

Computer Vision applied to Dengue's Larvae Death Rate Calculation **Preliminary Results** 

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# Introduction

#### Main task

 Development of more effective larvicides to combat Dengue's transmitter mosquito.

#### Requirements

- Many experiments with different substances
- Lab tests, such as larvae death rate (human task)

#### Problem

 Errors due to human limitations during analysis can reduce results quality (e.g. exhaustion, subjectivity, and inaccuracy)

#### Proposal

• LARVIC: Computer vision application for larvae counting

# Methodology

Fixed camera positioned above recipients with larvae
 Image sequences are captured and then processed by a computer vision application to classify larvae into two classes: death or alive.



### Work features

- Single recipient with only one larva
- Techniques: HMM, HMM+ML, ML
- One token extracted from each frame
- Segmentation: background subtraction, machine learning and semiautomatic
- Feature extraction: Hu Moments, K-Curvature Histogram, Shape Features (aspect ratio, form factor, roundness, compactness)

Classification: C4.5, KNN, SVM and MLP (weka)



### Experiments

Three image sequences of 1300 frames

- Dead larva: 2 sequences
- Live larva: 1 sequence
- Small shots extracted from sequences (~100 frames each)
- Dead larva: 24 shots
- Live larva: 10 shot
- Training set: 2/3 of shots
- Testing set: 1/3 of shots
- Analysis metrics: Hit rate and AUC

# Experiments and results

| Strategy                   | Hit Rate(%) | AUC    |
|----------------------------|-------------|--------|
| Random                     | 59%         | 0.625  |
| Pre-comp. manually         | 82%         | 0.8292 |
| Pre-comp. automat 2 states | 88%         | 0.7917 |
| Pre-comp. automat 3 states | 91%         | 0.7875 |
| Pre-comp. automat 4 states | 88%         | 0.7875 |

### Experiments and results

#### **Stopping Criteria**

- Three different strategies to define the number of iterations for HMM training
- 1) No increase happens, 2) difference is under a threshold and 3) fixed number of iterations.

#### Random

- Strategy 1: No increase happens: 12% higher using random probabilities
- Strategies 2 and 3: no changes

### **Pré-computed manually**

- Strategy 1: No changes
- Strategies 2 and 3: increases from 3 to 12%

### **Pré-computed automatically**

No gain

### Experiments and results

#### HMM+ML

No gain using the best initialization and stopping criteria found in previous experiments

#### **Only ML**

- Algorithms: IBK, J48, SVM, and MLP
- Fixed number of features
- Three sets of features: token counting (2 features), changes between tokens (4 features) and general token changes counting (1 feature).

Best results (Maximum AUC of 0.97)

# Conclusions

- Pre-computed initial probabilities obtained better results than random probabilities.
- Manually (onerous) and automatically pre-computed initial probabilities obtained close results.
- Considering computational cost, low fixed number of iterations was appropriate for training in this application.
- No improving detected with combined classifiers.
- HMM performance was lower than some "vector features" classifiers performances.

### Future work

- Analysis of larger sets of different samples of live and dead larvae
  Use of other algorithms for training HMM's
- Analysis of classifiers based on machine learning algorithms with different patterns

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