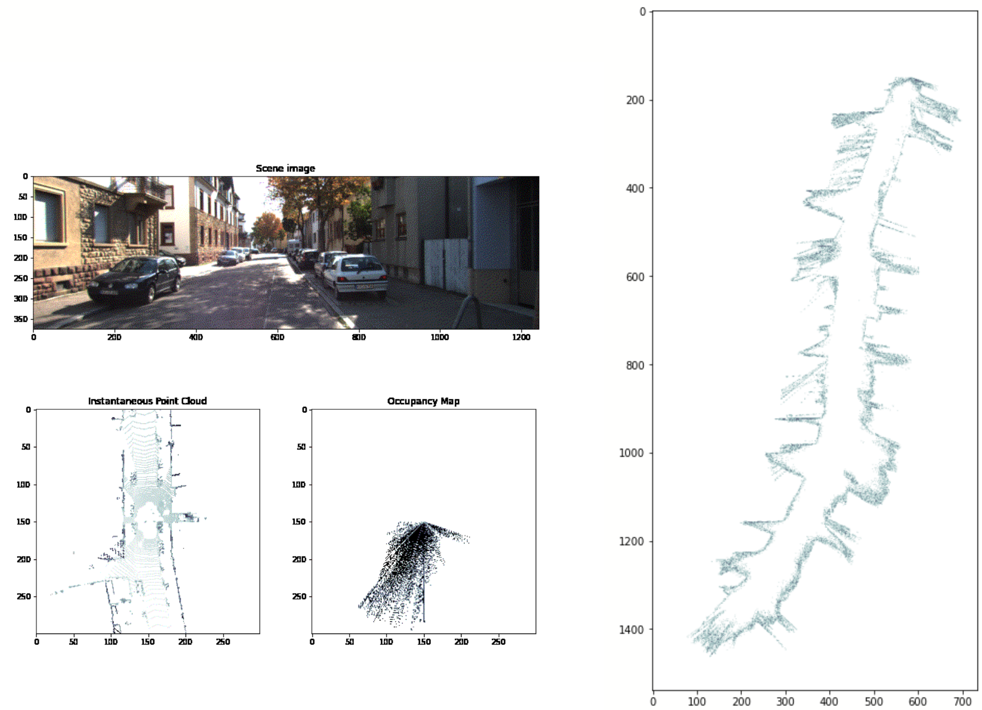


Figure 7: occupancy map (0.2m)

- Threshold 0.75 Hit/Miss prob 0.6/0.4:

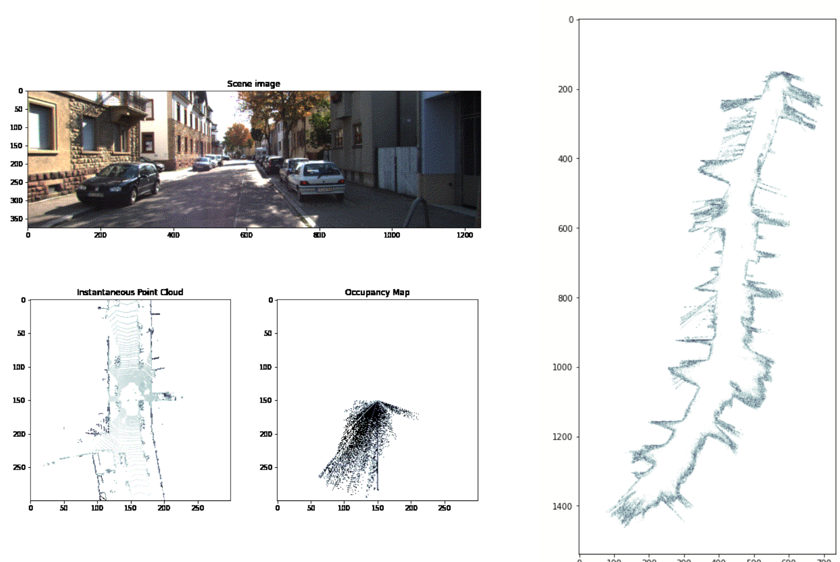


Figure 8: occupancy map (0.2m)

- **Threshold 0.9 Hit/Miss prob 0.6/0.4:**

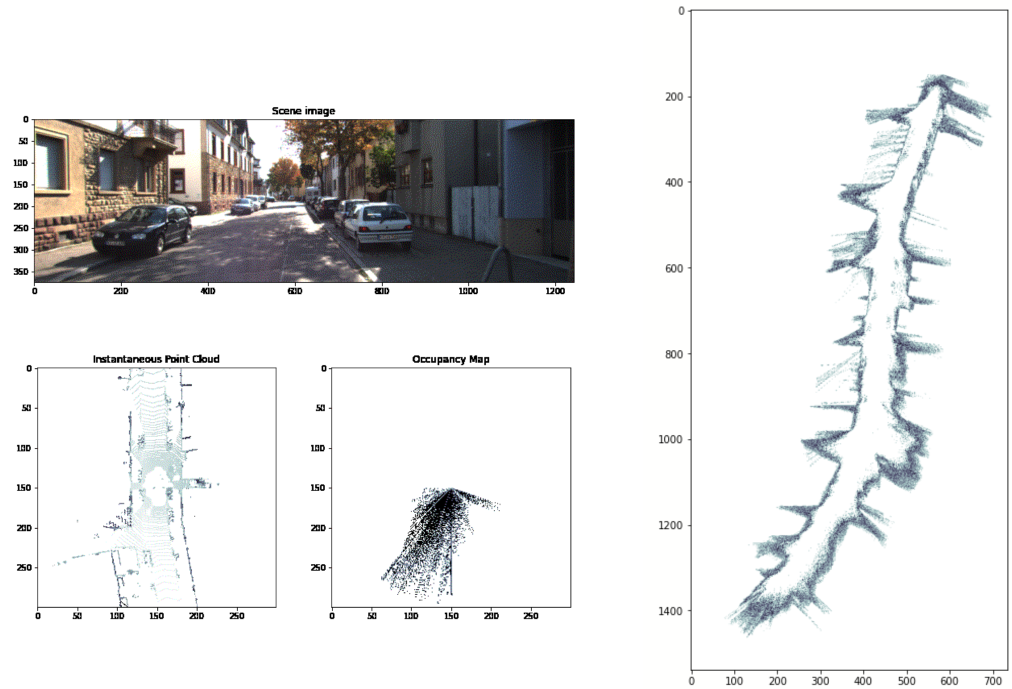


Figure 9: occupancy map (0.2m)

- **Threshold 0.6 Hit/Miss prob 0.9/0.1:**

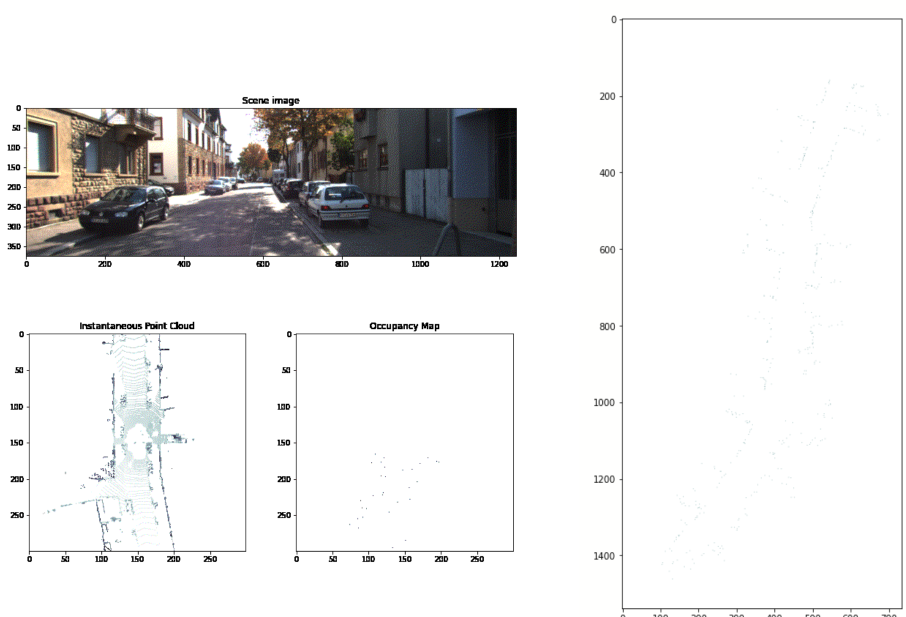


Figure 10: occupancy map (0.2m)

- **Threshold 0.75 Hit/Miss prob 0.9/0.1:**

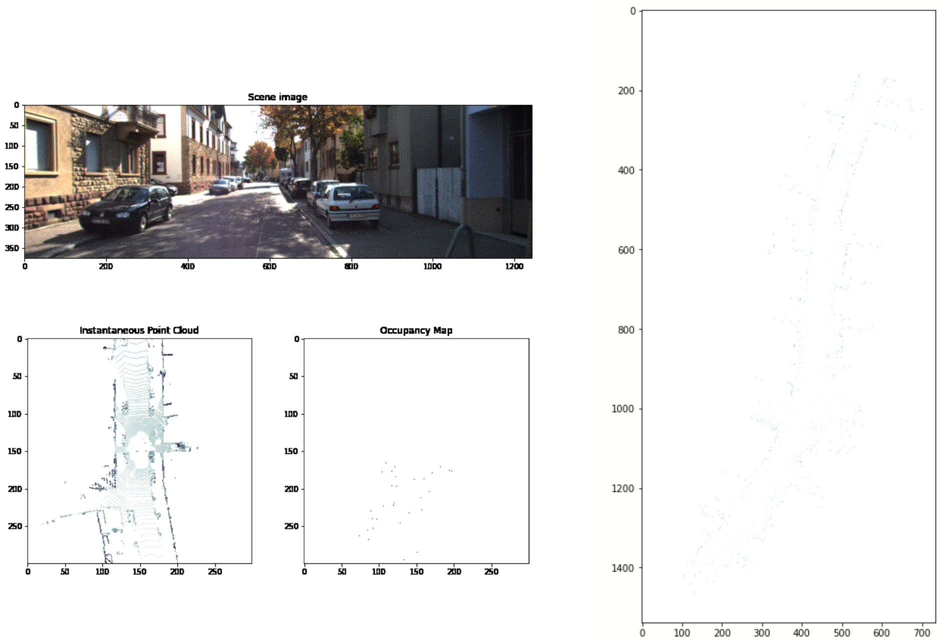


Figure 11: occupancy map (0.2m)

- **Threshold 0.9 Hit/Miss prob 0.9/0.1:**

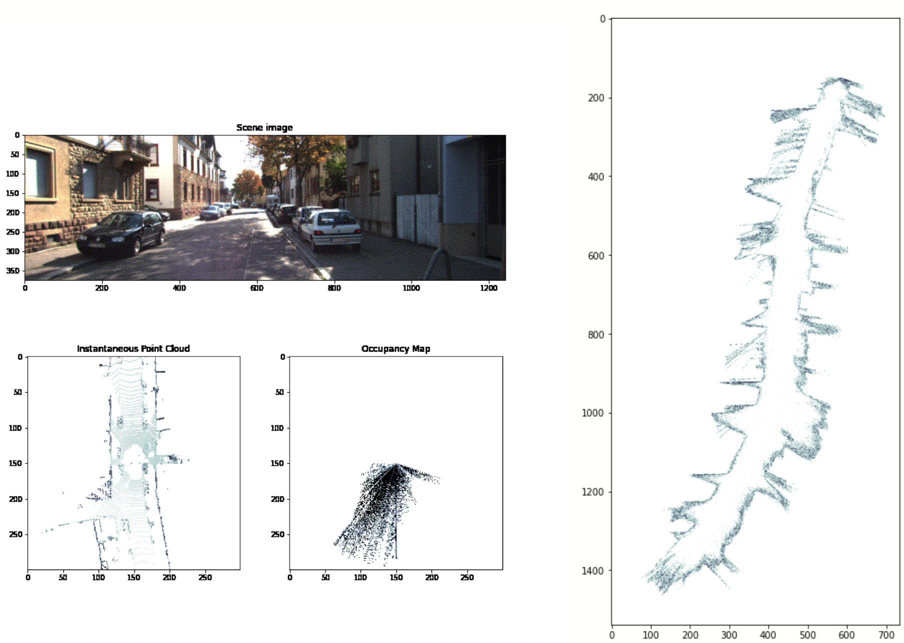


Figure 12: occupancy map (0.2m)

We can see that the dynamic objects have an impact on scans that hi/miss prob is hi and threshold is low this is because the model assumes that if it was hit, it is definitely static, although it is not. The threshold also plays a part in this as when the threshold is low it accepts cells that have been hit only a small amount of times, and cells that are occupied can be highly punished if they are missed in reality. Therefore the true occupied marked cells decrease and the model will detect moving objects as occupied cells as well. Increasing the threshold helps in this case. As can be seen in the corresponding figures.

3. Iterative closest point:

Adding gaussian noise to the ground-truth INS data, standard deviation of observation noise of local coordinates in meter (σE=0.5 , σN=0.5) and orientation in radian (σyaw=0.01):

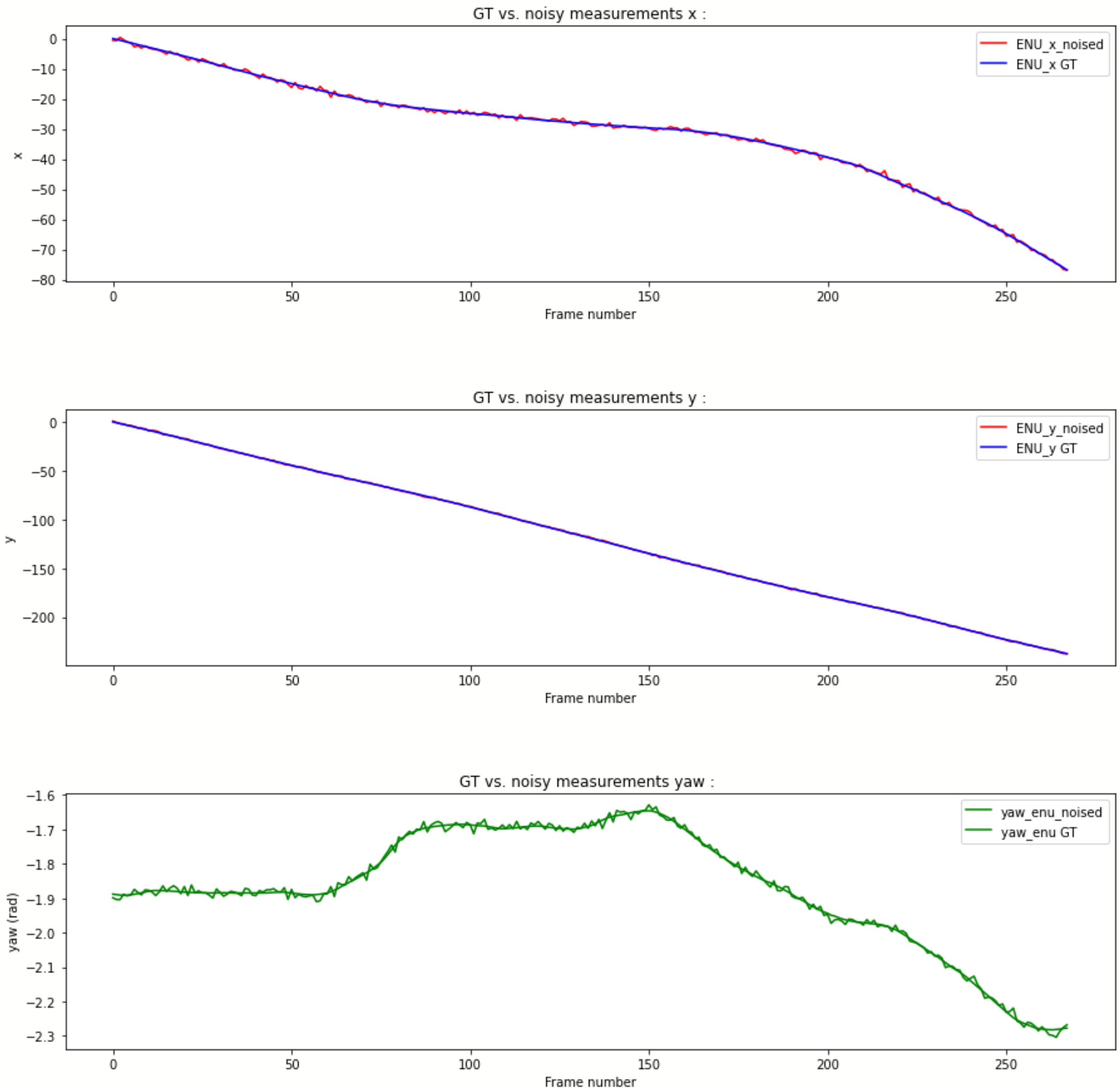


Figure 13

The full map with noise:

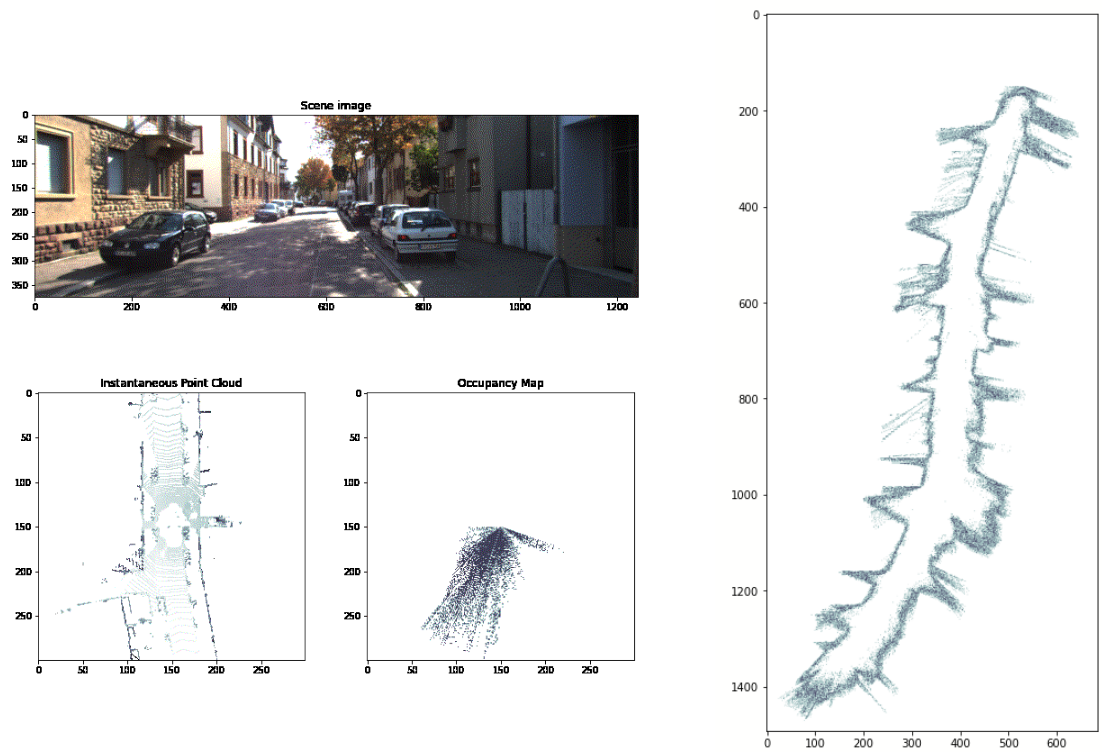


Figure 13 noised occupancy map(0.2m)

We can see that the orientation of the full occupancy map is slanted and more close to the bottom right point.

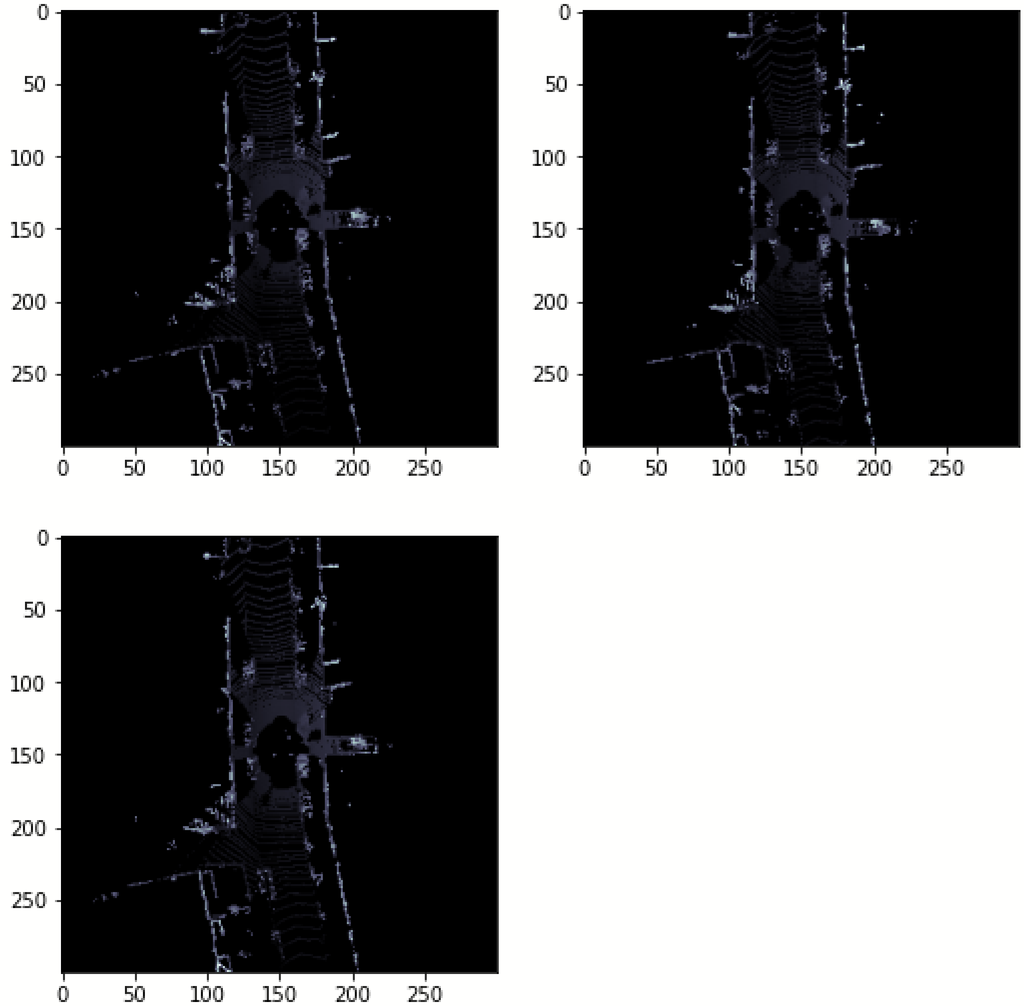


Figure 14: Point clouds after noise and rotation (point cloud 1 left image before icp, bottom image after icp and right image is point cloud 2 (0.2m))

We can see that the bottom image after icp is a better match for cloud 2 showing that our icp woks, with more iterations we could have got better results

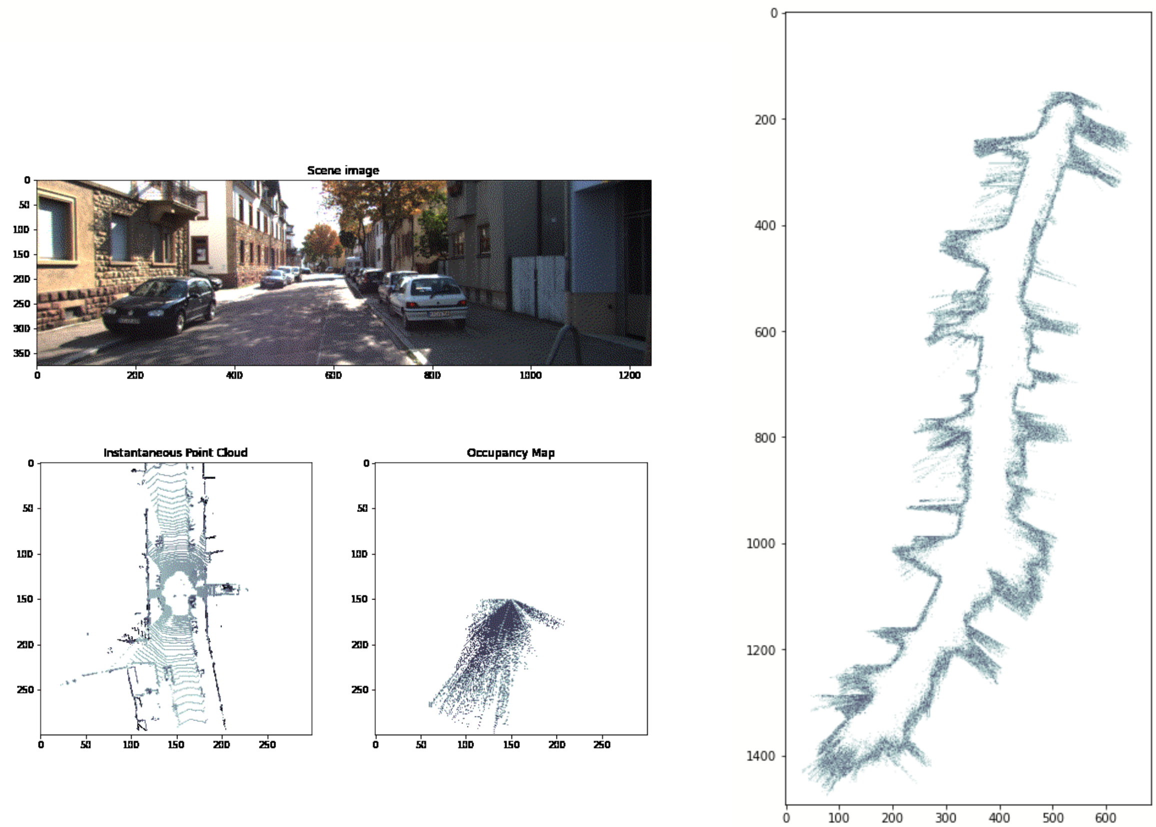


Figure 15: occupancy map with icp correction of corrupt imu measurements (0.2m)

As we can see we are able to improve the occupancy grid map by a lot even with hi noise measurements using the icp algorithm as the full occupancy map now resembles the original data without corruption using possibly using point to plane error(instead of point to point) metric for corresponding points would have even better results .

4. DeepICP

Pros of the network

- The system can avoid the inference of dynamic objects, leverages the help of sufficiently salient features on stationary objects, and as a result, achieves high robustness.
- Rather than searching the corresponding points among existing points, the key contribution is that innovatively generate them based on learned matching probabilities among a group of candidates, which can boost the registration accuracy
- The first end-to-end learning-based point cloud registration framework yielding comparable results to prior state-of-the-art geometric ones.

- The learning-based keypoint detection, novel corresponding point generation method and the loss function that incorporates both the local similarity and the global geometric constraints to achieve high accuracy in the learning-based registration task.
- There are actually no exact corresponding points in the target point cloud to the source due to its sparsity nature they use a novel network structure, the corresponding point generation (CPG) layer, to generate corresponding points from the extracted features and the similarity represented by them.
- Loss function incorporates both the local similarity and the global geometric constraints.
- The network only needs a single iteration to find the optimal corresponding keypoint and then estimate the transformation during inference

Summary

In this project we have implemented a full occupancy map from the kitti dataset we saw the impact of the different parameters for hit/miss probability and threshold. We saw the impact of corrupted imu data and how to fix this with the icp algorithm. It is possible that using the deep icp or point to plane in the corresponding indices would have gotten better results however with such small noise on the yaw the regular icp was able to get a good correction.

Appendix

The flow+main functions:

Question 2 -
Make_occupancy_map -> looped: Birds_eye_point_cloud ->
Find_messerment_from_lidar_to_vehichle - > occupancy_grid_map ->
Inverse_range_sensor_model
Functions:
Birds_eye_point_cloud -

Takes a point cloud received by lidar, translates it to body coordinates, if needed discards points that are too far away and returns the point cloud, or transforms the point cloud to image coordinates making it a birds eye view.

Find_messerment_from_lidar_to_vehichle - Transformers an image coordinate birds eye and calculates z_t the range and the angel from the forward heeding -180/180

Inverse_range_sensor_model - returning logit probabilities if occupancy cell is hit free kisse or out of range based on matching body angles and radius to cell and z_t.

Occupancy_grid_mapping - driver of the inverse_sensor function on every cell

Make_occupancy_map - driver of occupancy_grid_map, Birds_eye_point_cloud function,Find_messerment_from_lidar_to_vehichle, for each frame.

Question 3 -

implementations flow + main functions:
Perform_icp_between_clouds - At each occupancy update 2 frames were grabbed first point cloud was translated and rotated by the difference in angle and distances,uniformly subsamples the indices then calls icp_svd after this process is finished point cloud 1 is rotated back to original location and the building of the map continues as before.

Icp_svd - performs icp using svd finds calls centers the data get_correspondence_indices by kd tree alg then finds cross covariance removes unwanted indices using kernel outlier rejection computes svd rotates first point cloud and then repeats proces a number of iterations.

Make_occupancy_map - runs occupancy map with icp correction needed witch then runs all frames throw Perform_icp_between_clouds

Make_occupancy_map - > for every frame: Perform_icp_between_clouds - > runs icp_svd

Code:

Automatically generated by Colaboratory.

Original file is located at

    https://colab.research.google.com/drive/1NMzsJttFhRQ--mwRKyxiHLj-gWa7_q19

```
"""

import os

from pathlib import Path

#loading dive and path to kitty data

from google.colab import drive

drive.mount('/content/drive')

#%cd  '/content/drive/My Drive/Deep Learning Final Project'

!ls # (print the files and folders in the current folder)

path_kitty_data = Path('/content/drive/My Drive/mapping and
perception/project_1/kitty_data')

print(path_kitty_data)

path_oxts_kitty_data = Path('/content/drive/My Drive/mapping and
perception/project_1/kitty_data/2011_09_26/2011_09_26_drive_0095_sync/oxts/data')

filelist_oxts = os.listdir(path_oxts_kitty_data)
```

```
filelist_oxts = sorted(filelist_oxts)

print(filelist_oxts)

oxts_frame_list =[] #list of frames each containing a list of the oxts data

for oxts_file in filelist_oxts:

  #print (oxts_file)

  if oxts_file.endswith(".txt"):

    with open(Path.joinpath(path_oxts_kitty_data,oxts_file),"r") as f:

      contents = f.read()

      content_list = contents.split(" ")

      oxts_frame_list.append(content_list[:6])# taking the 6 first elements-- lat: latitude of the oxts-unit (deg), lon: longitude of the oxts-unit (deg), alt: altitude of the oxts-unit (m), roll: roll angle (rad) 0 = level, positive = left side up, range: -pi .. +pi , pitch: pitch angle (rad), 0 = level, positive = front down, range: -pi/2 .. +pi/2, yaw: heading (rad), 0 = east, positive = counter clockwise, range: -pi .. +pi

print (oxts_frame_list)

print(oxts_frame_list[1][0])



#LLA graph:

import matplotlib.pyplot as plt

import numpy as np



number_of_frames = len(oxts_frame_list)

print(number_of_frames)

number_of_frames_list_x_axes = np.arange(number_of_frames)
```

```
lat_list = [float(oxts_frame_list[i][0]) for i in range(number_of_frames)]

long_list = [float(oxts_frame_list[i][1]) for i in range(number_of_frames) ]

alt_list = [float(oxts_frame_list[i][2]) for i in range(number_of_frames) ]


# create a figure

fig = plt.figure(figsize=[15,15])


# define subplots and their positions in figure

plt1 = fig.add_subplot(311)

plt2 = fig.add_subplot(312)

plt3 = fig.add_subplot(313)


plt1.plot(number_of_frames_list_x_axes, lat_list, label = 'LAT', color ='b')

plt1.set_title('LAT vs Frame: ')

plt1.set_xlabel("Frame number")

plt1.set_ylabel("LAT (deg)")


plt2.plot(number_of_frames_list_x_axes, long_list , label = 'LONG', color ='r')

plt2.set_title('LONG vs Frame: ')

plt2.set_xlabel("Frame number")

plt2.set_ylabel("LONG (deg)")


plt3.plot(number_of_frames_list_x_axes, alt_list , label = 'ALT', color ='g')
```

```
plt3.set_title('ALT vs Frame: ')

plt3.set_xlabel("Frame number")

plt3.set_ylabel("ALT (m)")

print([float(oxts_frame_list[i][0]) for i in range(number_of_frames) ])

# show legends of each subplot

plt1.legend()

plt2.legend()

plt3.legend()


# adjusting space between subplots

fig.subplots_adjust(hspace=0.5)


# function to show plot

plt.show()


#transforming LLA to ENU:

import matplotlib.pyplot as plt

!pip install pymap3d

import pymap3d as pm

from mpl_toolkits.mplot3d import Axes3D

'''

from IPython.core.interactiveshell import InteractiveShell

InteractiveShell.ast_node_interactivity = "all"
```

```
#%matplotlib notebook

'''



fig = plt.figure(figsize=(12,12))


ax = fig.add_subplot(111, projection='3d')

ax.scatter(0,0,0,marker="x", c="red")

#plt.show()

lat_0 = lat_list[0]

long_0 = long_list[0]

alt_0 = alt_list[0]

ENU_cordes_list = []

ENU_cordes_list.append([0,0,0])

for i in range (number_of_frames-1):

  ENU_cordes =
pm.geodetic2enu(lat_list[i+1],long_list[i+1],alt_list[i+1],lat_0,long_0,alt_0)

  #ENU_cordes = np.asarray(ENU_cordes).round()

  #print (ENU_cordes)

  ENU_cordes_list.append(ENU_cordes)

  ax.scatter(ENU_cordes[0],ENU_cordes[1],ENU_cordes[2])


ENU_x_list  = [ENU_cordes_list[i][0] for i in range(number_of_frames)]

print(len(ENU_x_list))

ENU_y_list  = [ENU_cordes_list[i][1] for i in range(number_of_frames)]
```

```
ENU_z_list  = [ENU_cordes_list[i][2] for i in range(number_of_frames)]

#ax.plot3D(ENU_x_list,ENU_y_list,ENU_z_list)

ax.set_title('ENU cordanents:')

ax.set_xlabel('x(m)')

ax.set_ylabel('y(m)')

ax.set_zlabel('z(m)')


plt.show()


#ploting roll pitch yaw:




roll_enu_list = [float(oxts_frame_list[i][3]) for i in range(number_of_frames)]

pitch_enu_list = [float(oxts_frame_list[i][4]) for i in range(number_of_frames) ]

yaw_enu_list = [float(oxts_frame_list[i][5]) for i in range(number_of_frames) ]


# create a figure

fig = plt.figure(figsize=[15,15])


# define subplots and their positions in figure

plt1 = fig.add_subplot(313)

plt2 = fig.add_subplot(312)

plt3 = fig.add_subplot(311)
```

```
plt1.plot(number_of_frames_list_x_axes, roll_enu_list, label = 'roll', color ='b')

plt1.set_title('Roll vs Frame(enu): ')

plt1.set_xlabel("Frame number")

plt1.set_ylabel("roll (rad)")


plt2.plot(number_of_frames_list_x_axes, pitch_enu_list , label = 'pitch', color ='r')

plt2.set_title('Pitch vs Frame(enu): ')

plt2.set_xlabel("Frame number")

plt2.set_ylabel("pitch (rad)")


plt3.plot(number_of_frames_list_x_axes, yaw_enu_list , label = 'yaw', color ='g')

plt3.set_title('Yaw vs Frame(enu): ')

plt3.set_xlabel("Frame number")

plt3.set_ylabel("yaw (rad)")


# show legends of each subplot

plt1.legend()

plt2.legend()

plt3.legend()


# adjusting space between subplots

fig.subplots_adjust(hspace=0.5)
```

```
# function to show plot

plt.show()


#transforming ENU to NED:

import math

NED_x_list = ENU_y_list

NED_y_list = ENU_x_list

NED_z_list = [-ENU_z_list[i] for i in range(number_of_frames)]

yaw_ned_list = [-yaw_enu_list[i]+math.pi/2 for i in range(number_of_frames)]

pitch_ned_list = pitch_enu_list

roll_ned_list = roll_enu_list


fig = plt.figure(figsize=(12,12))

ax = fig.add_subplot(111, projection='3d')


ax.scatter3D(NED_x_list,NED_y_list,NED_z_list)

ax.set_title('NED cordanents:')

ax.set_xlabel('x(m)')

ax.set_ylabel('y(m)')

ax.set_zlabel('z(m)')


plt.show()
```

```
#ploting roll pitch yaw:



# create a figure
fig = plt.figure(figsize=[15,15])

# define subplots and their positions in figure
plt1 = fig.add_subplot(313)
plt2 = fig.add_subplot(312)
plt3 = fig.add_subplot(311)

plt1.plot(number_of_frames_list_x_axes, roll_ned_list, label = 'roll', color ='b')
plt1.set_title('Roll vs Frame(ned): ')
plt1.set_xlabel("Frame number")
plt1.set_ylabel("roll (rad)")

plt2.plot(number_of_frames_list_x_axes, pitch_ned_list , label = 'pitch', color ='r')
plt2.set_title('Pitch vs Frame(ned): ')
plt2.set_xlabel("Frame number")
plt2.set_ylabel("pitch (rad)")

plt3.plot(number_of_frames_list_x_axes, yaw_ned_list , label = 'yaw', color ='g')
```

```
plt3.set_title('Yaw vs Frame(ned): ')

plt3.set_xlabel("Frame number")

plt3.set_ylabel("yaw (rad)")


# show legends of each subplot

plt1.legend()

plt2.legend()

plt3.legend()


# adjusting space between subplots

fig.subplots_adjust(hspace=0.5)


# function to show plot

plt.show()


#Use Google Maps to find the trajectory of the recorded data. Plot the results:

from PIL import Image, ImageDraw

import pandas as pd

#from gps_class import GPSVis
```

```
# for the map at https://www.openstreetmap.org/export

max_long = max(long_list)

min_long = min(long_list)

max_lat = max(lat_list)

min_lat = min(lat_list)


upper_left_corner = [max_long,min_lat]

lower_right_corner = [min_long,max_lat]

print("upper_left_corner: {}" .format(upper_left_corner))

print("lower_right_corner: {}".format(lower_right_corner))


path_map_img = Path('/content/drive/My Drive/mapping and
perception/project_1/map.png')

path_map_result = Path('/content/drive/My Drive/mapping and
perception/project_1/result_map.png')


# points =[max_lat,min_long,min_lat,max_long]

def scale_to_img( lat_lon, h_w, points =[48.99668,8.46725,48.99386,8.47080] ):

    """

    Conversion from latitude and longitude to the image pixels.

    It is used for drawing the GPS records on the map image.

    :param points: Upper-left, and lower-right GPS points of the map (lat1, lon1, lat2,
lon2).

    :param lat_lon: GPS record to draw (lat1, lon1).

    :param h_w: Size of the map image (w, h).
```

```
    :return: Tuple containing x and y coordinates to draw on map image.
    """
    # https://gamedev.stackexchange.com/questions/33441/how-to-convert-a-number-from-one-min-max-set-to-another-min-max-set/33445
    old = (points[2], points[0])
    new = (0, h_w[1])
    y = ((lat_lon[0] - old[0]) * (new[1] - new[0]) / (old[1] - old[0])) + new[0]
    old = (points[1], points[3])
    new = (0, h_w[0])
    x = ((lat_lon[1] - old[0]) * (new[1] - new[0]) / (old[1] - old[0])) + new[0]
    # y must be reversed because the orientation of the image in the matplotlib.
    # image - (0, 0) in upper left corner; coordinate system - (0, 0) in lower left corner
    return int(x), h_w[1] - int(y)


gps_data = tuple(zip(lat_list, long_list))


image = Image.open(path_map_img, 'r')  # Load map image.
img_points = []
for d in gps_data:
    x1, y1 = scale_to_img(d, (image.size[0], image.size[1]))  # Convert GPS coordinates to image coordinates.
    img_points.append((x1, y1))
draw = ImageDraw.Draw(image)
```

```
draw.line(img_points, fill=(255, 0, 0), width=2)  # Draw converted records to the map image.

!ls

image.save(path_map_result)



#min/max lat long in linespace

x_ticks = map(lambda x: round(x, 4), np.linspace(48.99386, 48.99668, num=7))

y_ticks = map(lambda x: round(x, 4), np.linspace(8.46725, 8.47080, num=8)) #lat

y_ticks = sorted(y_ticks, reverse=True)  # y ticks must be reversed due to conversion to image coordinates.



fig, axis1 = plt.subplots(figsize=(10, 10))

axis1.imshow(plt.imread(path_map_result))  # Load the image to matplotlib plot.

axis1.set_xlabel('Longitude')

axis1.set_ylabel('Latitude')

axis1.set_xticklabels(x_ticks)

axis1.set_yticklabels(y_ticks)

axis1.grid()

plt.show()



"""starting from the top of the red line we can see that were drivung stright then turning left and then turning right this matches the photos"""
```

```
Rotation_mat_imu_to_velo = np.array([[9.999976e-01, 7.553071e-04 ,-2.035826e-03] ,
[-7.854027e-04, 9.998898e-01, -1.482298e-02] ,[2.024406e-03 ,1.482454e-02
,9.998881e-01]],dtype = float)

Translation_mat_imu_to_velo = np.array([[-8.086759e-01, 3.195559e-01
,-7.997231e-01]],dtype = float)


#question 2:

import cv2

from google.colab.patches import cv2_imshow


#!pip install open3d

#import open3d

#from open3d import *

#import mayavi.mlab as mlab


yaw_enu_array = np.array(yaw_enu_list,dtype = float)

roll_enu_array = np.array(roll_enu_list,dtype = float)

pitch_enu_array = np.array(pitch_enu_list,dtype = float)


#
============================================================================

#                                         SCALE_TO_255
```

```
#
================================================================================
============

def scale_to_255(a, min, max, dtype=np.uint8):

    """ Scales an array of values from specified min, max range to 0-255

        Optionally specify the data type of the output (default is uint8)

    """

    return (((a - min) / float(max - min)) * 255).astype(dtype)




#
================================================================================
============

#                               BIRDS_EYE_POINT_CLOUD

#
================================================================================
============

def birds_eye_point_cloud(points,

                          side_range=(-30, 30),

                          fwd_range=(-30,30),

                          res=0.2,

                          min_height = -1.73,

                          max_height = 1.27,

                          saveto=None,x_and_y_vector_coirdinants_needed =
False,translation_to_body_needed = True):

    """ Creates an 2D birds eye view representation of the point cloud data.
```

```
    You can optionally save the image to specified filename.

Args:
    points:     (numpy array)
                N rows of points data
                Each point should be specified by at least 3 elements x,y,z
    side_range: (tuple of two floats)
                (-left, right) in metres
                left and right limits of rectangle to look at.
    fwd_range:  (tuple of two floats)
                (-behind, front) in metres
                back and front limits of rectangle to look at.
    res:        (float) desired resolution in metres to use
                Each output pixel will represent an square region res x res
                in size.
    min_height:  (float)(default=-2.73)
                Used to truncate height values to this minumum height
                relative to the sensor (in metres).
                The default is set to -2.73, which is 1 metre below a flat
                road surface given the configuration in the kitti dataset.
    max_height: (float)(default=1.27)
                Used to truncate height values to this maximum height
                relative to the sensor (in metres).
```

```
                The default is set to 1.27, which is 3m above a flat road
                surface given the configuration in the kitti dataset.
        saveto:     (str or None)(default=None)
                Filename to save the image as.
                If None, then it just displays the image.
    """



    x_lidar = points[:, 0]
    y_lidar = points[:, 1]
    z_lidar = points[:, 2]
    # r_lidar = points[:, 3]  # Reflectance

    # conversion to body coirdinants
    if(translation_to_body_needed):
      PC_lidar = np.array([[x_lidar],[y_lidar],[z_lidar]])
      PC_lidar = np.reshape(PC_lidar,(PC_lidar.shape[0],PC_lidar.shape[2]))
      #print("PC_lidar.shape:{}".format(PC_lidar.shape))
      PC_body_imu = np.matmul(Rotation_mat_imu_to_velo.T,PC_lidar) -
Translation_mat_imu_to_velo.T
      #print("PC_body_imu.shape:{}".format(PC_body_imu.shape))
      #print("yaw_enu: {}".format(yaw_enu))
      x_lidar = PC_body_imu[0,:]
      y_lidar = PC_body_imu[1,:]
```

```
  z_lidar = PC_body_imu[2,:]


min_height += 0.3

max_height += 0.8


# INDICES FILTER - of values within the desired rectangle

# Note left side is positive y axis in LIDAR coordinates

ff = np.logical_and((x_lidar > fwd_range[0]), (x_lidar < fwd_range[1]))

ss = np.logical_and((y_lidar > -side_range[1]), (y_lidar < -side_range[0]))

indices = np.argwhere(np.logical_and(ff,ss)).flatten()




x = x_lidar[indices]

y = y_lidar[indices]

z = z_lidar[indices]


if(x_and_y_vector_coirdinants_needed):

  return x, y, z

# CONVERT TO PIXEL POSITION VALUES - Based on resolution

x_img = (-y_lidar[indices]/res ).astype(np.int32) # x axis is -y in LIDAR

y_img = (x_lidar[indices]/res).astype(np.int32)  # y axis is -x in LIDAR

                                                 # will be inverted later
```

```
# SHIFT PIXELS TO HAVE MINIMUM BE (0,0)
# floor used to prevent issues with -ve vals rounding upwards
x_img -= int(np.floor(side_range[0]/res))
y_img -= int(np.floor(fwd_range[0]/res))

# CLIP HEIGHT VALUES - to between min and max heights
pixel_values = np.clip(a = z_lidar[indices],
                       a_min=min_height,
                       a_max=max_height)



# RESCALE THE HEIGHT VALUES - to be between the range 0-255
pixel_values  = scale_to_255(pixel_values, min=min_height, max=max_height)

# FILL PIXEL VALUES IN IMAGE ARRAY
x_max = int((side_range[1] - side_range[0])/res)
y_max = int((fwd_range[1] - fwd_range[0])/res)
im = np.zeros([y_max, x_max], dtype=np.uint8)
im[-y_img, x_img] = pixel_values # -y because images start from top left

numpy_image = im
# Convert from numpy array to a PIL image
im = Image.fromarray(im)
```

```
    cropped_cloud = np.vstack([x, y, z]).transpose()
    '''
    # SAVE THE IMAGE
    if saveto is not None:
        im.save(saveto)
    else:
        im.show()
    '''
    return im, cropped_cloud , numpy_image


def load_velo_scan(file):
    """Load and parse a velodyne binary file."""
    scan = np.fromfile(file, dtype=np.float32)
    return scan.reshape((-1, 4))



def yield_velo_scans(velo_files):
    """Generator to parse velodyne binary files into arrays."""
    for file in velo_files:
        yield load_velo_scan(file)
```

```
path_velodyne_points_kitty_data = Path('/content/drive/My Drive/mapping and perception/project_1/kitty_data/2011_09_26/2011_09_26_drive_0095_sync/velodyne_points/data')

path_image_kitty_data = Path('/content/drive/My Drive/mapping and perception/project_1/kitty_data/2011_09_26/2011_09_26_drive_0095_sync/image_03/data')

filelist_velodyne_points = os.listdir(path_velodyne_points_kitty_data)

filelist_image_kitty_data = os.listdir(path_image_kitty_data)

img_demo_path = Path.joinpath(path_image_kitty_data,'0000000000.png')

img_demo = Image.open(img_demo_path)

img_demo.show()

velo_img_demo_path = Path.joinpath(path_velodyne_points_kitty_data,'0000000000.bin')

velo_img_demo = load_velo_scan(velo_img_demo_path)


image_demo_velo , cropped_cloud, image_demo_numpy = birds_eye_point_cloud(velo_img_demo)

x = cropped_cloud[:,0]

y = cropped_cloud[:,1]

z = cropped_cloud[:,2]




image_demo_velo.show()

plt.imshow(image_demo_velo,'bone')

plt.show()

#print(image_demo.size)
```

```
print(image_demo_numpy.shape)

print(image_demo_numpy)


#finding the meassserment z_t:

res= 0.2

z_max = 30/res


def find_messerment_from_lidar_to_vehichle(numpy_image):

 #orgin of image is left corner, x-heading right, yheading down:

 r_list = []

 theta_list = []

 x_list = []

 y_list = []

 img_width = numpy_image.shape[0]

 img_hight = numpy_image.shape[1]

 for j in range(img_hight):

  for i in range(img_width):

   if (numpy_image[i][j] != 0):

    r = math.sqrt(math.pow((i-img_width/2),2) + math.pow((j-img_hight/2),2))

    theta = (np.arctan2(i-img_width/2,((img_hight/2)-j)))

    #theta = (np.arctan2(((img_hight/2)-j),i-img_width/2))

    #x_list.append(i)

    #y_list.append(j)
```

```
        #print (r)

        #print("theta: {} ,y= j: {} , i: {}".format(theta,j,i))

        r_list.append(r)

        theta_list.append (theta)

  #z_t_list = zip(r_list,theta_list,x_list,y_list)

  z_t_list = zip(r_list,theta_list)

  return np.array(list(z_t_list))



z_t = find_messerment_from_lidar_to_vehichle(image_demo_numpy)


print(z_t)

print(z_t.shape)


# peramters

z_max = 60/res

alpha = 0.2

beta = 0.09*np.pi/180  #opining angle in radians


l_0 = 0


def inverse_range_sensor_model(i,x_t,z_t,l_occ = 0.85,l_free = -0.4):

  #notice to add l_occ and l_free in logits
```

```
# z_t is an array of tuples [(r_1,theta_1),(r_2,theta_2),...].T (theta)
z_t_theta_list = z_t[:,1]
z_t_r_list = z_t[:,0]
# x_i and y_i are center of mass m_i:
x = x_t[0]
y = x_t[1]
yaw_i = x_t[2]

# x and y reprsent the location of cell i in ocupancy grid:
x_i = i[0]
y_i = i[1]

# calc distanse and angle from car to cell i
r = math.sqrt(math.pow((x_i-x),2) + math.pow((y_i-y),2))
theta = math.atan2(y_i-y,x_i-x) - yaw_i

# find the matching angle from lidar indexed k:
k = np.argmin(abs(theta - z_t_theta_list))

# if out of range return l_0
if np.logical_or(r>min(z_max, z_t_r_list[k] + alpha/2) , abs(theta - z_t_theta_list[k]) >
beta/2):
  return l_0
```

```
  # if we have a hit return l_occ

  if np.logical_and(z_t_r_list[k] < z_max , abs(r-z_t_r_list[k]) < alpha/2):

    #print("hit x,y: {},{} from car location x_i, y_i {}, {} and z_t_theta_list {} and yaw {}, and theta {} ".format(x,y,x_i,y_i,z_t_theta_list[k],yaw_i,theta))

    #print (l_occ)

    return l_occ



  # if the we have a messerement in the same angle but the hit is farther away ,this means lasrer passed this cell so return l_free

  if (r <= z_t_r_list[k]):

    return l_free



#creating map:



res = 0.2




def occupancy_grid_mapping(occupancy_map, x_t, z_t, probability_saturation , l_occ = 0.85,l_free = -0.4):

  # x_t containing possition x_i, y_i and yaw:

  #updated_occupancy_map = occupancy_map

  map_hight = occupancy_map.shape[0]

  map_width = occupancy_map.shape[1]

  x_locatin = x_t[0]

  y_location = x_t [1]
```

```
  '''
  print("map_hight is: {}".format(map_hight))
  print("map_width is: {}".format(map_width))
  print("x_i is: {}".format(x_i))
  print("y_i is: {}".format(y_i))
  count = 0
  '''
  for j in range(map_hight):
    for i in range(map_width):
      occupancy_map_val = 0
      # cheek if m_i in perceptional field of z_t
      if (np.logical_and(abs(i-x_locatin)<(30/res),(abs(j-y_location)<(30/res)))):
        occupancy_map_val = (occupancy_map[j][i] +
inverse_range_sensor_model([i,j],x_t,z_t ,l_occ ,l_free) - l_0)
        if(occupancy_map_val>probability_saturation):
          occupancy_map_val = probability_saturation
        if(occupancy_map_val<  -probability_saturation):
          occupancy_map_val = -probability_saturation
        occupancy_map[j][i] = occupancy_map_val

      else:
        occupancy_map[j][i] = occupancy_map[j][i]
```

```
  return occupancy_map


filelist_image_kitty_data = sorted(filelist_image_kitty_data)

filelist_velodyne_points = sorted(filelist_velodyne_points)


def create_gif(images, filename, duration=200):

    progression_pil = [Image.fromarray(im) for im in images]

    progression_pil[0].save(filename, append_images=progression_pil[1:],
save_all=True, duration=duration)


import matplotlib as mpl

import matplotlib.animation as animation

from matplotlib.backends.backend_agg import FigureCanvasAgg as FigureCanvas

from matplotlib.figure import Figure


ENU_y_array = np.array(ENU_y_list)

ENU_x_array = np.array(ENU_x_list)

ENU_z_array = np.array(ENU_z_list)

yaw_enu_array = np.array(yaw_enu_list)


#rearanging enu x,y cordinants to fit map:

ENU_x_array_adjusted = ENU_x_array.copy()

ENU_y_array_adjusted = ENU_y_array.copy()

ENU_x_array_adjusted += max(abs(ENU_x_array_adjusted))+30
```

```
ENU_y_array_adjusted += max(abs(ENU_y_array_adjusted))+30

ENU_x_array_adjusted = ENU_x_array_adjusted/res

ENU_y_array_adjusted = ENU_y_array_adjusted/res





def
make_occupancy_map(ENU_x_array,ENU_y_array,yaw_enu_array,Occupied_threshold
,free_threshold,probability_saturation,l_occ,l_free,icp_correction_needed = False):


  # occupancy_map: np of zeroes , ENU_x_array/ENU_y_array: shited and scaled x and
y ,Occupied_threshold,free_threshold,probability_saturation,l_occ,l_free: all in logits

  occupancy_map =
np.zeros([int(np.ceil(max(ENU_y_array))+30/res),int(np.ceil(max(ENU_x_array))+30/res
)],dtype=float) # might need abs

  print("occupancy_map.shape = {}".format(occupancy_map.shape))

  img_list = []

  fig = plt.figure(figsize=(12, 12))

  for i in range(number_of_frames-1): #


    img_velo_path =
Path.joinpath(path_velodyne_points_kitty_data,filelist_velodyne_points[i])

    velo_img = load_velo_scan(img_velo_path)

    if(icp_correction_needed):

      velo_img =
perform_icp_between_clouds(ENU_x_array,ENU_y_array,yaw_enu_array,i)
```

```
    else:

      img_velo_path =
Path.joinpath(path_velodyne_points_kitty_data,filelist_velodyne_points[i])

      velo_img = load_velo_scan(img_velo_path)



    _ , _, velo_image_numpy = birds_eye_point_cloud(velo_img)

    z_t = find_messerment_from_lidar_to_vehichle(velo_image_numpy)

    occupancy_map =
occupancy_grid_mapping(occupancy_map,[int(np.floor(ENU_x_array[i]))
,occupancy_map.shape[0] -
int(np.ceil(ENU_y_array[i])),np.pi/2-yaw_enu_array[i]],z_t,probability_saturation,l_occ,l_f
ree)



    if(i%5 == 0): #

      print("filelist_image_kitty_data[i]: {}, filelist_velodyne_points[i]: {}
".format(filelist_image_kitty_data[i],filelist_velodyne_points[i]))

      img_rgb_path = Path.joinpath(path_image_kitty_data, filelist_image_kitty_data[i])

      img_rgb = Image.open(img_rgb_path)



      #zoom in to relvent area and display it:

      zoomed_occupancy_map = np.zeros((int(2*40/res),int(2*40/res)),dtype= float)

      print("zoomed_occupancy_map before
copy{}".format(zoomed_occupancy_map.shape))

      zoomed_occupancy_map =
occupancy_map[int(occupancy_map.shape[0]-int(np.ceil(ENU_y_array[i]))-30/res) :
int(occupancy_map.shape[0]-np.ceil(ENU_y_array[i])+30/res) ,
int(np.floor(ENU_x_array[i]-30/res)) : int(np.floor(ENU_x_array[i]+30/res))].copy()
```

```
    #print ("zoomed in location: y1={} y2=
{}".format(int(occupancy_map.shape[0]-np.floor(ENU_y_array[i])-40/res) ,
int(occupancy_map.shape[0]-np.floor(ENU_y_array[i]) + 40/res)))

    #print ("zoomed in location: x1={} x2=
{}".format(int(np.floor(ENU_x_array[i]-40/res)),int(np.floor(ENU_x_array[i]+40/res))))

    #print("occupancy_map.shape[0] {}".format(occupancy_map.shape[0]))



    zoomed_occupancy_map[np.where(zoomed_occupancy_map < free_threshold)] =
0

    zoomed_occupancy_map[np.where(zoomed_occupancy_map >
Occupied_threshold)] = 1



    zoomed_occupancy_map = np.uint8(zoomed_occupancy_map*255)

    zoomed_occupancy_map = 255 - zoomed_occupancy_map

    #print("zoomed_occupancy_map:{}".format(zoomed_occupancy_map.shape))

    #print("velo_image_numpy: {}".format(velo_image_numpy.shape))

    zoomed_occupancy_map_image = Image.fromarray(zoomed_occupancy_map)


    #plot on one figure:



    fig = plt.figure(figsize=(12, 12))

    plt.axis('off')

    # setting values to rows and column variables



    rows = 2
```

```
columns = 2

# Adds a subplot at the 1st position

fig.add_subplot(rows, 0.5*columns, 1)

# showing image

plt.imshow(img_rgb)


plt.title("Scene image")

# Adds a subplot at the 3rd position

fig.add_subplot(rows, columns, 3)

# showing image

plt.imshow(Image.fromarray(255-velo_image_numpy),cmap = 'bone')


plt.title("Instantaneous Point Cloud")

# Adds a subplot at the 4th position

fig.add_subplot(rows, columns, 4)

# showing image

plt.imshow(zoomed_occupancy_map_image, cmap= 'bone')

plt.title("Occupancy Map")



canvas = FigureCanvas(fig)

canvas.draw()       # draw the canvas, cache the renderer

image_from_plot = np.frombuffer(canvas.tostring_rgb(), dtype='uint8')
```

```
    image = image_from_plot.reshape(fig.canvas.get_width_height()[::-1] + (3,))

    img_list.append(image)
    plt.clf()
    print("image mumber: {}".format(i))

  create_gif(img_list,'/content/drive/My Drive/mapping and
perception/project_1/{}.gif'.format(l_occ) )

  occupancy_map[np.where(occupancy_map < free_threshold)] = 0
  occupancy_map[np.where(occupancy_map > Occupied_threshold)] = 1

  occupancy_map = np.uint8(occupancy_map*255)
  occupancy_map = 255 - occupancy_map
  occupancy_map_image = Image.fromarray(occupancy_map)

  fig = plt.figure(figsize=(12, 12))
  plt.imshow(occupancy_map_image,'bone')
  plt.show()
  print("occupancy_map.shape : {}".format(occupancy_map.shape))
```

```
def logits(x):

  return (np.log(x) - np.log(1-x))


# defining first section 1:


#rearanging enu x,y cordinants to fit map:

ENU_x_array_adjusted = ENU_x_array.copy()

ENU_y_array_adjusted = ENU_y_array.copy()

ENU_x_array_adjusted += max(abs(ENU_x_array_adjusted))+40

ENU_y_array_adjusted += max(abs(ENU_y_array_adjusted))+40

ENU_x_array_adjusted = ENU_x_array_adjusted/res

ENU_y_array_adjusted = ENU_y_array_adjusted/res

print("ENU_x_array_adjusted[0]: {} ,ENU_y_array_adjusted[0]:
{}".format(ENU_x_array_adjusted[0],ENU_y_array_adjusted[0]))




# defining second qustion section 2:

probability_saturation = (np.log(0.95)-np.log(0.05))

Occupied_threshold_1 = (np.log(0.8) - np.log(0.2))

free_threshold_1 = (np.log(0.2) - np.log(0.8))

l_occ_1 = 0.85

l_free_1 = -0.4

#make_occupancy_map(ENU_x_array_adjusted, ENU_y_array_adjusted,
yaw_enu_array, Occupied_threshold_1, free_threshold_1, probability_saturation,
l_occ_1, l_free_1)
```

'''

make_occupancy_map(ENU_x_array,ENU_y_array,yaw_enu_array,Occupied_threshold,free_threshold,probability_saturation,l_occ,l_free):

occupancy_map: np of zeroes , ENU_x_array,ENU_y_array: shited and scaled x and y ,yaw_enu_array,Occupied_threshold,free_threshold,probability_saturation,l_occ,l_free: all in logits

'''

```
occupancy_map = np.zeros([int(np.floor((max(abs(ENU_y_array)+100))/res)),(int(np.floor(max(abs(ENU_x_array)+100))/res))],dtype=float) # might need abs

Occupied_threshold_2 = logits(0.9)

free_threshold_2 = logits(0.1)



l_occ_2 = logits(0.9)

l_free_2 = logits(0.1)

#make_occupancy_map( ENU_x_array_adjusted, ENU_y_array_adjusted, yaw_enu_array, Occupied_threshold_2, free_threshold_2, probability_saturation, l_occ_2, l_free_2)
```

```
Occupied_threshold_2 = logits(0.75)

free_threshold_2 = logits(0.25)

#l_occ_2 = logits(0.9)

#l_free_2 = logits(0.1)

#make_occupancy_map( ENU_x_array_adjusted, ENU_y_array_adjusted,
yaw_enu_array, Occupied_threshold_2, free_threshold_2, probability_saturation,
l_occ_2, l_free_2)


Occupied_threshold_2 = logits(0.6)

free_threshold_2 = logits(0.4)

l_occ_2 = logits(0.6)

l_free_2 = logits(0.4)

make_occupancy_map( ENU_x_array_adjusted, ENU_y_array_adjusted,
yaw_enu_array, Occupied_threshold_2, free_threshold_2, probability_saturation,
l_occ_2, l_free_2)



# defining first qustion section 3:

occupancy_map =
np.zeros([int(np.floor((max(abs(ENU_y_array)+100))/res)),(int(np.floor(max(abs(ENU_x
_array)+100))/res))],dtype=float) # might need abs

Occupied_threshold_3 = logits(0.9)

free_threshold_3 = logits(0.1)


l_occ_3 = logits(0.9)

l_free_3 = logits(0.1)
```

#make_occupancy_map(ENU_x_array_adjusted, ENU_y_array_adjusted, yaw_enu_array, Occupied_threshold_3, free_threshold_3, probability_saturation, l_occ_3, l_free_3)

Occupied_threshold_3 = logits(0.6)

free_threshold_3 = logits(0.4)

l_occ_3 = logits(0.9)

l_free_3 = logits(0.1)

make_occupancy_map(ENU_x_array_adjusted, ENU_y_array_adjusted, yaw_enu_array, Occupied_threshold_3, free_threshold_3, probability_saturation, l_occ_3, l_free_3)

Occupied_threshold_3 = logits(0.9)

free_threshold_3 = logits(0.1)

l_occ_3 = logits(0.6)

l_free_3 = logits(0.4)

#make_occupancy_map(ENU_x_array_adjusted, ENU_y_array_adjusted, yaw_enu_array, Occupied_threshold_3, free_threshold_3, probability_saturation, l_occ_3, l_free_3)

question 3:

#3.1:

x noising:

ENU_x_array_noised = ENU_x_array.copy()

noise_x = np.random.normal(0,0.5, ENU_x_array_noised.shape)

```
#print("noise_x: {}".format(noise_x))
ENU_x_array_noised += noise_x


#y noising:
ENU_y_array_noised = ENU_y_array.copy()
noise_y = np.random.normal(0,0.5, ENU_y_array_noised.shape)
#print("noise_y: {}".format(noise_y))
ENU_y_array_noised += noise_y


'''
#z noising: (no noise reqiured in excersice on z)
ENU_z_array_noised = ENU_z_array.copy()
noise_z = np.random.normal(0,0.5, ENU_z_array_noised.shape)
#print("noise_y: {}".format(noise_y))
ENU_z_array_noised += noise_z
'''


# yaw noising:
yaw_enu_array_noised = yaw_enu_array.copy()
noise_yaw = np.random.normal(0,0.01, yaw_enu_array_noised.shape)
#print("noise_yaw: {}".format(noise_yaw))
#print("yaw_enu_array_noised: {}".format(yaw_enu_array_noised))
yaw_enu_array_noised += noise_yaw
```

```
#print("yaw_enu_array_noised: {}".format(yaw_enu_array_noised))


# create a figure

fig = plt.figure(figsize=[15,15])


# define subplots and their positions in figure

plt1 = fig.add_subplot(311)

plt2 = fig.add_subplot(312)

plt3 = fig.add_subplot(313)


plt1.plot(number_of_frames_list_x_axes, ENU_x_array_noised, label = 'ENU_x_noised', color ='r')

plt1.plot(number_of_frames_list_x_axes, ENU_x_array, label = 'ENU_x GT', color ='b')


plt1.set_title(' GT vs. noisy measurements x : ')

plt1.set_xlabel("Frame number")

plt1.set_ylabel("x")


plt2.plot(number_of_frames_list_x_axes, ENU_y_array_noised, label = 'ENU_y_noised', color ='r')

plt2.plot(number_of_frames_list_x_axes, ENU_y_array, label = 'ENU_y GT', color ='b')


plt2.set_title(' GT vs. noisy measurements y : ')

plt2.set_xlabel("Frame number")
```

```
plt2.set_ylabel("y")


plt3.plot(number_of_frames_list_x_axes, yaw_enu_array_noised , label =
'yaw_enu_noised', color ='g')

plt3.plot(number_of_frames_list_x_axes, yaw_enu_array , label = 'yaw_enu GT', color
='g')

plt3.set_title('GT vs. noisy measurements yaw : ')

plt3.set_xlabel("Frame number")

plt3.set_ylabel("yaw (rad)")


# show legends of each subplot

plt1.legend()

plt2.legend()

plt3.legend()


# adjusting space between subplots

fig.subplots_adjust(hspace=0.5)


# function to show plot

plt.show()


# 3.2 rearanging enu x,y cordinants to fit map:

ENU_x_array_adjusted = ENU_x_array_noised.copy()

ENU_y_array_adjusted = ENU_y_array_noised.copy()
```

```
ENU_x_array_adjusted += max(abs(ENU_x_array_adjusted))+30

ENU_y_array_adjusted += max(abs(ENU_y_array_adjusted))+30

ENU_x_array_adjusted = ENU_x_array_adjusted/res

ENU_y_array_adjusted = ENU_y_array_adjusted/res

print("ENU_x_array[0]: {} ,ENU_y_array[0]:
{}".format(ENU_x_array_adjusted[0],ENU_y_array_adjusted[0]))


probability_saturation = (np.log(0.95)-np.log(0.05))

Occupied_threshold_1 = (np.log(0.8) - np.log(0.2))

free_threshold_1 = (np.log(0.2) - np.log(0.8))

l_occ_1 = 0.85

l_free_1 = -0.4

make_occupancy_map(ENU_x_array_adjusted, ENU_y_array_adjusted,
yaw_enu_array_noised, Occupied_threshold_1, free_threshold_1,
probability_saturation, l_occ_1, l_free_1)


# 3.3:


import sys

import numpy as np

import matplotlib.pyplot as plt

from matplotlib import animation, rc

from math import sin, cos, atan2, pi

from IPython.display import display, Math, Latex, Markdown, HTML
```

```
from sklearn.neighbors import KDTree

#

def plot_data(data_1, data_2, label_1, label_2, markersize_1=8, markersize_2=8):

    fig = plt.figure(figsize=(10, 6))

    ax = fig.add_subplot(111)

    ax.axis('equal')

    if data_1 is not None:

        x_p, y_p = data_1

        ax.plot(x_p, y_p, color='#336699', markersize=markersize_1, marker='o',
linestyle=":", label=label_1)

    if data_2 is not None:

        x_q, y_q = data_2

        ax.plot(x_q, y_q, color='orangered', markersize=markersize_2, marker='o',
linestyle=":", label=label_2)

    ax.legend()

    return ax




def yaw_rotation(delt_theta):

  R_yaw = np.array([[np.cos(delt_theta), -np.sin(delt_theta)],[np.sin(delt_theta),
np.cos(delt_theta)]])

  return R_yaw



# get 2 point clouds function frame i = p and frame i+1 =q and display them:

def transform_point_clouds_1_to_2(point_cloud, x_1, x_2, yaw_1, yaw_2):
```

```
  delta_theta = yaw_2 - yaw_1

  delta_x = (x_2-x_1)/10

  point_cloud_transformed = np.matmul(yaw_rotation(delta_theta), point_cloud) +
delta_x.T

  return point_cloud_transformed


def transform_point_clouds_2_to_1(point_cloud, x_1, x_2, yaw_1, yaw_2):

  delta_theta = yaw_2 - yaw_1

  delta_x = (x_2-x_1)/10

  point_cloud_transformed = np.matmul(yaw_rotation(delta_theta).T, point_cloud) -
delta_x.T

  return point_cloud_transformed



def get_correspondence_indices(P, Q , random_indices):

    """For each point in P find closest one in Q."""

    p_size = P.shape[1]

    q_size = Q.shape[1]

    correspondences = []

    P = P[:,random_indices].copy()

    Q = Q[:,random_indices].copy()
```

```
    tree = KDTree(Q.T, leaf_size=2)
    for i in range(P.shape[1]):
      dist, ind = tree.query([P.T[i]], k=1)
      #removing indices that are not a good enough match
      if dist<0.05:
        correspondences.append((i, int(ind)))
    return correspondences


def center_data(data, exclude_indices=[]):
    reduced_data = np.delete(data, exclude_indices, axis=1)
    center = np.array([reduced_data.mean(axis=1)]).T
    return center, data - center


'''
center_of_P, P_centered = center_data(P)
center_of_Q, Q_centered = center_data(Q)
ax = plot_data(P_centered, Q_centered,
               label_1='Moved data centered',
               label_2='True data centered')
plt.show()


correspondences = get_correspondence_indices(P_centered, Q_centered)
ax = plot_data(P_centered, Q_centered,
```

```
            label_1='P centered',
            label_2='Q centered')
draw_correspondeces(P_centered, Q_centered, correspondences, ax)
plt.show()

'''


def compute_cross_covariance(P, Q, correspondences, kernel=lambda diff: 1.0):
    cov = np.zeros((3, 3))
    exclude_indices = []
    for i, j in correspondences:
        p_point = P[:, [i]]
        q_point = Q[:, [j]]
        weight = kernel(p_point - q_point)
        if weight < 0.01: exclude_indices.append(i)
        cov += weight * q_point.dot(p_point.T)
    return cov, exclude_indices


from functools import partial
def kernel(threshold, error):
    if np.linalg.norm(error) < threshold:
        return 1.0
    return 0.0
```

```
#itrativly:

def icp_svd(P, Q, random_indices, iterations=10, kernel=lambda diff: 1.0):

    """Perform ICP using SVD."""

    center_of_Q, Q_centered = center_data(Q)

    norm_values = []

    P_values = [P.copy()]

    P_copy = P.copy()

    corresp_values = []

    exclude_indices = []

    for i in range(iterations):

        center_of_P, P_centered = center_data(P_copy, exclude_indices=exclude_indices)



        correspondences = get_correspondence_indices(P_centered, Q_centered,
random_indices)

        corresp_values.append(correspondences)

        norm_values.append(np.linalg.norm(P_centered - Q_centered))

        cov, exclude_indices = compute_cross_covariance(P_centered, Q_centered,
correspondences, kernel)

        U, S, V_T = np.linalg.svd(cov)

        R = U.dot(V_T)

        t = center_of_Q - R.dot(center_of_P)

        P_copy = R.dot(P_copy) + t

        P_values.append(P_copy)
```

```
    corresp_values.append(corresp_values[-1])

    return P_values, norm_values, corresp_values


def perform_icp_between_clouds(ENU_x_array,ENU_y_array,yaw_enu_array,i):


    ENU_x_y = np.array([[ENU_x_array],[ENU_y_array]])

    ENU_x_y = np.reshape(ENU_x_y,(ENU_x_y.shape[0],ENU_x_y.shape[2]))

    #print(ENU_x_y.shape)


    # geting piont cloud 1:

    img_velo_path_1 =
Path.joinpath(path_velodyne_points_kitty_data,filelist_velodyne_points[i])

    velo_im_1 = load_velo_scan(img_velo_path_1)

    x_1 , y_1, z_1 =
birds_eye_point_cloud(velo_im_1,x_and_y_vector_coirdinants_needed = True)

    x_1 = np.reshape(np.array(x_1),(1,x_1.shape[0]))

    y_1 = np.reshape(np.array(y_1),(1,y_1.shape[0]))

    z_1 = np.reshape(np.array(z_1),(1,z_1.shape[0]))

    point_cloud_1 = np.array([x_1,y_1])

    point_cloud_1_original =
np.reshape(point_cloud_1,(point_cloud_1.shape[0],point_cloud_1.shape[2]))




    # getting point cloud 2
```

```
    img_velo_path_2 =
Path.joinpath(path_velodyne_points_kitty_data,filelist_velodyne_points[i+1])

    velo_im_2 = load_velo_scan(img_velo_path_2)

    x_2 , y_2, z_2 =
birds_eye_point_cloud(velo_im_2,x_and_y_vector_coirdinants_needed = True)

    x_2 = np.reshape(np.array(x_2),(1,x_2.shape[0]))

    y_2 = np.reshape(np.array(y_2),(1,y_2.shape[0]))

    z_2 = np.reshape(np.array(z_2),(1,z_2.shape[0]))

    point_cloud_2 = np.array([x_2,y_2])

    point_cloud_2 =
np.reshape(point_cloud_2,(point_cloud_2.shape[0],point_cloud_2.shape[2]))

    point_cloud_2_with_z = np.concatenate((point_cloud_2,z_2),axis = 0)



    # transforming point cloud:

    point_cloud_1 = transform_point_clouds_1_to_2(point_cloud_1_original,
ENU_x_array[i], ENU_x_array[i+1], yaw_enu_array[i], yaw_enu_array[i+1])

    point_cloud_1_with_z = np.concatenate((point_cloud_1,z_1),axis = 0)

    _ , _, velo_image_numpy_1 =
birds_eye_point_cloud(point_cloud_1_with_z.T,translation_to_body_needed = False)

    _ , _, velo_image_numpy_2 =
birds_eye_point_cloud(point_cloud_2_with_z.T,translation_to_body_needed = False)

    '''

    im_1 = Image.fromarray(velo_image_numpy_1)

    plt.imshow(im_1,cmap = 'bone')

    plt.show()
```

```
    im_2 = Image.fromarray(velo_image_numpy_2)

    plt.imshow(im_2,cmap = 'bone')

    plt.show()

    print(point_cloud_1.shape)


    correspondence_indice =
np.array(get_correspondence_indices(point_cloud_1_with_z,point_cloud_2_with_z))

    print(correspondence_indice.shape)

    '''




    if(point_cloud_1_with_z.shape[1]<point_cloud_2_with_z.shape[1]):

      indexes_to_make_same_size = np.ones(point_cloud_1_with_z.shape[1],dtype =
bool)

      indexes_to_make_same_size =
np.argwhere(indexes_to_make_same_size).flatten()

      point_cloud_2_with_z = point_cloud_2_with_z[:,indexes_to_make_same_size]


    if (point_cloud_1_with_z.shape[1]>point_cloud_2_with_z.shape[1]):

      indexes_to_make_same_size = np.ones(point_cloud_2_with_z.shape[1],dtype =
bool)

      indexes_to_make_same_size =
np.argwhere(indexes_to_make_same_size).flatten()

      point_cloud_1_with_z = point_cloud_1_with_z[:,indexes_to_make_same_size]

      z_1 = z_1[:,indexes_to_make_same_size]
```

```
    #choosing random indicies

    random_indices = np.random.choice(2,size = point_cloud_1_with_z.shape[1])

    random_indices = np.argwhere(random_indices).flatten()



    P_values, norm_values, corresp_values = icp_svd(point_cloud_1_with_z,
point_cloud_2_with_z,random_indices,kernel=partial(kernel, 0.4))

    P_values = np.array(P_values[-1])

    _ , _, velo_image_numpy_3 =
birds_eye_point_cloud(P_values.T,translation_to_body_needed = False)

    '''

    im_3 = Image.fromarray(velo_image_numpy_3)

    plt.imshow(im_3,cmap = 'bone')

    plt.show()

    '''

    P_values = transform_point_clouds_2_to_1(P_values[:2,:], ENU_x_array[i],
ENU_x_array[i+1], yaw_enu_array[i], yaw_enu_array[i+1])

    P_values_with_z = np.concatenate((P_values,z_1),axis = 0)

    return P_values_with_z.T




perform_icp_between_clouds(ENU_x_array_noised,ENU_y_array_noised,yaw_enu_arr
ay_noised,0)
```

```
make_occupancy_map(ENU_x_array_adjusted, ENU_y_array_adjusted,
yaw_enu_array_noised, Occupied_threshold_1, free_threshold_1,
probability_saturation, l_occ_1, l_free_1, icp_correction_needed = True)
```