Seminar Presentation: Mosquito Vision

EN.601.456 Computer Integrated Surgery II

Project 5

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Mentors: Balazs Vagvolgyi, Dr. Russell Taylor

Project Overview

Goal: 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.

Team Members:

Akash Chaurasia, Alan Lai, Parth Vora

Mentors:

Balazs Vagvolgyi, Dr. Russell Taylor

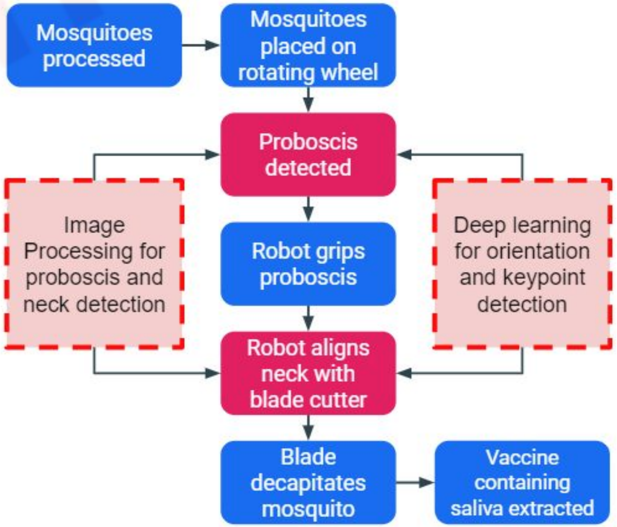


Figure 1. Process flow diagram for mosquito keypoint localization

Paper Selection and Relevance

Multi-Mosquito Object Detection and 2D Pose Estimation for Automation of PfSPZ Malaria Vaccine Production

Hongtao Wu, Jiteng Mu, Ting Da, Mengdi Xu, Russell H. Taylor, *Life Fellow, IEEE*, Iulian Iordachita, *Senior Member, IEEE*, and Gregory S. Chirikjian, *Fellow, IEEE*

- Usage of deep learning to tackle Mosquito keypoint detection
  - Relevant keypoints to workflow
  - Clear description of deep learning architectures
- Comparison of deep learning with image processing techniques

Problem Statement

- Computer vision support for automated Mosquito Micro-dissection System (MMS) to identify location to hold and manipulate mosquito (proboscis) and location to decapitate mosquito (neck)
- Comparison of deep learning and image processing approaches

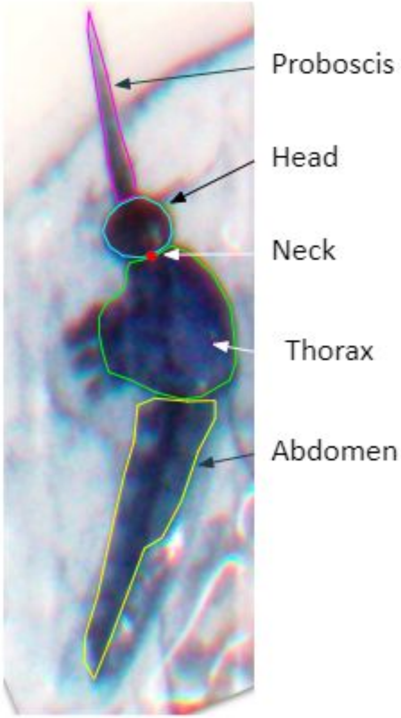


Figure 2. Parts of a Mosquito

Key Results and Significance

The deep learning approach outperforms the image processing approach in both mosquito detection and body part detection

- Deep learning approach is more robust and versatile
- Image processing has a faster runtime
- Mask R-CNN and DeeperCut effective

Approach	Deep Learning	Image Processing
Detection mAP (IoU>0.5)	0.97	0.80
Detection Recall	0.97	0.90
Head Position RMSE	1.61 pixels	2.70 pixels
Proboscis Orientation Error	14.3°	24.7°
Processing Speed	2.5 fps	20 fps

Figure 3. Table from Wu et al. comparing results of Deep Learning and Image Processing approaches (Wu)

Background

- Malaria infected more than 200 million people and caused more than $12B USD loss globally in 2017
- Sanaria has developed a PfSPZ vaccine shown to be very effective in clinical trials
- Previous workflow involved laborious manual processing to extract vaccine

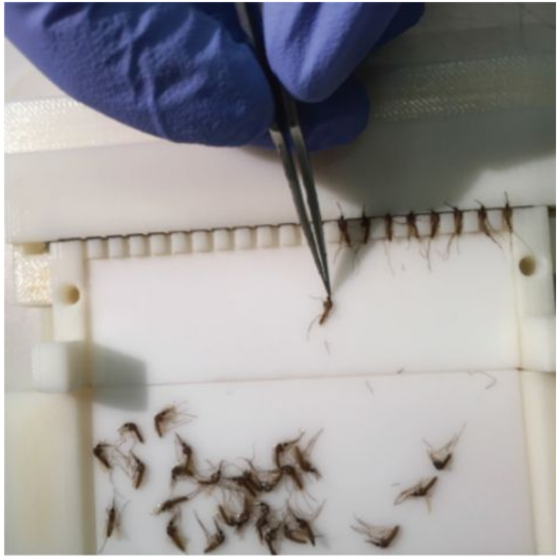


Figure 4. Semi-automatic Mosquito Micro-dissection System (saMMS) (Schrum)

Background

- Proposed automatic MMS

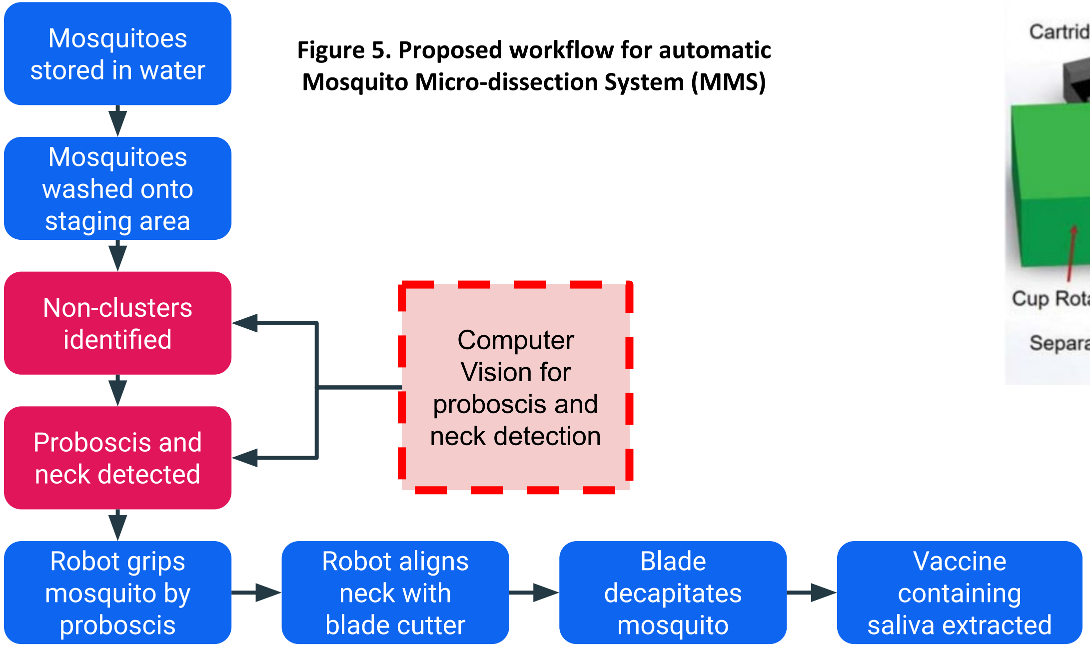


Figure 5. Proposed workflow for automatic Mosquito Micro-dissection System (MMS)

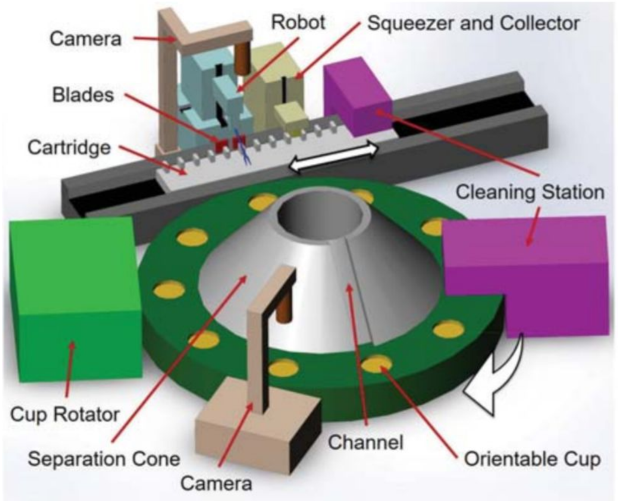


Figure 6. Proposed MMS (Phalen)

Experimental Approach: Dataset

- Manual placement and automatic water transfer
- Varied water flow, scale, and luminance conditions
- 1460 images total, all manually labeled
- 7:2:1 split for training, validation, testing

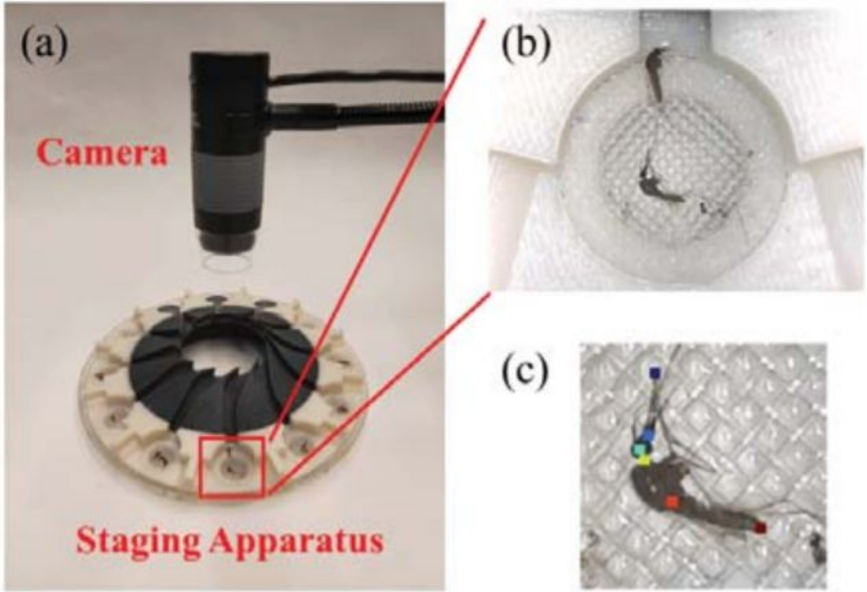


Figure 7. Dataset collection. (a) camera staging apparatus for MMS (b) image taken from camera (c) keypoints labeled on mosquito (Wu)

Experimental Approach: Deep Learning

- Transfer learning (Mask R-CNN on COCO, DeeperCut on ImageNet)

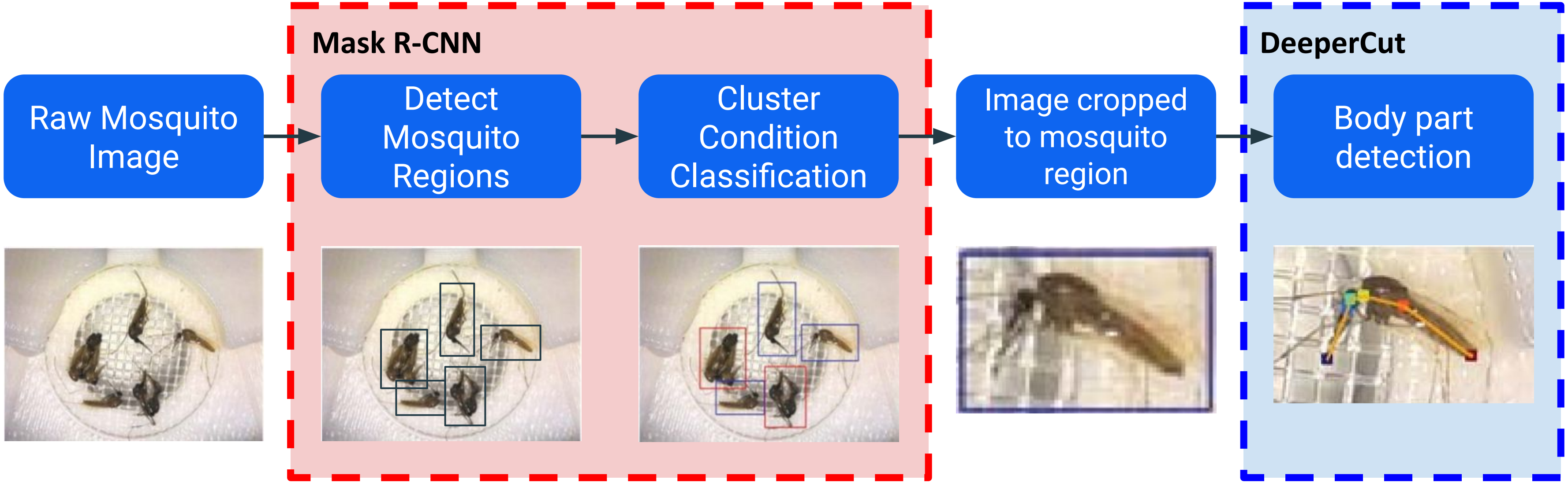


Figure 8. Process workflow for deep learning approach (Images from Wu et al.)

Images from: Wu, H., Mu, J., Da, T., Xu, M., Taylor, R. H., Iordachita, I., & Chirikjian, G. S. (2019). Multi-mosquito object detection and 2d pose estimation for automation of PfSPZ malaria vaccine production. In 2019 IEEE 15th International Conference on Automation Science and Engineering, CASE 2019 (pp. 411-417). [8842953] (IEEE International Conference on Automation Science and Engineering; Vol. 2019-August). IEEE Computer Society. https://doi.org/10.1109/COASE.2019.8842953

Experimental Approach: Image Processing

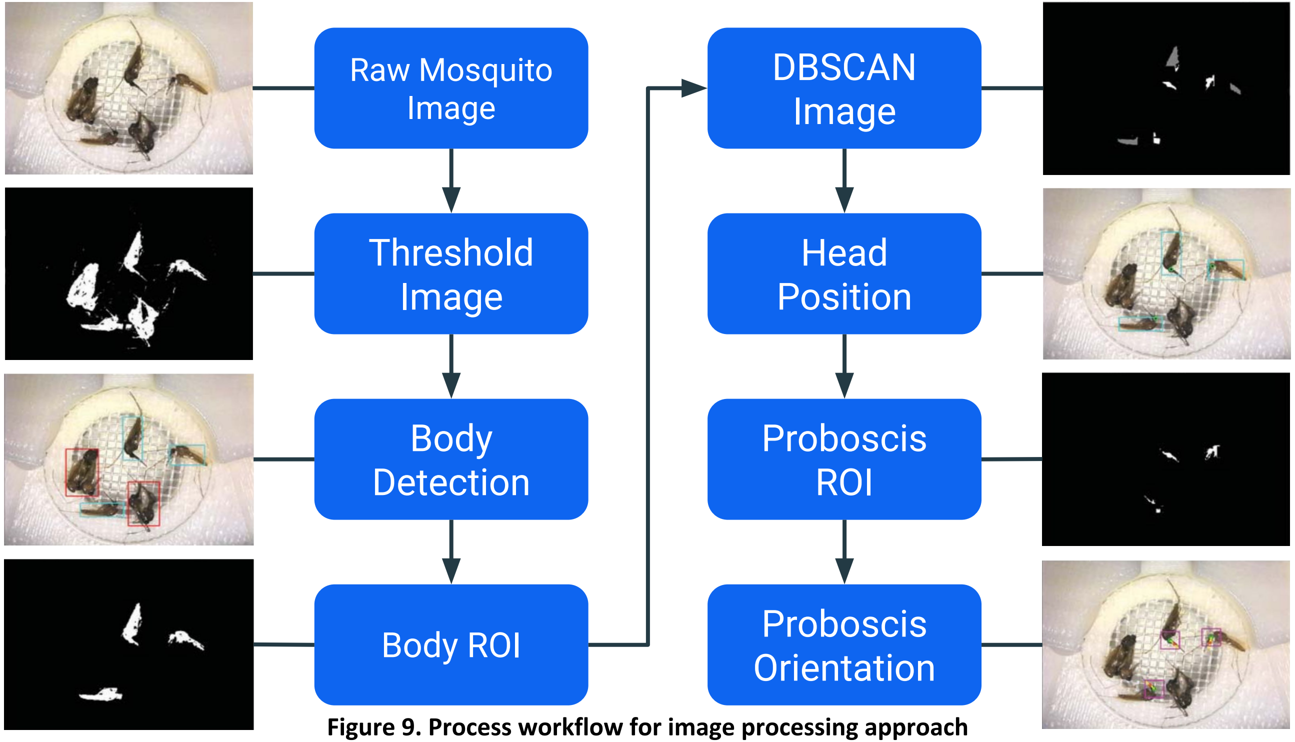


Figure 9. Process workflow for image processing approach (Images from Wu et al.)

Images from: Wu, H., Mu, J., Da, T., Xu, M., Taylor, R. H., Iordachita, I., & Chirikjian, G. S. (2019). Multi-mosquito object detection and 2d pose estimation for automation of PfSPZ malaria vaccine production. In 2019 IEEE 15th International Conference on Automation Science and Engineering, CASE 2019 (pp. 411-417). [8842953] (IEEE International Conference on Automation Science and Engineering; Vol. 2019-August). IEEE Computer Society. https://doi.org/10.1109/COASE.2019.8842953

Experimental Approach: Final Output

Figure 10. Output of Deep Learning Approach (Wu)

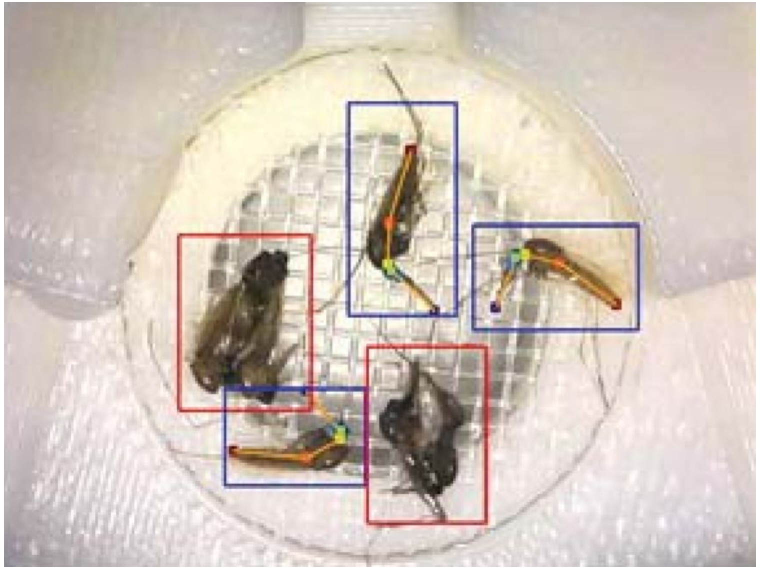
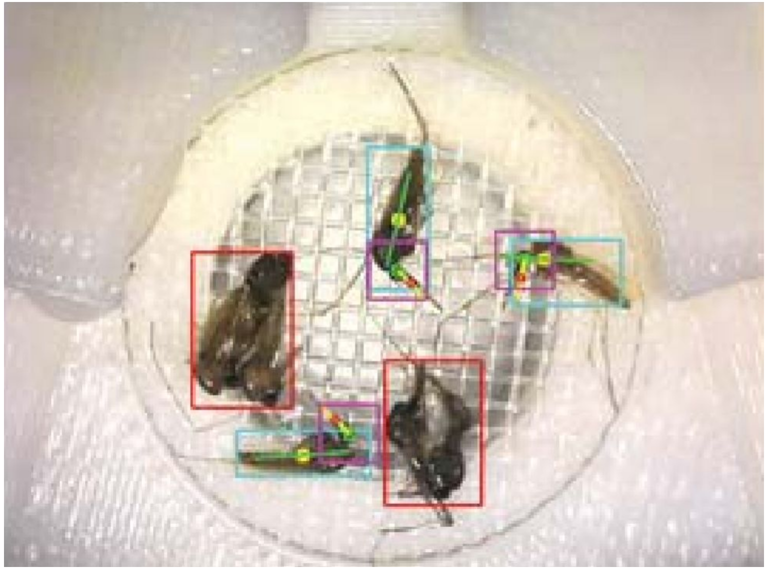


Figure 11. Output of Image Processing Approach (Wu)



Results: Deep Learning

For IoU > 0.75

- Precision - clustered: 0.88, non-clustered: 0.86
- Average precision - clustered: 0.82, non-clustered: 0.85
- Mean average precision - 0.84

For IoU > 0.5, mean average precision - 0.96

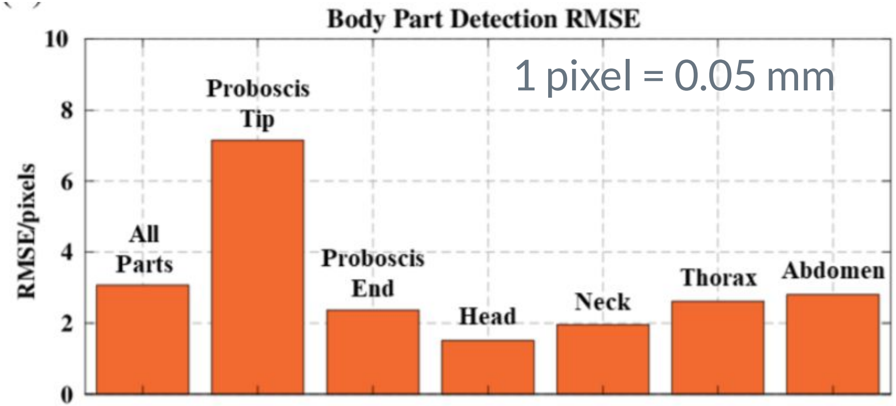


Figure 12. Body Part Detection RMSE for Deep Learning Approach (Wu)

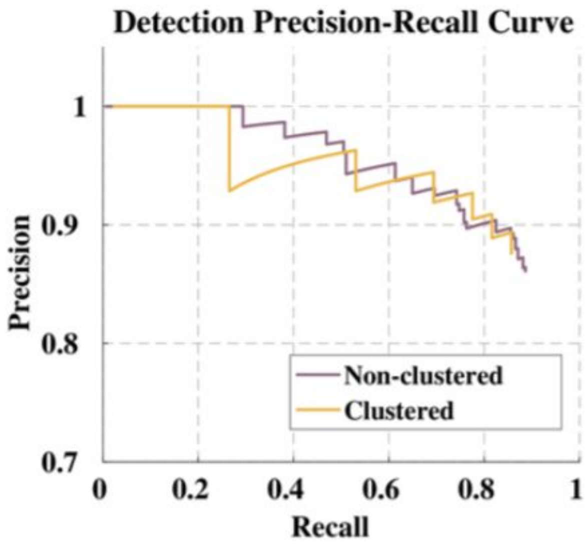


Figure 13. PR Curve for Deep Learning (Wu)

Results: Comparison

- Image processing variant to both luminance and scale

Approach	Deep Learning	Image Processing
Detection mAP (IoU>0.5)	0.97	0.80
Detection Recall	0.97	0.90
Head Position RMSE	1.61 pixels	2.70 pixels
Proboscis Orientation Error	14.3°	24.7°
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Figure 14. Table from Wu et al. comparing results of Deep Learning and Image Processing approaches (Wu)

Paper Assessment

Validated the usage of deep learning as a method for mosquito detection and keypoint identification within the proposed workflow of an automatic mosquito microdissection system

Relevance

- Framework/process flow for deep learning of keypoint detection
- Expected precision, mAP, and RMSE for deep learning approaches
- Validation of deep learning as approach
- Identified pitfalls and limitations of deep learning and image processing approaches

Strengths

- Comprehensive dataset
- Complete system workflow implemented for both deep learning and image processing
- Comparative study between image process and DL

Limitations

- Insufficient result reporting for image processing method
- Comparison of two models does not consider problem context
    - No comparison of proboscis end accuracy

Next Steps and Future Work

Work done after paper publication

- Change of proposed MMS system to current system (right)
  - Manual placement
  - Change in staging area, especially with regards to background
- Addition of the need for orientation detection of mosquito
- New image processing approaches for proboscis detection implemented

Current work related to paper

- Reimplementation of more robust deep learning system
- Documentation of deep learning system
- Integration of new DL system with ROS and the MMS.

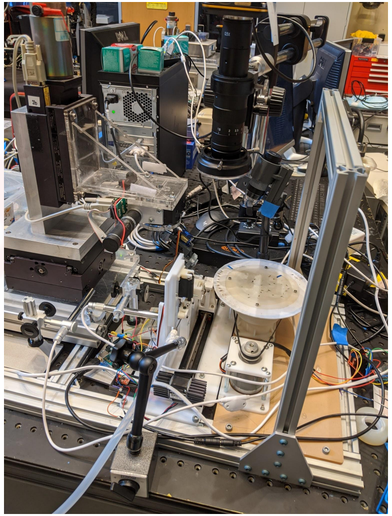

Figure 15. Current MMS system

References

[1] Wu, H., Mu, J., Da, T., Xu, M., Taylor, R. H., Iordachita, I., & Chirikjian, G. S. (2019). Multi-mosquito object detection and 2d pose estimation for automation of PfSPZ malaria vaccine production. In 2019 IEEE 15th International Conference on Automation Science and Engineering, CASE 2019 (pp. 411-417). [8842953] (IEEE International Conference on Automation Science and Engineering; Vol. 2019-August). IEEE Computer Society. https://doi.org/10.1109/COASE.2019.8842953

[2] M. Schrum, A. Canezin, S. Chakravarty, M. Laskowski, S. Comert, Y. Sevimli, G. S. Chirikjian, S. L. Hoffman, R. H. Taylor, "An efficient production process for extracting salivary glands from mosquitoes", arXiv:1903.02532, 2019.

[3] H. Phalen, P. Vagdargi, M. Pozin, G. S. Chirikjian, I. Iordachita, R. H. Taylor, "Mosquito pick-and-place: Automating a key step in pfspz-based malaria vaccine production", Accepted to the 2019 15th IEEE International Conference on Automation Science and Engineering (CASE 2019).

Thank you!

Appendix: Metrics

Precision - % of predictions correct

Recall - how well you find all positives

IoU - intersection over union

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

TP = True positive

TN = True negative

FP = False positive

FN = False negative

$$IoU = \frac{\text{area of overlap}}{\text{area of union}}$$

AP (Average Precision)

mAP (Mean Average Precision)

$$\text{AP@k} = \frac{1}{\text{GTP}} \sum_{i=1}^{k} \frac{\text{TP seen}}{i}$$

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

Tan, Ren Jie. Breaking Down Mean Average Precision (mAP). Towards Data Science. 2019. https://towardsdatascience.com/breaking-down-mean-average-precision-map-ae462f623a52
Hui, Jonathan. mAP (mean Average Precision) for Object Detection. Medium.com. 2018. https://medium.com/@jonathan_hui/map-mean-average-precision-for-object-detection-45c121a31173