Autonomous Rover for Vineyard Yield Prediction

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Project Summary

The Vitibot is rover that can autonomously navigate a vineyard throughout the grape growing season and predict the end of season crop yield. As data is collected, the pictures are fed into a machine learning model that predicts the yield of the vineyard at harvest. The current model has been trained on pictures of pinot noir grapes from the Crawford-Beck Vineyard in Amity.

The rover is mechanically complete, but it is not yet fully autonomous. This year's team focused on improving the autonomous driving capabilities for both the speed adjustment and end-of-row turning.

In addition, we made significant progress in our post prediction capabilities, which greatly improves the accuracy of image location data in relation to the vineyard. This was accomplished by creating an HMM to assign row and bay numbers from the post tagger.

Finally, we placed a significant emphasis on documentation, both in terms of our own work and updates to the documentation from the previous year's code.

Outside of Rover

Background

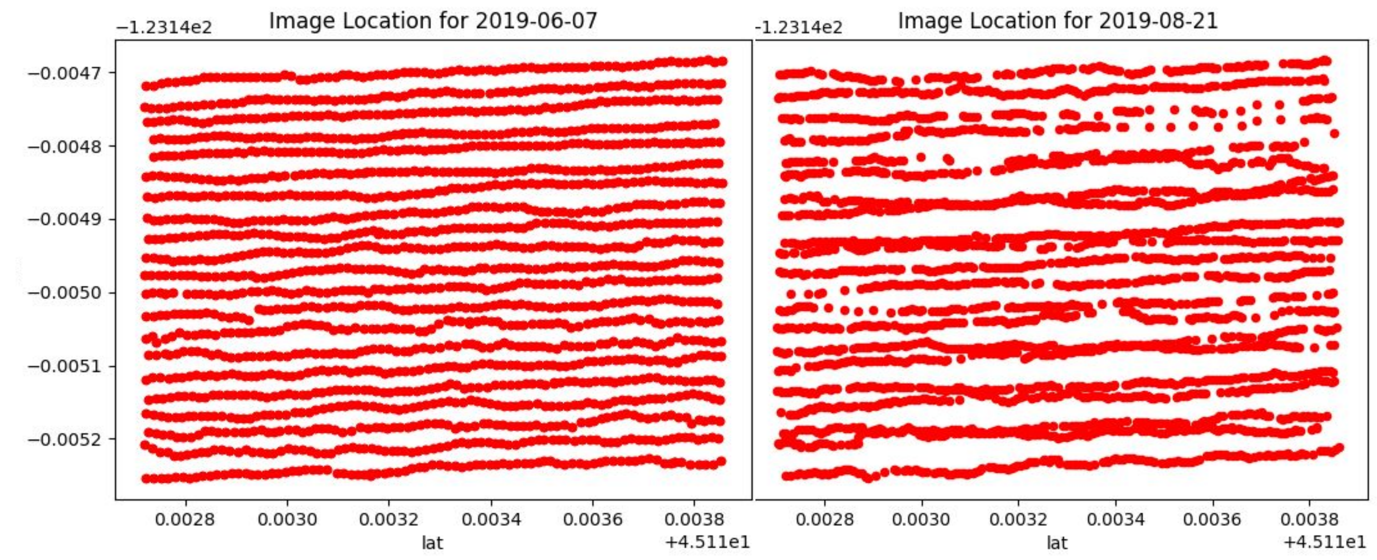
At the start of the year, the autonomous rover exhibited the capability to traverse along the vineyard rows. However, it lacked the capability to dynamically adjust its speed to account for changes in topographical incline or decline. This inadequacy resulted in inconsistencies in the number of photos captured per row, thereby impeding the efficacy of the machine learning algorithms in predicting the yield. Moreover, while the rover could reliably move along a single row, it lacked the ability to turn and continue down adjacent rows, thus requiring Dr. Orr to expend additional time and effort to gather data manually throughout the summer. This functionality is pivotal for the rover to evolve into a fully autonomous entity that does not require a physical guide in the future.

The Team

Team Members: (Left to right) Sam, Josh, Isaac, Cassie, and Kyler.

Data Validation

Our multi-year project is focused on predicting the yield of a vineyard through the use of photos captured by a rover. A key aspect of this project involves accurately tagging images to associate them with specific rows and bays in order to improve yield prediction. This tagging process enables us to determine the weight of each bay and to make more precise yield predictions. In the past, we used GPS and timestamp data to associate each image with a particular bay. However, our data validation and analysis scripts revealed some inaccuracies in this approach. Specifically, we found that the embedded GPS sensors in our GoPro cameras could "drift" during extended operation at high temperatures, which is a common occurrence during the summer months when most photo collection takes place. To address this issue, we are exploring alternative approaches to image tagging and association that can improve the accuracy of our yield predictions.



Left: An example of good GPS data, Right: An example of bad GPS data

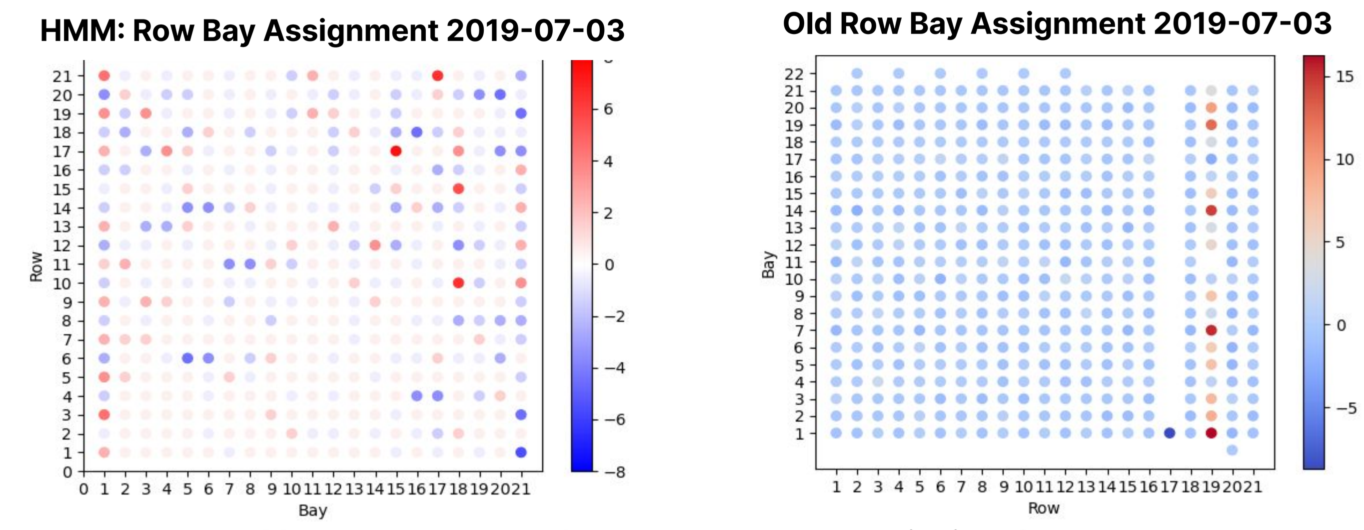
Post Predictions

After utilizing the aforementioned data validation and visualization scripts, we arrived at the conclusion that GPS and timestamp data were not precise enough to accurately determine row and bay numbers for each image. To address this issue, we developed a machine learning model that can detect the presence of a "post" in a photo, which serves as a marker between bays. By leveraging this information along with the timestamp data, we are now able to accurately count the number of posts seen in previous images and assign the corresponding bay numbers based on the number of posts seen.

Our "post-tagger" machine learning model achieved a high level of accuracy, approximately 96%. However, in order to further enhance the accuracy of our approach and assign row and bay numbers more accurately, we have implemented a Hidden Markov Model (HMM). This HMM model uses pattern recognition to assign corresponding row and bay numbers to each image, theoretically further increasing the accuracy of our yield predictions. The plots presented below are a vital component of our data validation scripts and serve to verify the accuracy of our machine learning pipeline, which includes the "post-tagger" and HMM models.

Example image that contains a "post"

These plots depict each bay in the vineyard as a single "dot" and are color-coded based on the number of images within that bay in relation to the average number of images per bay for that specific day. This color-coded representation facilitates the detection of potential anomalies or errors in our machine learning pipeline, allowing us to conduct the necessary adjustments to ensure the precision and reliability of our yield predictions.



Number of images per row/bay, colored by deviation from the average number of images per bay

Autonomous Navigation

The rover is equipped with a suite of programs that receive sensory input and relay it to the robot's central processor. Our team has made significant enhancements to the software, laying the groundwork for future improvements. These advancements include modifications to the speed acceleration curve, incorporating knowledge of North/South direction to enable optimal turning decisions, and implementing a state-saving mechanism to retain rover memory across manual and automatic adjustments.

Additionally, we have introduced new functionalities to the rover's central processor to enable it to turn independently when reaching the end of a row. By employing vineyard knowledge and LiDAR data, the rover can determine the direction of the turn and recognize when it has reached the end of the row. Once the end-of-row threshold is met, the rover employs a pivot point to execute a 180-degree turn, allowing it to regain visibility of both rows before gently guiding itself back between them and continuing along its path. As a result of these enhancements, the rover is now capable of autonomously navigating vineyard rows with the ability to self-correct during a turn as needed.

Adaptive Speed

In addition to autonomous driving, the steep incline and decline of the vineyard terrain often lead to an inconsistent number of photos being taken per row. To address this issue, we implemented a solution based on analyzing the motor encoder data. Specifically, we determined the optimal number of ticks that would occur between each passing message and compared the actual number of ticks received against this ideal value, allowing us to adjust the system accordingly.

Despite these efforts, our analysis revealed that the encoders were not functioning as expected, particularly at higher speeds. This led us to re-evaluate our methods and explore alternative solutions. After conducting thorough testing, we concluded that GPS coordinates could be used to accurately calculate the speed of the system, by measuring the Euclidean distance between coordinates and the time between received messages.

Looking Forward

Future teams will continue implementing the rover's autonomous driving, using this year's work as their foundation. They will be able to test the rover's decisions and build on the basic algorithm we've created. Because of the steps we've taken to improve the safety and reliability of the rover, development of new functionalities will be much easier.

The next major milestone is to improve upon the adaptive speed control and operator feedback. There is also a goal to add a physical display to the rover show live lidar output, image count, and other useful data for the operator.

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