First of all, this project sounds very interesting, and the motivation is pretty clear. There is a specific target application, though it addresses a more general problem: how to automatically navigate an underwater vehicle, or how an underwater vehicle can track its own location. It would be nice to provide more information about the target application and environment, such as, how deep might the underwater sensors be, expected travel distance between sensors and overall, and how close the stingray needs to be to the sensors to extract information.

Response: I made the mistake of leaving the target application too broad and not really clarifying how this work would actually be used. The underlying goal is to research the underwater navigation and position, which can be used in multiple situations. The specific target I described was Moorea, which is an environment with shallow, clear waters. The sensors here are also relatively shallow, and the distance separating the sensors can vary. I should make it more clear that this would be the end goal for iterations down the line, and that the actual target application for this work is the AUVSI underwater competition. This environment will be very shallow with clear waters and no current or waves. The course will only be in the meters as far as distance traveled, compared to likely in the kilometers for an application like Moorea.

The answers to questions like these are important when defining your requirements and evaluating your alternatives. You did indicate that the environment involved relatively shallow, clear water. If this is the case, I am surprised that you disregarded GPS. Would it be feasible to use GPS to recalibrate your position by having the stingray rise to the surface?

Answer: I did consider GPS in the early stages of research. I do think that this would be a worthwhile thing to pursue for applications like Moorea. Even in deeper waters, a GPS could be a reliable way to rectify location. For instance, the vehicle could have multiple rectification techniques such as a priori maps based on geophysical data or vision. If the vehicle goes for a period of time without seeing an a priori element that it recognizes, it could surface to rectify its location. Future iterations of this research could further investigate this option. The main reasons I disregarded GPS for this project are funds and course size. There is not currently a GPS on the Stingray and I do not have the time or funding to install the system. Also, since the AUVSI course is so small, the GPS would have to be extremely accurate (and therefore more expensive) in order to give useful location.
I am curious about how effective the Kalman filter will be in making position estimates more accurate, and how accurate you need the position estimates to be.

**Response:** Research shows that Kalman filters can increase the accuracy of a single result by considering sensor data and previous status in a continuous manner. So the Kalman filter would help alleviate some of the compounding error effects of calculating location based solely on basic sensor history. The accuracy needed for the position estimate may vary depending on application. It turns out that the accuracy that is useful for the AUVSI competition happens to be very strict. In order for this position data to be useful in determining the next task, location would need to be accurate to within a meter or two.

*How noisy is the INS data?*

**Answer:** It turns out that the INS data is not very noisy at all, nor is the pressure sensor. I ran a test where I logged the INS and pressure sensor data for about 25 minutes at once per second. The vehicle was placed on a stand in the lab and did not move for the entirety of the test. Here are the resulting standard deviations for each variable produced by the INS and pressure sensor:

<table>
<thead>
<tr>
<th>pitch</th>
<th>roll</th>
<th>yaw</th>
<th>psi</th>
<th>accel1</th>
<th>accel2</th>
<th>accel3</th>
<th>ang1</th>
<th>ang2</th>
<th>ang3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1362</td>
<td>0.1519</td>
<td>0.1519</td>
<td>0.0033</td>
<td>0.0311</td>
<td>0.0358</td>
<td>0.0295</td>
<td>0.0058</td>
<td>0.0066</td>
<td>0.0058</td>
</tr>
</tbody>
</table>

You can see that the values are very consistent in this controlled situation. It is especially clear that the pressure sensor is very reliable in terms of consistency.

*How much of a drift do you expect to observe?*

**Answer:** I will answer this from two points of view. First of all there is the use of the vehicle in an ocean environment. Whether it be a shallow coastal area or out at sea, there will be currents involved that will cause drift. On top of this, there will be the natural drift that occurs when the motors slow or stop after propelling the vehicle forward. Now the other point of view is that in the tank for the AUVSI competition, the only drift will occur as a result of the forward motion after the vehicles motors have cut. I expect a small amount of drift in my tests, which is why I need a more reliable positioning technique such as vision to rectify the position whenever possible.

*How much of a drift is considered reasonable?*

**Answer:** I dont have a specific metric on this. The amount of compounding error will be directly related to the drift, so for my test, the goal is to minimize the
drift error using the Kalman filter and later the computer vision rectification.

*Do you plan to evaluate this, comparing operation with and without filtering noise?*

**Answer:** I am not entirely sure what this question means, but I will answer as best I can. It seems the question is if I plan to evaluate the drift and how well my Kalman filter fixes this problem. At some point it would make since to try and quantify the effectiveness of the Kalman filter, but for now, my goal is to get a position estimation. Since I intend to continue this work, I will likely attempt to calculate a metric at a later date.

*Here is a thought that came to mind: can you leverage the fact that you have both INS data and pressure data to estimate the error in your position estimate? The depth that you calculate from your pressure sensor is absolute, or non-drifting. You can also estimate your depth from INS data using some past absolute reference point, which would be the last time you knew your latitude/longitude. Could you then take your depth drift as a rough estimate of your latitude/longitude drift?*

**Answer:** This is a good suggestion, which I have not yet considered. I think that I can estimate the error at least in the Y-axis by comparing to the pressure sensor. I would have to take a lot of real location measurements to calculate X and Z drift and determine if the depth error between INS and pressure sensor is accurate enough in estimating X and Z error. I will definitely pursue this at some point, whether it be this quarter or in my continuing work.

*I was a little confused about how you use the term “dead reckoning”. When you say dead reckoning, are you referring to a method distinct from the INS (like measuring relative current), or are you simply referring to what you do with the INS data?*

**Answer:** I hope that my briefing helped clear up the difference, though it is subtle. Dead reckoning refers to using a compass, depth sensor, and velocity sensor (or water speed sensor) to calculate location. This is simply distance math using heading and speed and depth changes to determine location. The INS gives more complete information about the position and movements of the vehicle, which can be used similarly to calculate position. My understanding is that “dead reckoning” refers specifically to the use of the cheap sensors for calculating location.

*This is probably beyond the scope of what you will accomplish by the end of the quarter, but since you mentioned it several times, how will the computer vision approach with the a priori map work?*

**Answer:** The local positioning system (LPS) will tell the vision module what to
be looking for based on its estimate of current position. Then if the vision module finds the object and returns a result, then the LPS can update its estimate to be at the location where the object is known to be.

*What would the map consist of?*

**Answer:** The map will effectively be a matrix where each entry corresponds to a local \((x, y)\) coordinate. Zeros will represent open water, while numbers one and up will represent certain objects. The current position estimate will be plugged into the matrix to determine what object is nearby to begin looking for visually.

*Would it indicate the depth of the ocean floor at given locations?*

**Answer:** The depth could be indicated in this map, or potentially in another matrix. The depth would most likely be used to help determine how far away an object is and therefore what the position rectification should be based on a found object.

*Would it be an image?*

**Answer:** No it would most likely be a matrix (or \(2 \times 2\) array) containing the locations of known objects as described above.

*Would it work in environments where there are few distinguishing features, or where lighting is not good?*

**Answer:** This is a valid drawback to the use of vision. It is the specific position rectification choice for situations with dense features and good visibility. It would not be a particularly useful solution in murky water or area with few features. That said, it has the potential to help with position even when there aren’t very many features, and it is cheap compared to long baseline (LBL) or other acoustic techniques.

*Again, this is a good project. If you are short on time, I hope you are able to implement some form of functional position detection and use it to navigate to a given fixed point, even if it is not super accurate or your Kalman filter is not optimal.*

**Response:** Thank you for your questions and comments. I too hope that I can complete a working Kalman filter by quarters end. My consolation is knowing that I will continue this work into the summer and get a working version in the near future. In addition, I will be able to continue by incorporating computer vision and potentially hydrophone triangulation.