Automated Mosquito Dissection – Vision

Project Proposal

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Objective/Goal

The goal of this project is to create a ROS-integrated computer vision system for mosquito detection and keypoint identification to guide an automated mosquito dissection robotic system for live malaria vaccine production. The target keypoints on the mosquito to be identified include the proboscis, the head, and the neck. This project is in conjunction with Sanaria Inc. (Rockville, MD).

Background and Prior Work

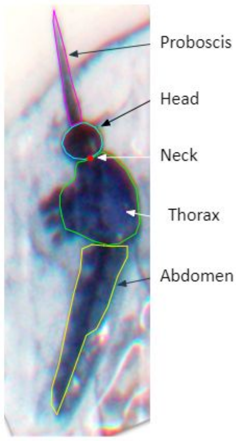


Figure 1. Parts of a mosquito

Malaria is a mosquito-borne disease that affects humans and is caused by a single-celled organism of the Plasmodium group. In 2017, there were over 200 million clinical cases of malaria, causing over 435,000 deaths, and over $12 billion USD loss in Africa alone. Despite the impact that malaria has and the clear need, there currently exists no effective malaria vaccine in the market. However, Sanaria, a biotechnology company in Rockville MD, has recently been successful in developing a live malaria vaccine that has shown to be up to 100% effect in clinical cases. These vaccines are made from attenuated Plasmodium falciparum sporozoites (PfSPZ), the very bacteria that causes malaria. Because of the live nature of these vaccines, they must be cultivated within live mosquitoes, and hence must also be extracted from mosquito salivary glands before being able to be used as a vaccine.

Currently, the workflow to create this vaccine is slow, requiring manual extraction of the attenuated PfSPZ from salivary glands using syringes. Hence, an autonomous robotic system is currently being developed in order to automate the process. The full workflow for automated PfSPZ extraction is outlined in Figure 2. Our project will focus on leveraging computer vision techniques to allow the robot to autonomously detect keypoints on the mosquito. This will allow the robot to optimally position the mosquito for decapitation and salivary gland extraction while minimizing human input.

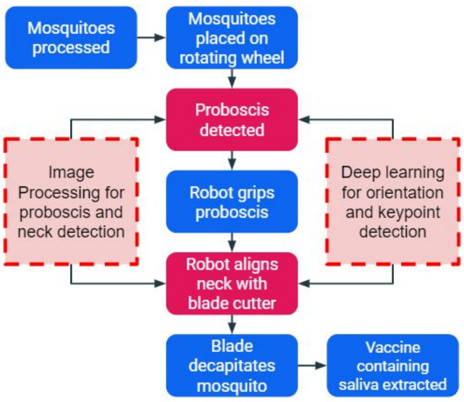


Figure 2. Process flow diagram for automated mosquito dissection

Technical Approach

The main goals of the model-based approaches are to (1) detect and locate mosquitos, (2) locate the center of the neck, and (3) locate the center of the proboscis. The goals of each of these steps is to find where the mosquitos are on the rotating wheel, determine how far the robot must drag the mosquito to align it with the blade cutter, and determine where to grab the mosquito respectively. Each of these steps will be performed using traditional computer vision methods as follows:

1. Image processing to isolate correct mosquito, error checking
    a. Thresholding
    b. Binary image processing (erosion, dilation)
    c. Connected components labeling
    d. Filtering, creating bounding boxes

2. Template matching, model-based optimization for head/neck localization
3. Image processing to identify proboscis
    a. Model-based optimization to find endpoints of proboscis

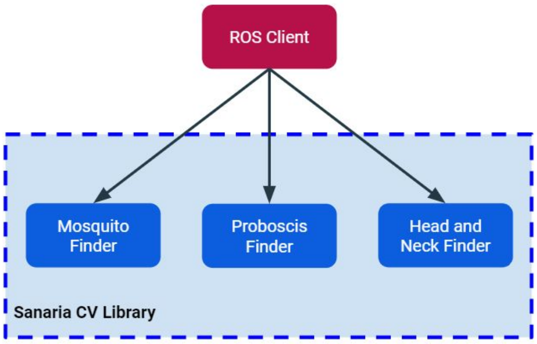


Figure 3. Process flow diagram for mosquito keypoint detection

Ultimately, these algorithms will be encapsulated in a single library with a function each to find a mosquito, locate its neck, and locate the endpoints of its proboscis. Furthermore, since the entire robot system and its individual components will be integrated in ROS, we will create a ROS service which can be called by the robot driver client, ultimately using these algorithms and seamlessly transmitting the outputs to later stages in the workflow.

With regards to the orientation detection, deep learning (DL) is the preferred modality, since orientation is conveyed by the textures of the mosquito rather than distinct features that one can easily identify. Hence the use of deep learning to automatically learn these implicit features would have more success. The process of creating (called training, shown in the blue box) the deep learning model and classifying (called inference, shown in the red box) using said model is shown in figure 4.

Training images are fed into a pretrained network (transfer learning, shown on the left side of the blue box), or into a custom network (shown on the right side of the blue box), where a series of forward and back propagations are performed to tune the parameters of the network to predict the orientation of each image. PyTorch will be used for deep learning. Validation images are used to evaluate the success rate of the models. Both transfer learning and training from scratch will be attempted to determine which has a higher success rate. After training, the inference occurs by loading the saved model, and inputting a processed image to the trained model to yield a prediction of the orientation of the mosquito. The proposed workflow is as below:

1. Image processing/cleanup
2. Training neural network to classify orientation via PyTorch
    a. Training a network from scratch via CNN, fully connected layers
    b. Transfer learning - pretrained models via pretrained models from PyTorch
3. Creation of a ROS service that uses the trained model to infer the orientation of the mosquito from an input image taken from the camera.

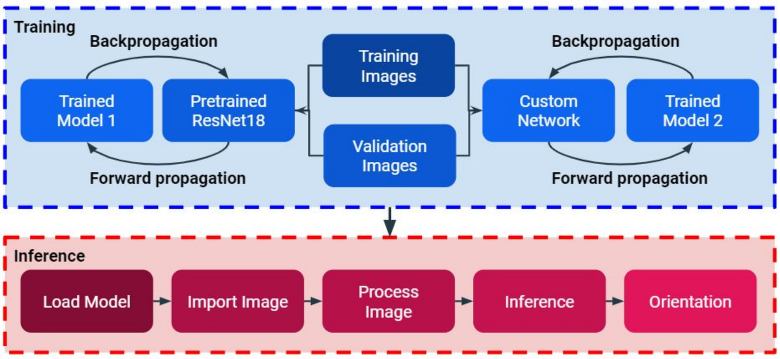


Figure 4. Process flow diagram for training and inference for deep learning

Besides using deep learning for orientation determination, an exploratory side of this project is to use deep learning for automatic detection of keypoints of the mosquito, such as the proboscis tip and base, neck, midpoint between thorax and abdomen, and the end of the abdomen. It is the hope that if deep learning is successful, then it will be able to support (or even replace) the image processing algorithms, as sufficient training will make the detection robust to lighting conditions and other factors that may stump the image processing algorithm, providing more confident estimations of the location of the neck and other keypoints of the mosquito. The proposed approach is shown below, with the training steps largely reflecting those shown in the transfer learning section (left side of blue box) in figure 4.

1. Image processing/cleanup, labeling
2. Training neural network via transfer learning (Mask-R CNN) for bounding box detection, in order to delineate the region of the image that contains the mosquito
3. Training a second neural network for keypoint detection using DeepLabCut, where it will take in regions proposed by the previous neural network that should contain a mosquito and determines the keypoints of the mosquitoes, such as the neck, proboscis tip, and midpoint.
4. Integration of bounding box detection with keypoint detection into a ROS service for interfacing with the robotic system.

Testing Plan

Mosquito Finder Algorithm:

- A testing set of 100 mosquito images will be obtained and fed into the mosquito finder algorithm to generate bounding boxes around detected mosquitos. We expect that 95% of mosquitos will be detected and have a bounding box placed around them. We desire that bounding boxes have an IoU score of at least 0.7. The IoU need not be extremely high (i.e. 0.9) since mosquito bounding boxes will be expanded for following algorithms.

Proboscis Finder Algorithm:

- A testing set of 100 mosquito images, with a mix of visible and occluded proboscis, will be obtained and fed into the proboscis finder algorithm. We expect that for 95% of mosquitos with visible proboscis, we will be able to generate a bounding box around the proboscis, and for 95% of mosquitos with occluded proboscis, the algorithm will accurately report failure. We desire that the mean squared error between the centre of the bounding box and the proboscis to be less than 5 pixels (0.1 mm) on average, as the robot must be able to accurately grasp the proboscis in order to continue steps further in the workflow.

Head & Neck Finder Algorithm:

- A testing set of 100 mosquito images will be obtained and fed into the head and neck finder algorithm. We expect that 95% of mosquito heads will be identified correctly. We desire that the calculation of the midpoint of the neck not have more than a mean squared error of 5 pixels (0.1 mm), as the robot must be able to accurately decapitate the mosquito to properly extract the salivary glands.

Orientation Detection Algorithm:

- A new testing set of mosquito images (at least 100) will be obtained. They will be fed into the orientation classifier and the results will be compared against the ground truth. The desired success rate is 95%. That is, the algorithm should be able to correctly determine the orientation of the mosquito at least 95% of the time.

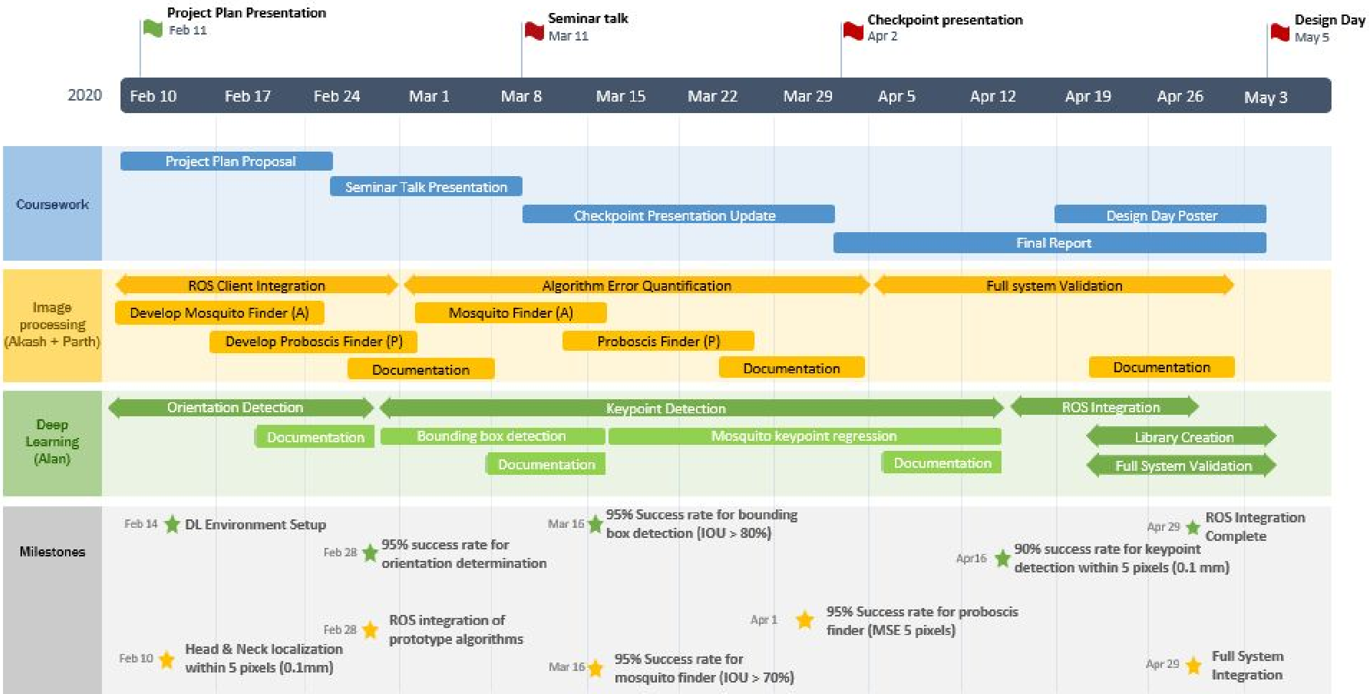
Deep Learning Keypoint Detection Algorithm:

- A testing set of mosquito images together with the labeled keypoints will be provided to the algorithm for labeling. The geometric pixel distance between the predicted keypoint location and ground truth keypoint locations will be calculated, and it is expected that the algorithm will be able to find the desired keypoint within 5 pixels difference 90% of the time.

Deliverables

Minimum	● Library for head/neck/proboscis detection and corresponding algorithms ● Working algorithm on orientation detection ● Framework for training DL algorithm on keypoint detection ● Thorough documentation of all algorithms and usage
Expected	● In addition to the above... ● Integration of DL model with ROS for real-time classification & detection ● Integration of head/neck/proboscis detection workflow in library ● ROS integration of head/neck/proboscis detection and DL algorithms
Maximum	● In addition to the above... ● Creation of library to streamline process of training mosquito keypoint detection ● Fully validated libraries using mosquitos & robot system ● Research paper summarizing methods used, validation, and analysis of results

Milestones, Timeline, and Responsibilities



Management Plan

With regards to meeting times with group members, mentors, and lab members, the communication modalities and weekly meeting times are outlined in the table below. With regards to version control of code, all code will be stored in a GitLab repository here.

Table 2. Outlining communication modalities and meeting times with members, mentor, and lab

	Communication Modality	Weekly Meeting Time
Team Members	Instant messaging services, email	Sundays, 12:30 ~ 14:00 Thursdays, 18:00 ~ 20:00
Mentor (Balazs)	Email	Wednesdays, 14:00 ~ 15:00
Lab Members	Email	Mondays, 10:00AM ~ 11:00AM

Dependencies

Table 1. Dependency list of project, with solution, alternative plans, deadlines, and progress

	Dependency	Solution	Alternative Plan	Progress & Deadline
1	Mosquito images for image processing	Manually capture images in lab (other lab members)	Manually capture images in lab (self); use old images	Solved 2020/02/06
2	Mosquito images for DL (+2000)	Image files present in lab computers	Collection of more images in lab	Solved 2020/02/06
3	Computational resources	Lab computer (NVIDIA Titan Xp, 12GB)	CS Ugrad Servers, Personal Computer	Solved 2020/02/14
4	Libraries (OpenCV, Pytorch, DL Models)	Free online access/open source	N/A	Solved 2020/02/06
5	Integration with robotic system (ROS)	Communicate and work with Balazs	Communicate and work with Dr. Simon Leonard	Solved 2020/03/01
6	Feedback from Mentors	Lab meetings	Communication via email	Solved
7	Support for robot system validation	Lab group members	N/A	Solved
8	Access to autonomous robot system	Communicate with Balazs	N/A	Solved

Reading List:

1. H. Phalen, P. Vagdargi, M. Pozin, S. Chakravarty, G. S. Chirikjian, I. Iordachita, and R. H. Taylor, "Mosquito Pick-and-Place: Automating a Key Step in PfSPZ-based Malaria Vaccine Production", in IEEE Conference on Automation Science and Engineering (CASE), Vancouver, BC, August 22-26, 2019. pp. 12-17.
2. M. Schrum, A. Canezin, S. Chakravarty, M. Laskowski, S. Comert, Y. Sevimli, G. S. Chirikjian, Stephen L. Hoffman, and R. H. Taylor, "An Efficient Production Process for Extracting Salivary Glands from Mosquitoes", arXIV, 2019, http://arxiv.org/abs/1903.02532.
3. H. Wu, J. Mu, T. Da, M. Xu, R. H. Taylor, I. Iordachita, and G. S. Chirikjian, "Multi-mosquito object detection and 2D pose estimation for automation of PfSPZ malaria vaccine production", in IEEE 15th International Conference on Automation Science and Engineering (CASE), Vancouver, BC, August 22-26, 2019.
4. M. Xu, S. Lyu, Y. Xu, C. Kocabalkanli, B. K. Chirikjian, J. S. Chirikjian, J. Davis, J. S. Kim, I. Iordachita, R. H. Taylor, and G. S. Chirikjian, "Mosquito Staging Apparatus for producing PfSPZ Malaria Vaccines",

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