Project Proposal Vision Guided Mosquito Dissection for the Production of Malaria Vaccine

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EN.601.656 CIS II Spring 2021

5/6/21

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1 Abstract

An effective vaccine to combat Malaria has been developed by the company Sanaria, however a major obstacle to large-scale deployment of this vaccine is the cost of production. The bottleneck in the need for salivary glands from Mosquitos infected with Malaria. Currently, mosquitos must be manually dissected by highly trained workers in order to extract their salivary glands. The need for skilled labor is very expensive, and it is also very slow. Researchers at Johns Hopkins are developing a robotic system which will automate the process of mosquito salivary gland extraction. In this project, four computer vision algorithms are developed for various classification and segmentation tasks which are necessary for efficient and robust functioning of the robotic system.

2 Motivation

Malaria is a major global human health issue. In 2019, there were 229 million cases of malaria, with 411 000 deaths [4]. A successful effort to prevent the spread of malaria would have a dramatic impact on the lives of millions of people. Currently, the most successful method for combating malaria on a large scale is by preventing mosquito-human contact through various means such as mosquito nets and insecticides [3]. These have proved remarkably effective, however there has been an apparent observable plateau in their effectiveness in recent years.

Sanaria is a company which has developed the first malaria vaccine which is effective and feasible to produce [1]. Malaria is a parasite which spreads among humans by inhabiting the salivary glands of a host mosquito, which spreads the malaria parasite when it bites humans. The production and distribution of Sanaria's vaccine involves the extraction of these infected mosquito salivary glands. This step during production is a severe bottleneck and is preventing large scale production and deployment of the Sanaria vaccine.

A robotic mosquito dissection system for automating the extraction of infected salivary glands is being developed to make salivary gland extraction significantly more efficient which will enable large scale production of the malaria vaccine [2].

3 Prior Work

The prior work, as outlined in [2], is the mechanical design and software architecture of a robot system which is able to position, decapitate, and extract the salivary glands of mosquitoes in parallel. In addition, a handful of vision algorithms based on both image processing and deep learning have been implemented and are fully integrated with the ROS system. Figure 2 shows a rendering of the robot hardware and the results one of the vision algorithms. The existing hardware and software architecture can accommodate the addition of new camera sensors and vision algorithms without requiring any additional development.

The main design feature of the system is turntable which contains many small slots which are perpendicular to the outer edge of the circular turntable. The slots are formed by two walls rising above from the turntable, and are uncovered on all other sides, and these slots get loaded with mosquitoes. There are multiple processing "stations" located along the outer edge of the turntable. The turntable advances mosquito's along to these stations sequentially by rotating. In order to extract the salivary glands from the mosquito, it passes through three stations. First is a cutting station where a robotic gripper moves the mosquito into position so that it's head is removed by a blade. Second is a squeezing station where the mosquito's salivary glands are squeezed out in a blob of exudate. Finally, a cleaning station, where the mosquito body is washed away from the turntable slot so that a new mosquito can be loaded in.



Figure 1: Activities and Deliverables

4 Goals

The goal of this project is to create vision algorithms which will further the development progress of the robotic mosquito dissection system which was described in section 3. These algorithms are important for the robust and efficient performance of the system, for error detection and prevention, and for analysis and evaluation of the system.

The specific vision algorithms this project focuses on are: classification of the turntable cleaning station outcome, classification of the gripper cleaning outcome, and classification and regression of the mosquito exudate volume which is the final product of each mosquito dissection. The turntable cleaning station algorithm determines if there is a mosquito body stuck inside of the turntable slot in order to see if the cleaning station needs to make another attempt at cleaning the slot. The gripper cleaning algorithm determines if any mosquito parts got stuck to the gripper during the cutting stage so that it can be cleaned. Finally, the mosquito exudate volume estimation algorithm first determines if the mosquito was successfully squeezed such that the exudate was extruded correctly. This part then determines the cross-sectional area of the exudate blob which can be used to estimate the volume of the blob.

The turntable cleaning algorithm has two different implementations, one with traditional image processing, and one with deep learning. The gripper cleaning has a deep learning implementation, and the exudate volume estimation has a classical implementation. In total there are four algorithms.

5 Technical Approach

This section outlines the technical approach for each method and for the system integration.

5.1 Image Processing Methods

5.1.1 Turntable Classification

The image processing methods use a combination of color adjustment, filtering, and thresholding, and manually defined regions of interest to accomplish their tasks. Note that the incoming images are in the BGR color format.

The turntable classification algorithm has two stages, one to segment particular and occasional kind of specular reflections, and one to segment the mosquito. The specular reflection segmentation is as follows: Apply a Gaussian blur the input image and extract the region of interest. Convert the image from BGR to HLS color space and invert saturation channel. Convert the image back to Convert back to BGR, and then threshold the image based on BGR Range Values. Finally a median blur is applied By doing this we are able to segment some strange particular reflections which interfere with the following steps which particularly look to segment for the mosquito.

The mosquito segmentation stage is as follows: Starting from the blurred region of interest, convert the image from BGR to HSV color space. Set the Value Channel to it's maximum value for every pixel in the image. Convert the image back to BGR Threshold the mosquito based on BGR Range Values. Finally, apply a small median blur.

Some Final steps are to subtract out specular the segmented specular reflections from the segmented mosquito. Then determine the remaining of the image which are mosquito pixels and compare this area to a threshold value to determine if there is a mosquito or not.

This process can be seen in Figure 3

5.1.2 Exudate Classification and Volume Estimation

The algorithm for the exudate detection is broken into classification and segmentation stages. Preprocessing steps befor both stages include the region of interest extration with a predefined binary image mask, and a gaussian blur.

The classification stage's purpose is to determine if there is an exudate blob at all. Using a BGR color based threshold, we can segment the exudate from the background. This color threshold is slightly responsive to the edges of stray mosquito parts, however it is able to clearly distinguish the exudate from both the background and extraneous mosquito limbs.

In order to determine whether or not the "segmented" parts of the image are actually exudate we take advantage of fact that the mosquito parts only show up as thin outlines. We apply a median blur with a very large kernel size of 13. Only the densly filled exudate blob's will survive this step. Any features which are thin or sparse are removed. Finally the total area of the remaining pixels after the median blur is compared against a threshold to determine the classification outcome. This can be seen in Figure **?**?

If the classification determines that the exudate was squeezed out successfully, then the this stage segments the mosquito pixels. It does so by similarly using a color based threshold, however it is less specific than the color threshold from the classification stage. Finally a median blur is used to filter small holes. The area of the segmented blob pixels is returned and this can be used to infer the volume.



Figure 2: Exudate classification processing steps for the squeezer. The leftmost column was a successful squeeze and the right two columns are failed squeezes. The classifier responds appropriately

5.2 Machine Learning Approach

Considering the small amount of ground truth data available, transfer, about 300 and 600 images for the two datasets, transfer learning seemed to be the most feasible approach to creating machine learning models for the turntable and gripper classification tasks.

5.2.1 Turntable Cleaning Classification

The dataset size for the turntable cleaning task was approximately 300 images. Using transfer learning with VGG16 pretrained on ImageNet where only the fully connected layers at the end are fine-tuned, the performance achieved was 100 on the Test dataset and 98.6% over the entire dataset. The false positive rate was 0.6% and the false negative rate was 0.6% for the whole dataset. Compared to transfer learning with ResNet50 pretrained on ImageNet, VGG16 achieved about 10% better accuracy.



Figure 3: Pipeline for the classical turntable cleaning algorithm. From left to right: input image, segmented reflections, result of setting the HSV value channel to maximum on the input image, final segmentation

5.2.2 Gripper Cleaning Classification

In a very similar manner to the turntable cleaning method, a transfer learning model was used for the gripper cleaning task. The dataset size for this was was just over 600 images. Again VGG16 had the best results with in the same configuration where the fully connected layers at the end were fine tuned. VGG16 outperformed ResNet50 by about 15% for this task. I reached 98.3% accuracy in classification with a 0.6% false positive rate and a 1.05% false negative rate. Figure 4 is an example of the gripper images which the network was trained on.



Figure 4: training images for the gripper cleaning task

5.3 System Integration

In the current layout of the system, there are two computers. The main robot computer interfaces with the actuators and cameras of the robot, while the vision computer, which contains a GPU and which performs the vision tasks, is remote. Integration was completed be done by creating ROS Service wrappers around each image processing and machine learning algorithm. This will allow the robot main computer to call all of the remote vision functions as needed. The flow of data though the system can be seen in figure 5

6 Key Activities and Deliverables

The key activities and deliverables are outlined below in Figure 6. Note that they are categorized into minimum, expected, and maximum tiers. For brevity the chart is condensed;



Figure 5: System Overview

the contents of the minimum tier will be repeated for the respective tasks of the expected and maximum tiers.

	Activity	Deliverable	Deadline
Min	Collect images of cleaning station and annotate	Annotated cleaning station dataset	
	Implement image processing method for cleaning station	Functioning image processing based code and high quality documentation in a wik	
	Develop and train a neural network on the cleaning station dataset	a neural network on the cleaning station dataset Trained parameters of a neural network classifier, along with code and high quality documentation in a wiki	
	Integrate both with the rest of the system using ROS	Working ROS services which can be successfully interfaced with from the robot control computer, and thorough documentation for how to use them in a wiki page	3/22
Exp.	Repeat for gripper cleaning	Same deliverables as for turntable cleaning station.	
Max	Discuss with hardware team about collecting exudate data	Plan for collecting exudate ground truth data	
	Repeat for exudate volume estimation	Same deliverables as for previous two tasks.	5/1

Figure 6: Activities and Deliverables

For each of the three tasks, cleaning station classification, gripper cleaning classification, and exudate estimation, the deliverables consist of the following components:

Machine Learning Approach

- Dataset of 300 hand annotated images
- PyTorch based python code for training a neural network for the task
- PyTorch based python function for quickly evaluating the network's prediction on an image
- ROS service python wrapper for integrating the neural network predition with ROS

 Wiki documentation detailing the network architecture, training procedure, and ROS integration in python

Image Processing Approach

- OpenCV based C++ code of an image processing algorithm for the task
- C++ ROS service wrapper for integrating the algorithm with ROS
- Wiki documentation detailing the image processing algorithm and the ROS integration in C++.

In the end all of the deliverables were reached aside from those associated with an image processing based approach for the gripper cleaning classification task and those associated with a deep learning approach for exudate volume estimation. Specifically I reached all minimum deliverables, half of my expected deliverables and half of my maximum deliverables. The reason I completed half of my maximum deliverables at the expense of fully completing the expected deliverables was because my mentor reccomended I do so. We discussed that the benefit of having a working algorithm for a new task was greater than having an additional working algorithm for the gripper cleaning task. Also, the timing of the hardware development, along with the end of the semester meant it significantly more feasible.

7 Dependencies

The dependencies, and their respective contingency plans are explained in detail in figure 7. All of my dependencies were met and there were no major issues which completely halted progress. Acquiring images in the very beginning was a bit slower than anticipated but it didn't have a significant impact on the project outcome.

8 Roles and Management Plan

I am the sole group member for this project and my mentors are Balazs Vagvolgyi, Alan Lai, and Parth Vora. Balazs will be my main contact for help with the robot system and with the ROS interfacing. Alan and Parth previously implemented similar machine learning and image processing based vision algorithms which are currently in use. They were a valuable resource for consulting about practical implementations.

The management plan was the following. I attended weekly meetings every with the full mosquito project team where was able to discuss with the other teams, receive feedback, and keep up to date with the status of the project as a whole. I additionally met with my mentor Balazs approximately once every other week on a regular basis to discuss details about the implementations and to and to ask for help.

9 Lessons

The most important lesson I learned was that accomplishing a task on a real system with real data takes much much more time at each step than I would have anticipated. I underestimated every task by a significant amount. Another very important lesson that I

Dependency	Need	Status	Contingency Plan	Planned Deadline	Hard Deadline
Continued access to GPU	GPU for training neural network	Currently have access to the Diva computer	I have a very capable personal GPU	Ongoing	Ongoing
Cameras for collection of images of each task need to be mounted and integrated	To collect images for annotation	Cameras mounted for turntable cleaning station and squeezing station but not for gripper cleaning	Use existing but less desirable views from the other existing cameras.	3/14	3/22 (for remaining camera)
Hardware team	300+ images of turntable cleaning station in progress with mosquitos.	Hardware team is currently running experiments and collecting these images on a near daily basis while they run their experiments	Begin working on the image processing methods for the other tasks while waiting for additional training data collection.	3/1	3/7
Hardware team	300+ images of gripper cleaning in progress with mosquitos.	The gripper cleaning water jet has not yet been installed, so there are no ongoing gripper cleaning experiments	Small Delay: Begin working "out of order" on the image annotation and image processing for the exudate estimation task Long Delay or Expected Failure: Change from the gripper cleaning task to one of the are many remaining vision tasks	3/14	3/22
Hardware team	Method for ground truth collection of mosquito exudate volume for training images	I will <u>bring this up</u> during the weekly meetings	Abandon neural network approach and only do image processing for this task	3/15	4/1

Figure 7: Dependencies

learned is that using the simpler methods if possible is much better for everyone in the long run. When I initially began working on the first image processing method for the turntable cleaning task, I spent a lot of time in the weeds with overly-complicated pipelines that were not generalizable. I eventually achieved better performance with just color threshold and filtering.

10 Reading List

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