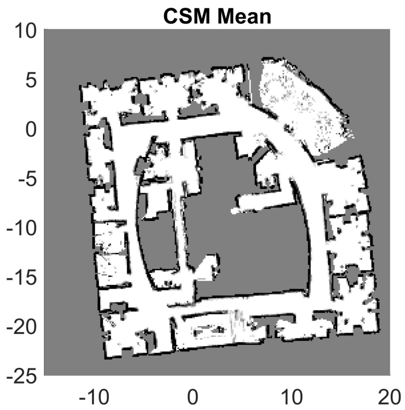
NAVARCH 568: Mobile Robotics
Problem Set 3

Harrison Chen

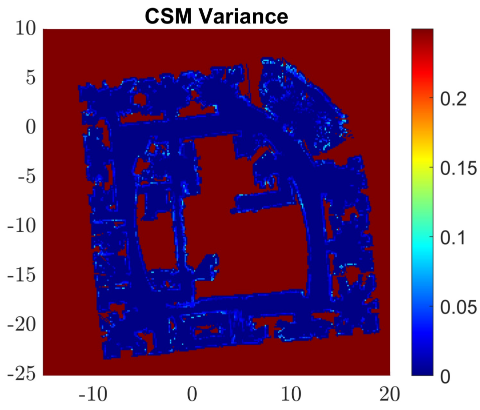
February 23, 2020

Task 1: Counting Sensor Model

Part A



(a) Mean plot

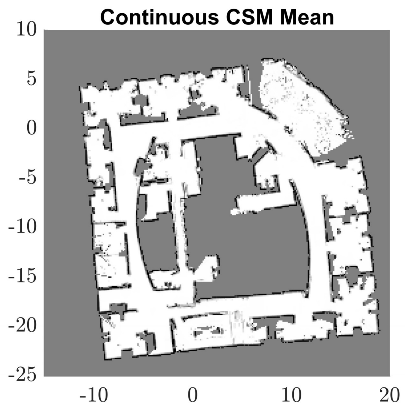


(b) Variance plot

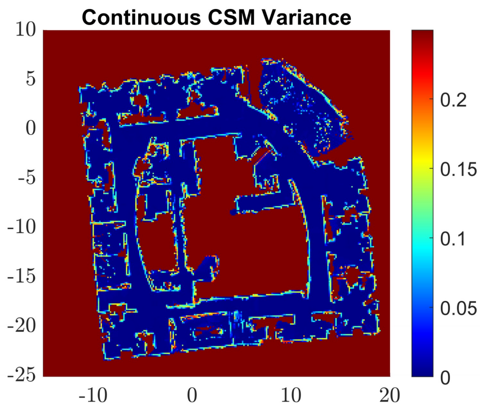
Figure 1: Maps from the counting sensor model with `grid_size = 0.135`

Task 2: Continuous Counting Sensor Model

Part A



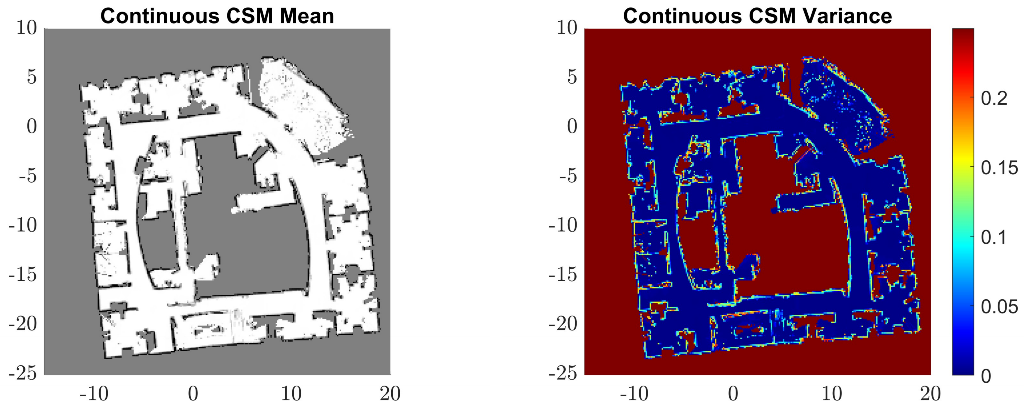
(a) Mean plot



(b) Variance plot

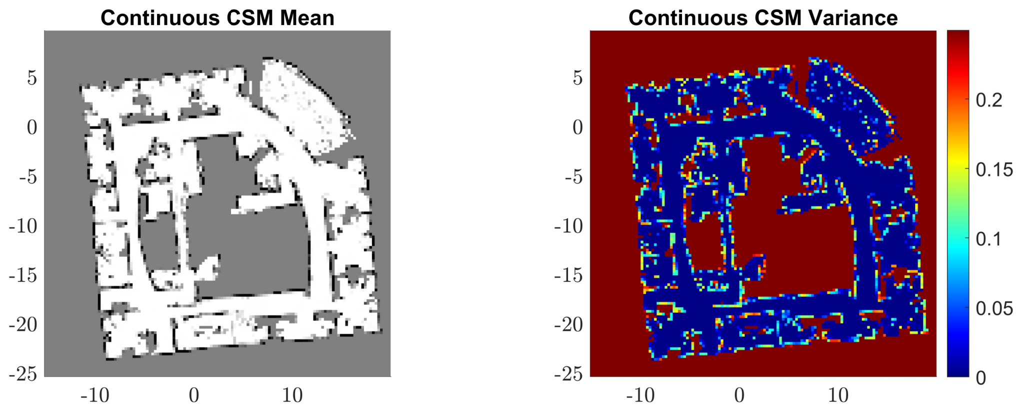
Figure 2: Maps from the continuous counting sensor model with `grid_size = 0.135`

Part B



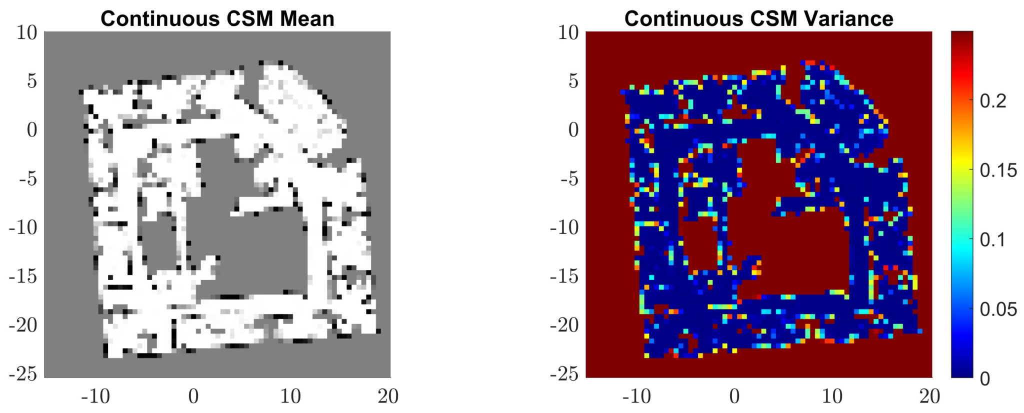
(a) Mean plot (b) Variance plot

Figure 3: Maps from the continuous counting sensor model with `grid_size = 0.135`



(a) Mean plot (b) Variance plot

Figure 4: Maps from the continuous counting sensor model with `grid_size = 0.270`



(a) Mean plot (b) Variance plot

Figure 5: Maps from the continuous counting sensor model with `grid_size = 0.500`

As the grid size being used in the sensor model increases, naturally the resolution of the generated maps decreases. The resulting images for `grid_size = 0.270` and `grid_size = 0.500` are not only more pixelated, but the decrease in resolution also slightly alters the shape of the map, specifically the separation between the different rooms, which are no longer distinct. The variance map suffers from lowered resolution as well, where it is difficult to conclude any correlation between variance and occupancy due to the larger pixels.

Additionally, for the mean plots, the categorization of each pixel is also less certain. For the binary models, the darker the pixel, the larger the respective mean, which implies a greater α value relative to its β. For example, at `grid_size = 0.270`, the walls of the map have larger spans of gray or white cells than at `grid_size = 0.135`, and this problem worsens for `grid_size = 0.500`. This is because what was previously perceived as multiple cells is now combined into one cell, and if those multiple contained both occupied and unoccupied cells, the combined result ends up somewhere in between, represented as a gray cell. This in-between categorization is not helpful in determining the shape or layout of the area we are mapping, making it a less desirable outcome.

From these observations, we can conclude that there is no discernible benefit to using a larger `grid_size`, as it worsens our mapping ability significantly. The only reason to lower the resolution is to reduce the computation time, if that is a factor in real-time mapping or a similar application.

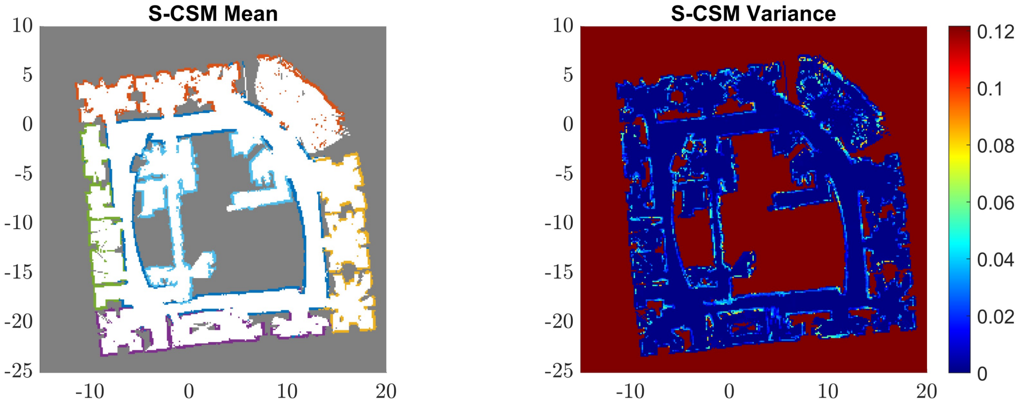
Part C

From my observations, it seems that when continuous and discrete CSM methods are used with the same `grid_size`, the continuous model is able to map features with a smaller thickness than the discrete model; in other words, it has a greater resolution that is unrelated to pixel density. Walls in the continuous CSM mean plot are thinner compared to discrete CSM, and features located in the middle of rooms are also smaller. There may be a concern that several areas of the continuous mean plot have discontinuities in the walls, but they are few and far between, and the increased accuracy outside of it is a notable advantage. Another difference I observed is that for the noisy, ambiguous regions, the continuous model tended more towards unoccupied in comparison to the discrete model, meaning it showed as a lighter shade of gray.

The variance plots also vary significantly, where the continuous model yields much higher variances at occupied areas, ranging from $0.1 - 0.2$, while unoccupied areas have a variance of 0. The discrete model variance map is much less colorful and varied, with no cell exceeding a variance of 0.1.

Task 3: Semantic Counting Sensor Model

Part A

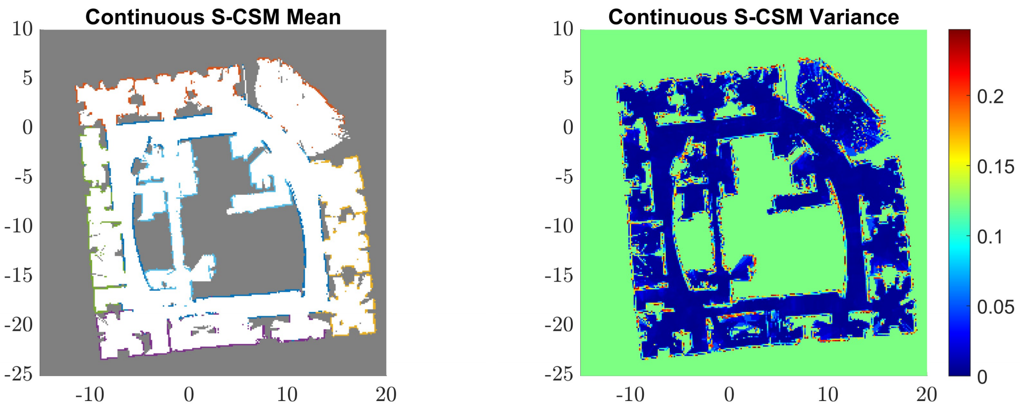


(a) Mean plot (b) Variance plot

Figure 6: Maps from the semantic counting sensor model with `grid_size = 0.135`

Task 4: Continuous Semantic Counting Sensor Model

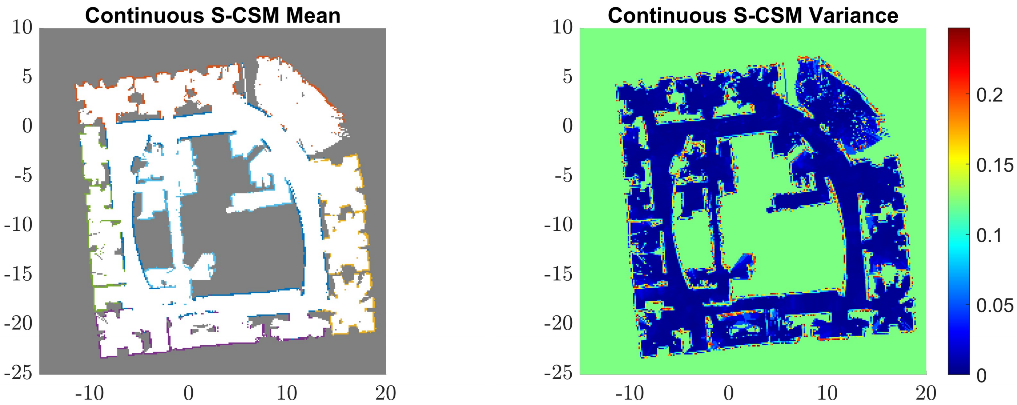
Part A



(a) Mean plot (b) Variance plot

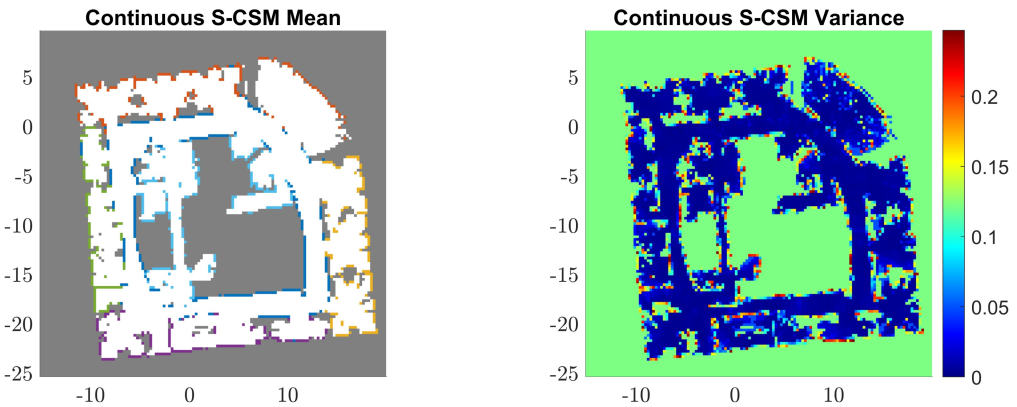
Figure 7: Maps from the semantic continuous counting sensor model with `grid_size = 0.135`

Part B



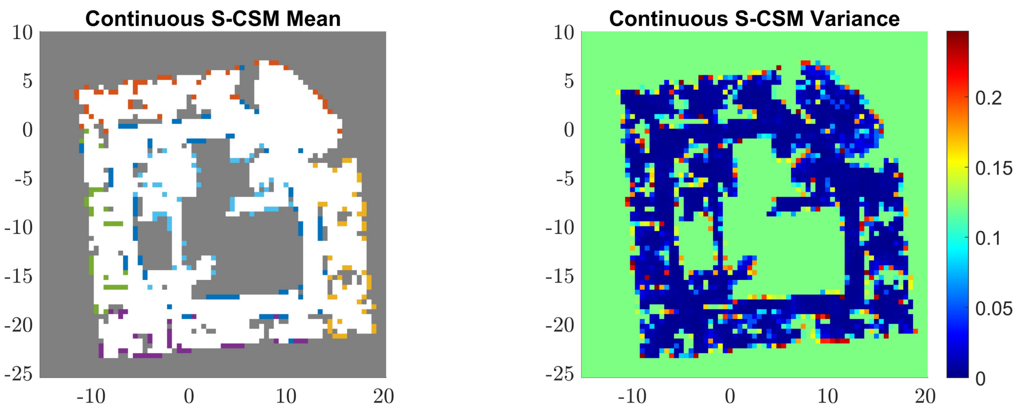
(a) Mean plot (b) Variance plot

Figure 8: Maps from the semantic continuous counting sensor model with `grid_size = 0.135`



(a) Mean plot (b) Variance plot

Figure 9: Maps from the semantic counting sensor model with `grid_size = 0.270`



(a) Mean plot (b) Variance plot

Figure 10: Maps from the semantic counting sensor model with `grid_size = 0.500`

Similar to the binary sensor models, the increased grid size leads to a decreased resolution. The resulting mean plot images for `grid_size = 0.270` and `grid_size = 0.500` are more pixelated, and gaps in the walls are just as present as they were in the binary modeling equivalent. More problematic with this issue, however, is that as a result, the classification and separation between rooms becomes nearly indistinguishable. Instead of clearly defined hallways, there are just specks of dark blue scattered throughout the map at `grid_size = 0.500`. If a robot wanted to know what room it was in, it would have a much more difficult time. This problem also carries over into the variance plot, where it's lowered pixel density yields the same range of variances, but arranged in a way that makes it difficult to associate with any features in the map. For smaller `grid_size` values, the separation between high-variance occupied areas and low-variance unoccupied areas is clear, whereas for large `grid_size` values, it is not an observable pattern.

From these observations, we can again conclude that there is no discernible benefit to using a larger `grid_size` besides reducing computation time, if relevant.

Part C

Differences between the discrete and continuous semantic models are similar to those of the binary model. Once again, in the mean plots, the continuous model is able to map features with a finer resolution than the discrete model. Walls are thinner and objects in rooms are more precisely traced out, and noise, most notably in the upper right, is noticeably reduced from the discrete model to the continuous one. The color boundaries between the halls and rooms are equally distinct in both maps.

The differences in variance plots also mirror their binary counterparts; the semantic discrete model still does not have any areas in the map exceed 0.1 (not including the unmeasured region), while the semantic continuous model has most walls at variances ranging from $0.1 - 0.2$. Additionally, while in the binary models, the unoccupied areas had a variance of almost exclusively 0. In the continuous semantic CSM, there are certain regions in the floor where the variance creeps up between $0.05 - 0.1$, which is informative in term s of indicating to the robot what unoccupied areas also have greater uncertainty, not just occupied areas.

Given the observations made, I believe the continuous semantic CSM is the better of the two models to use, as it seems to map the environment more precisely and is more informative with how it maps the variance to unoccupied areas.