Task 1A

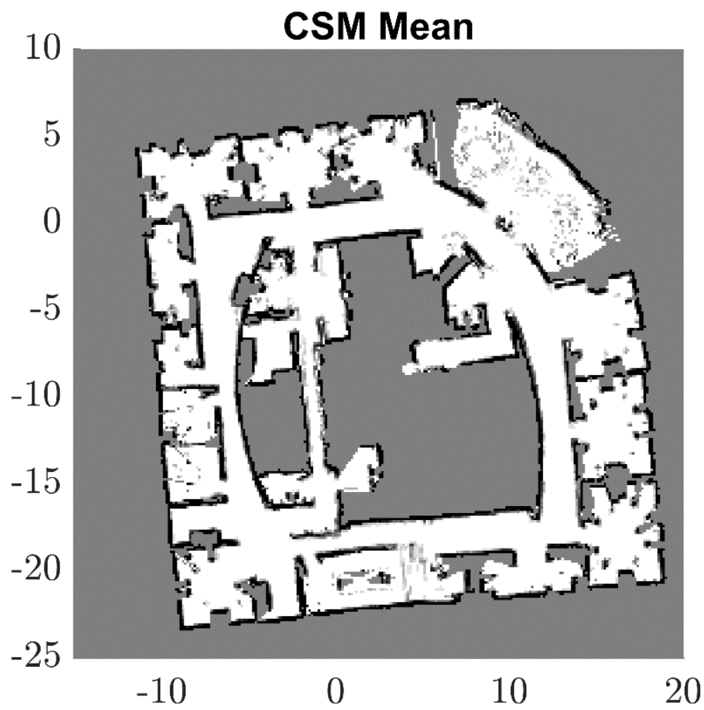

Figure 1: Discrete Occupancy Grid Map mean (grid size: 0.135)

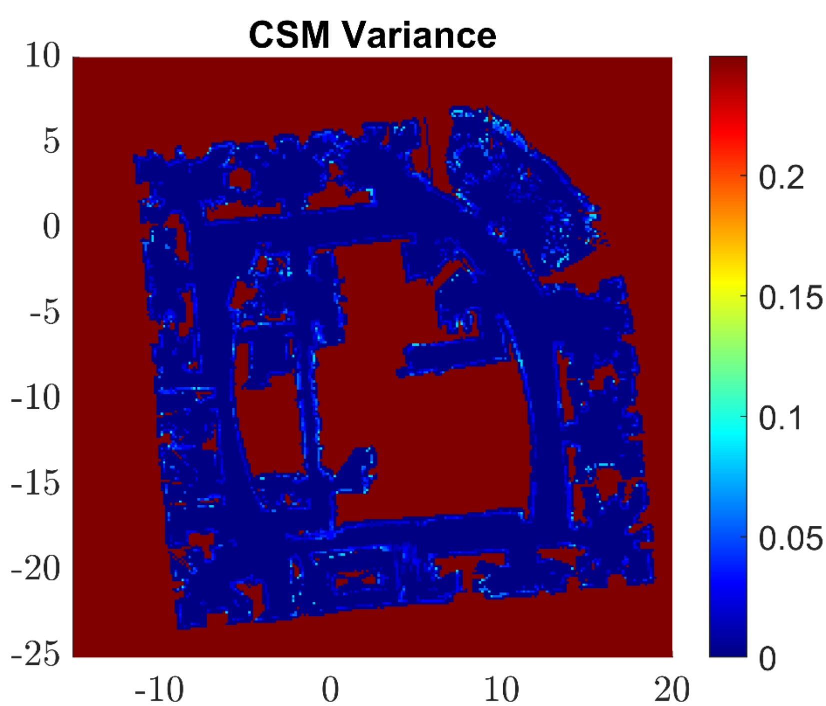

Figure 2: Discrete Occupancy Grid Map variance (grid size: 0.135)

Task 2A

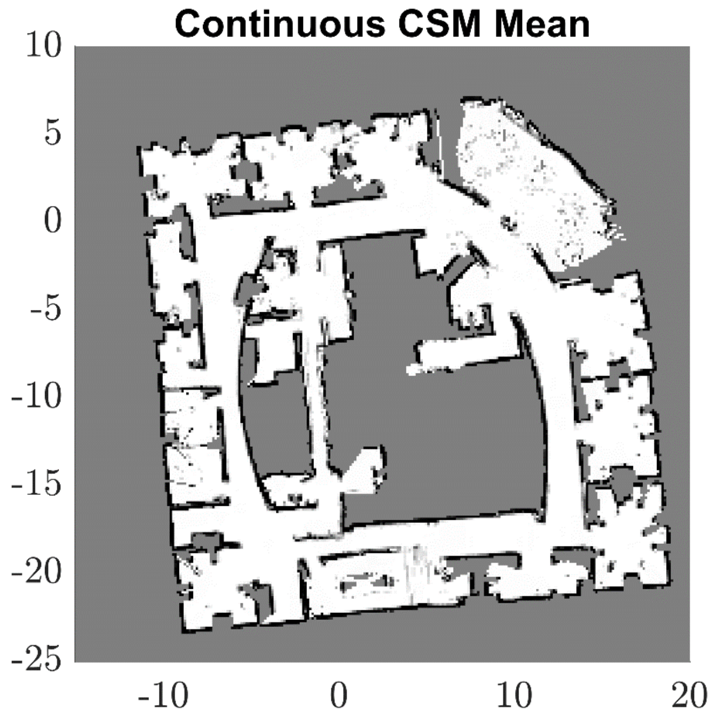

Figure 3: Continuous Occupancy Grid Map mean (grid size: 0.135)

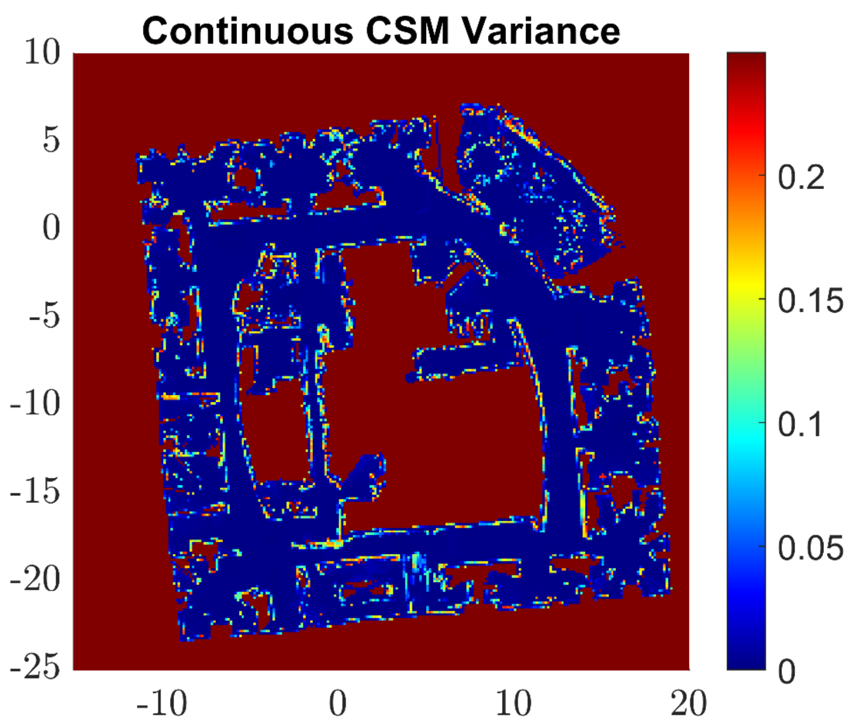

Figure 4: Continuous Occupancy Grid Map variance (grid size: 0.135)

Task 2B

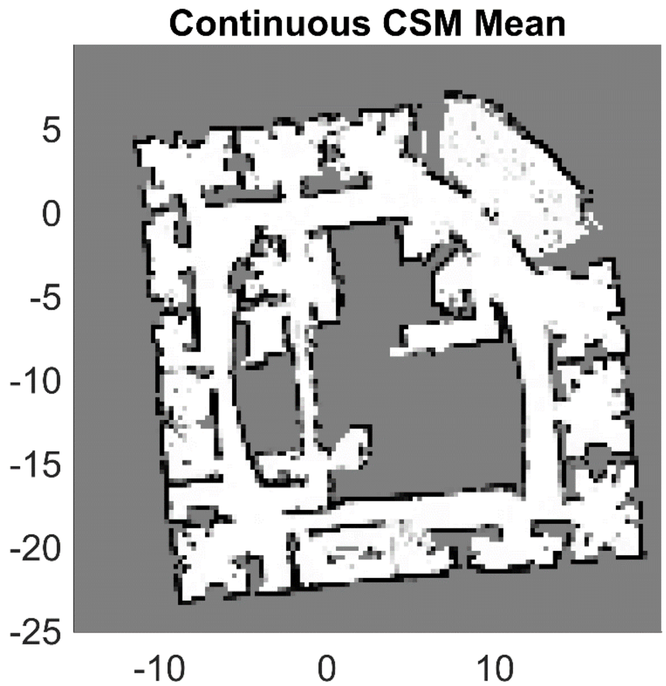

Figure 5: Continuous Occupancy Grid Map mean (grid size: 0.27)

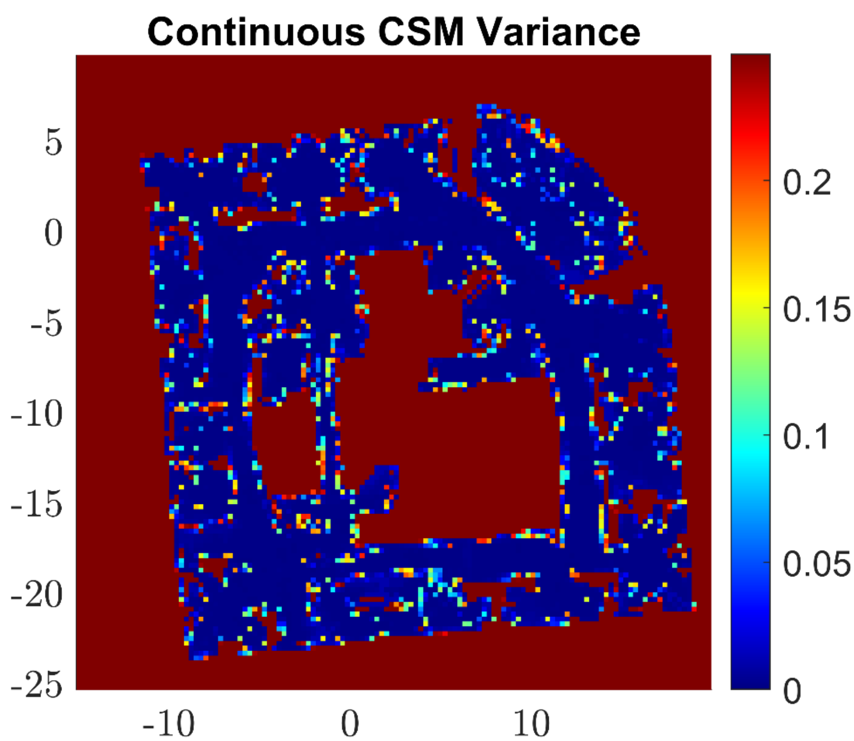

Figure 6: Continuous Occupancy Grid Map variance (grid size: 0.27)

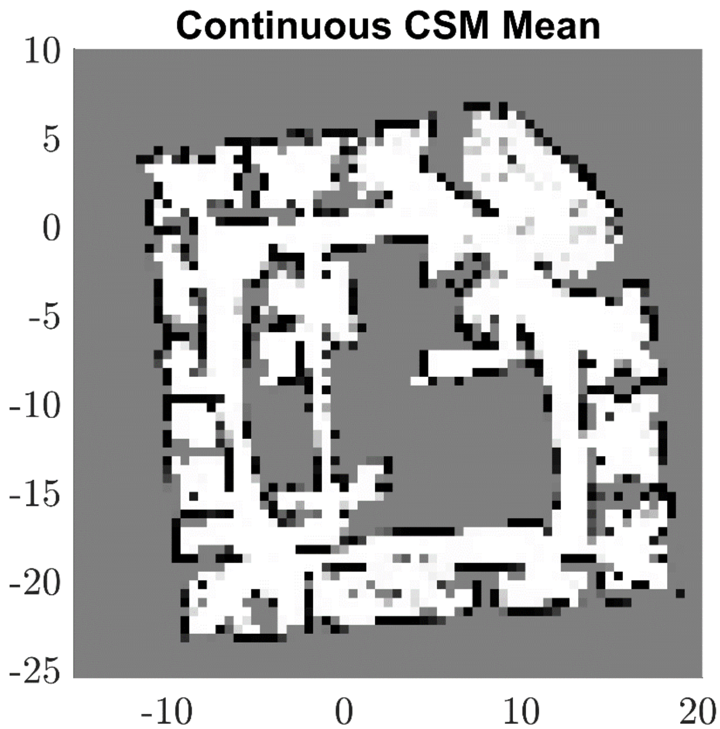

Figure 7: Continuous Occupancy Grid Map mean (grid size: 0.5)

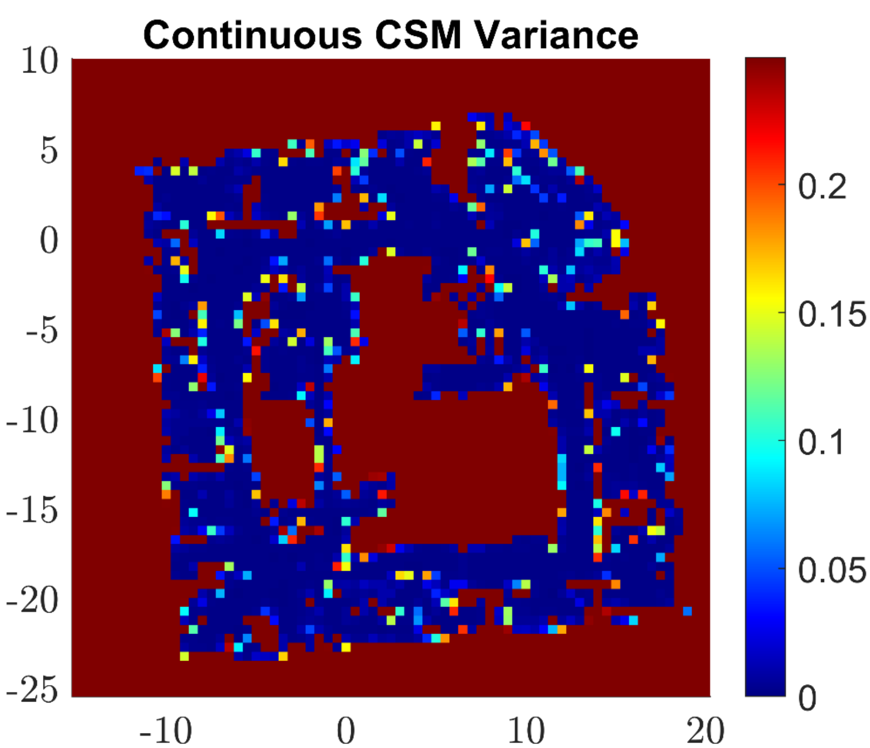

Figure 8: Continuous Occupancy Grid Map mean (grid size: 0.5)

Comparison between different grid sizes

Observations:

As we increase the grid size:

- The resolution of the map reduces, and the map appears to be pixelated when compared to a smaller grid size map. This is because grids per unit area decreases as we increase grid size.
- The compute time decreases (since number of cells decreases)
- When we compare the mean maps, the boundaries are thicker, but broken. The thick boundary is directly related to the larger grid size. The broken nature of the boundary is due to instances where a block of 3 white and 1 black cells in smaller grid size map get converted to a single white cell in large grid size map.
- Variance at the boundaries is supposed to be higher, but as grid size increases the variance at boundaries remains low at several places.

Conclusion:

Smaller grid size gives more information about the occupancy, especially around the boundaries. This allows for better path planning and exploration. But this comes at a higher computation and memory cost. The use of efficient data structures to store and access the grid map is beneficial in mapping.

The case of broken boundaries, when working with large grid size, could be dangerous for a robot which is exploring new frontiers, i.e. trying to go from unoccupied (white) region to the unexplored (gray) region. The robot could run into boundaries while exploring.

Task 2C

Comparison between discrete and continuous CSM

- On comparing mean maps of discrete and continuous CSM of equal grid size, we observe that they look very similar apart from the fact that the continuous map is much smoother than the discrete map. This is because of how the prior is updated using a kernel function rather than updating by 1 each time.
- On comparing variance maps of discrete and continuous CSM of equal grid size, we observe that the variance at boundaries is higher for the continuous case.

Advantage of continuous model

- The continuous model enables prediction about occupancy in regions unobserved by the range sensor based on local measurements.
- The continuous variance map is a more appropriate representation of the uncertainty at the boundaries. Similarly, the continuous mean map is more accurate description of the probability distribution of occupancy across the map.
- This model also enables us to calculate the occupancy at any arbitrary query point
- The model has a smooth transition of prior distribution in regions lacking sufficient data.
- The model can be used to track higher order moments of probability distribution, which can be used to infer occupancy in unobserved regions.

Task 3A

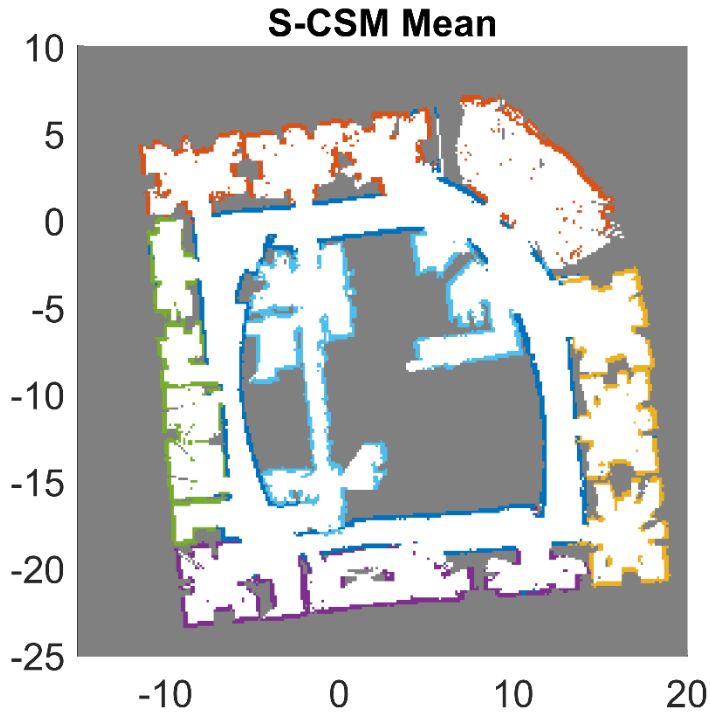

Figure 9: Discrete Semantic Map mean (grid size: 0.135)

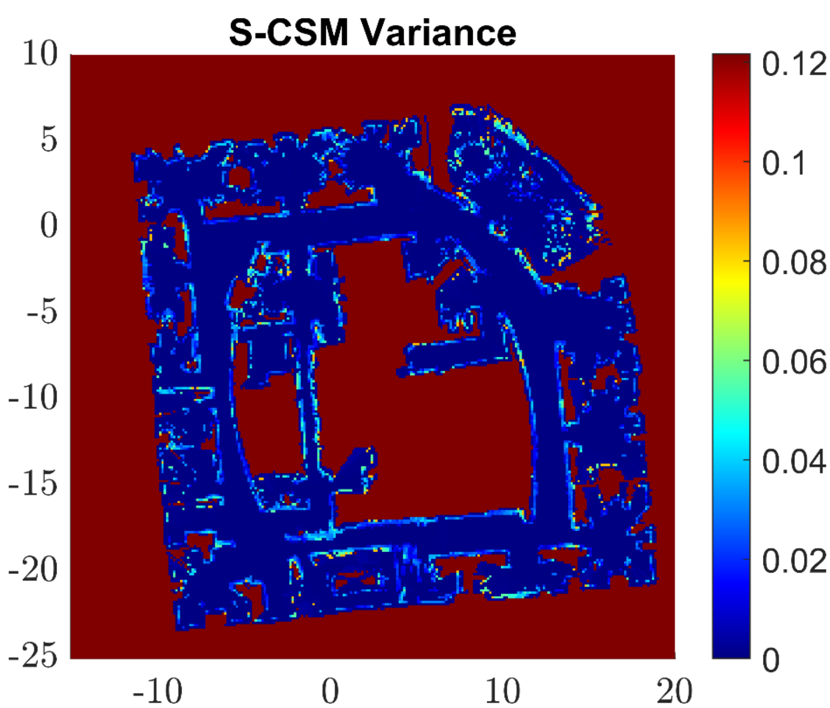

Figure 10: Discrete Semantic Map variance (grid size: 0.135)

Task 4A

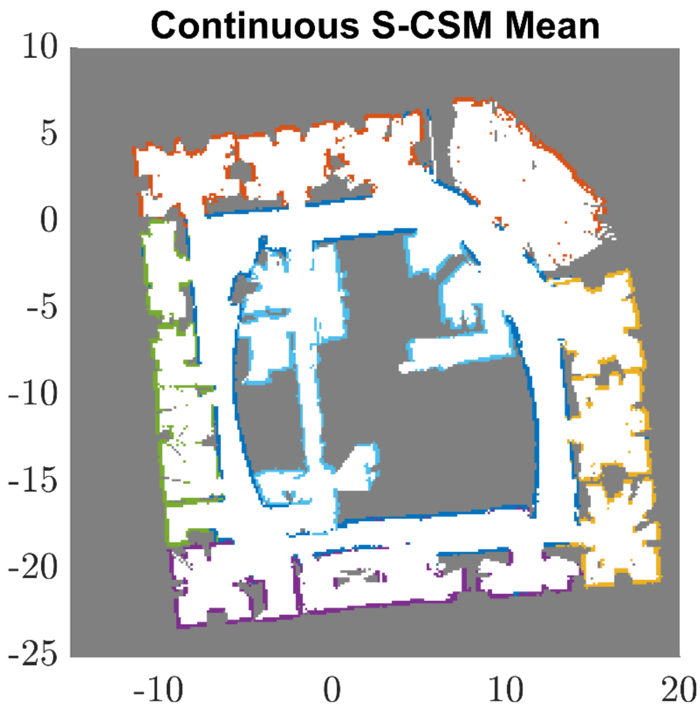

Figure 11: Continuous Semantic Map mean (grid size: 0.135)

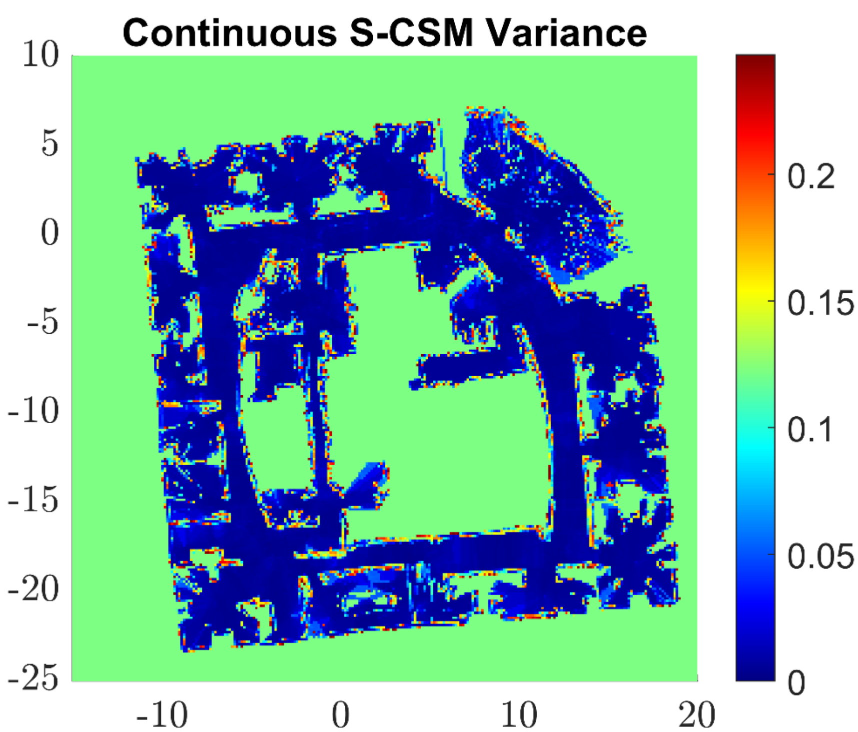

Figure 12: Continuous Semantic Map variance (grid size: 0.135)

Task 4B

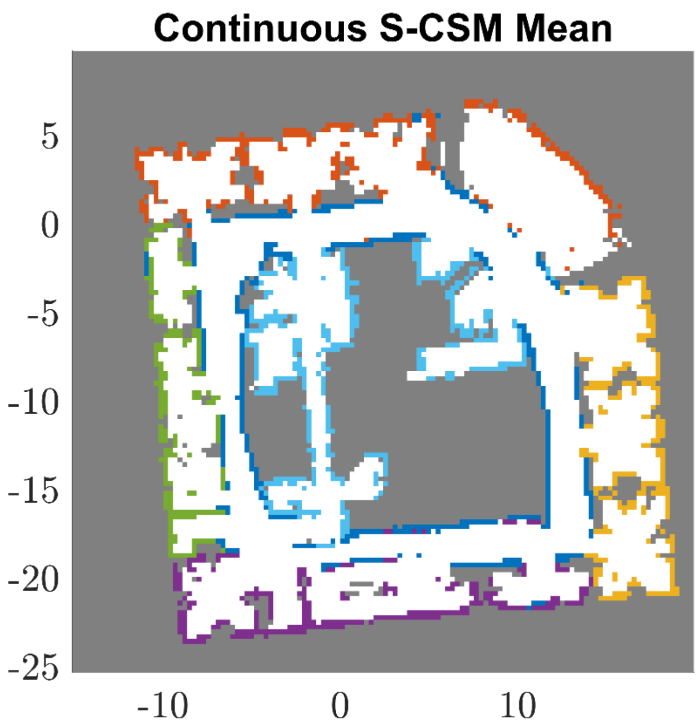

Figure 13: Continuous Semantic Map mean (grid size: 0.27)

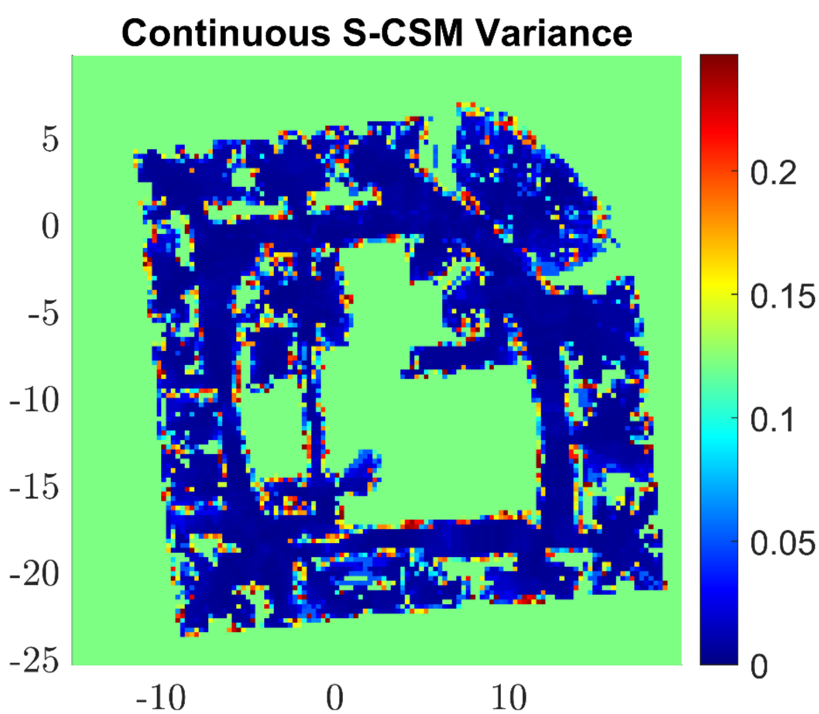

Figure 14: Continuous Semantic Map variance (grid size: 0.27)

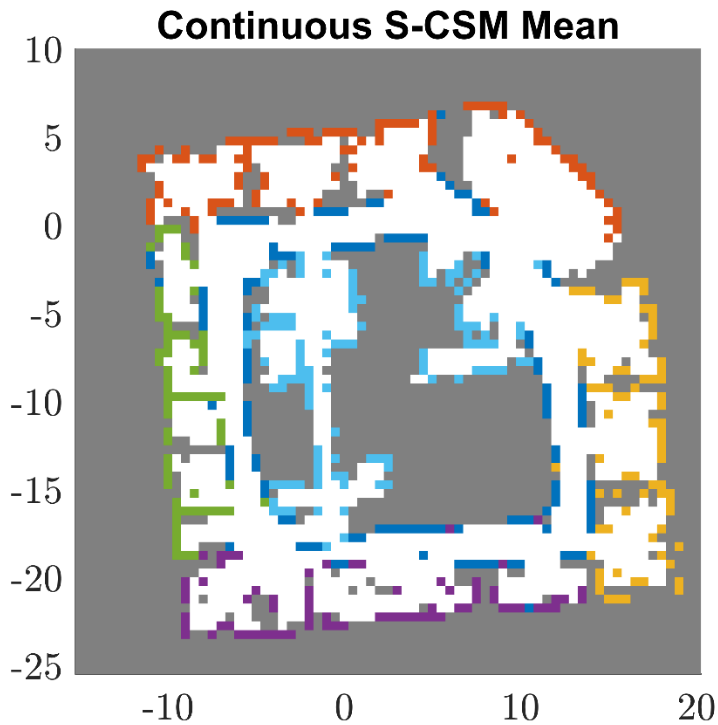

Figure 15: Continuous Semantic Map mean (grid size: 0.5)

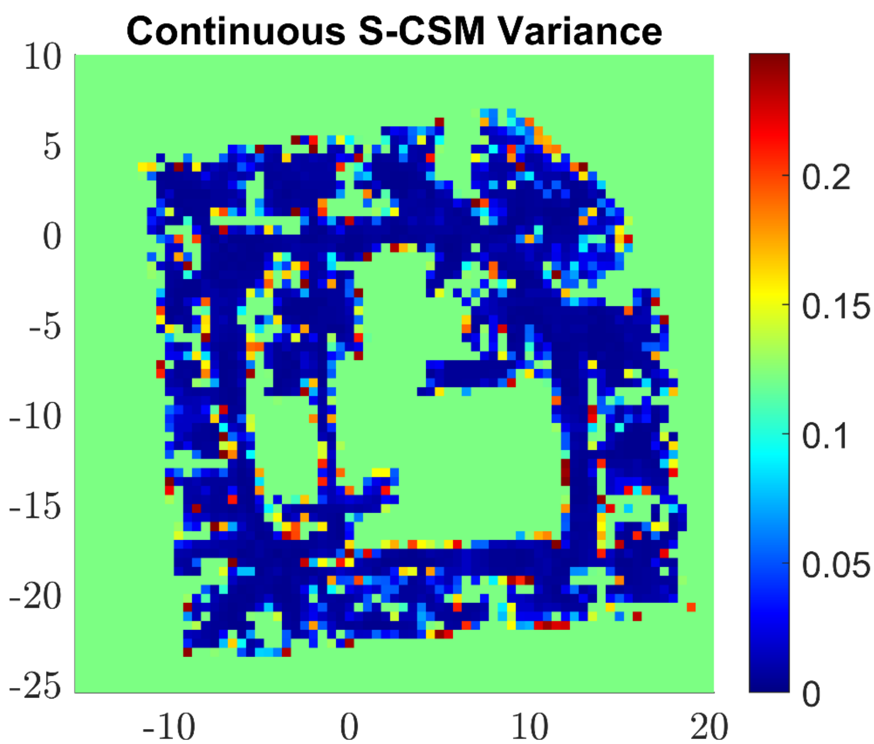

Figure 16: Continuous Semantic Map variance (grid size: 0.5)

Comparison between different grid sizes

Observations:

As we increase the grid size:

- The resolution of the map reduces, and the map appears to be pixelated when compared to a smaller grid size map. This is because grids per unit area decreases as we increase grid size.
- The compute time decreases (since number of cells decreases)
- When we compare the mean maps, the boundaries are thicker, but broken. The thick boundary is directly related to the larger grid size. The broken nature of the boundary is due to instances where a block of 3 unoccupied and 1 occupied cells in smaller grid size map get converted to a single unoccupied cell in large grid size map.
- A mix-up of colours can be observed at the boundaries between various classes, due to which ability to distinguish between classes decreases at the boundaries.
- Variance at the boundaries is supposed to be higher, but as grid size increases the variance at boundaries remains low at several places.

Conclusion:

Smaller grid size gives more information about the occupancy, especially around the boundaries. This allows for better path planning and exploration. But this comes at a higher computation and memory cost.

Smaller grid size also allows for clearer demarcation between different classes, and inconsistencies like having a cell of a different class amongst a group of cells of the same class, is reduced.

The case of broken boundaries, when working with large grid size, could be dangerous for a robot which is exploring new frontiers, i.e. trying to go from unoccupied region to the unexplored region. The robot could run into boundaries while exploring.

Task 4C

Comparison between discrete and continuous S-CSM

- On comparing mean maps of discrete and continuous CSM of equal grid size, we observe that they look very similar apart from the fact that the continuous map is much smoother than the discrete map. This is because of how the prior is updated using a kernel function rather than updating by 1 each time.
- On comparing variance maps of discrete and continuous CSM of equal grid size, we observe that the variance at boundaries is higher for the continuous case.

Advantage of continuous model

- The continuous model enables prediction of semantic information in regions unobserved by the range sensor based on local measurements.

- The continuous variance map is a more appropriate representation of the uncertainty at the boundaries. Similarly, the continuous mean map is more accurate description of the probability distribution of occupancy across the map.
- This model also enables us to calculate the occupancy at any arbitrary query point
- The model has a smooth transition of prior distribution in regions lacking sufficient data.
- The model can be used to track higher order moments of probability distribution, which can be used to infer occupancy in unobserved regions.

Task 4C (Extra Credit)

We implemented four mapping algorithms in this problem set and produced four types of maps – continuous map with semantic information, discrete map with semantic information, continuous map with occupancy information, and discrete map with occupancy information.

Continuous vs Discrete

The advantages of building a map with continuous model have been discussed in earlier parts. It would be highly beneficial to use the continuous CSM algorithm as it allows us to predict semantic or occupancy information in regions where there is insufficient or noisy sensor data. The continuous CSM model also produces smoother maps and accurately captures the uncertainties at boundaries.

Grid Size

As discussed earlier a smaller grid size is better as it contains more information, which is a big help at the boundaries. Our mapping algorithm should use data structures to store and access sparse cell information efficiently, so that compute time could be reduced. The use of such data structures becomes a necessity for 3D maps. The appropriate grid size will depend on the sizes of the robot and obstacles as well as the memory and speed of the processor running our algorithm.

Semantic vs Occupancy

Whether we use semantic or binary mapping is dependent on the type of sensor data we have. Semantic classification in real-time, although challenging, is achievable using deep learning architectures like MobileNet. It's essential that such classifiers are precise (even at the cost of accuracy). Also running a classifier reliably, necessitates a lot of training in environments similar to that being mapped. Hence given the resources in terms of trained semantic labels and compute power, running a semantic model won't be a problem.

In conclusion, if we can effectively use the current state-of-the-art algorithms, we should implement a continuous semantic CSM on our mobile robot.