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

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Abstract

This work investigates the applicability of some computer vision and pattern recognition algorithms in Aedes aegypt larvae behavior classification. Hidden Markov models and four different supervised learning techniques have been experimented, alone and in combination, to classify image sequences of dead and live larvae inside a recipient containing liquid substances.

1. Introduction

Dengue's epidemic aroused in recent years in Brazil reinforcing the need for more effective ways to combat its transmitter mosquito. Experiments with new larvicides involve the analysis of larvae mortality using various concentrations and combinations of different larvicides in several repetitions. Hundreds and even thousands of experiments should be performed to find a substance that produces the desired effect. During the development of some larvicide, lab tests are performed in order to analyze its substances effect. Larvae death rate is one of those tests, obtained by visual examination of recipients with larvae exposed to test substances during 24 hours. At certain times, a specialist observes recipients, identifies and records the amount of live and dead larvae. At the end of the experiment, based on these records, some conclusions are reached regarding the effect of larvicide analyzed [4].

The counting of live and dead larvae is generally performed by humans, who naturally have their limitations, such as subjectivity, inaccuracy and exhaustion. Thus some counting errors are possible. In this paper, some results related to a system that aims to automate the counting of mortality of larvae is reported. Images of larvae are captured by a fixed camera positioned above the recipients containing some larvae [3]. Subsequently, these images are processed by image processing and computer vision algorithms. Then, based on information from the previous processing, each behavior of larvae is classified and recorded. The goal of this work is to analyze the application of Hidden Markov Model (HMM) and some other supervised learning approaches, in the classification stage, exploring different initial probabilities, criteria for stopping training and associations between classifiers.

The initial probabilities used for the models were calculated using uniform distributions and direct estimation from training data. The training modes considered different stop criteria, which directly interferes in the number of iterations of the algorithm used. Finally, we used two modes of classification: the traditional, which considers the probabilities of symbols generation of models, and combined, where machine learning techniques are embedded in HMM-based classifier's classification. This combined approach can achieve superior performance in certain applications than traditional HMM's [6]. This improvement can be seen especially in applications whose classifications show considerable uncertainty.

The next section provides a brief theoretical background on the technique explored in this work, the HMM, and issues related to it. In Sections 3 and 4, we describe experiments and results, respectively. The fifth section presents the analysis of these results, discussing the performance of classifiers and pointing out possible justifications for relevant behaviors, and suggesting future works.

2. Hidden Markov Models Review

The Hidden Markov Models (HMM) are widely applied in modeling problems with temporal variations. The classification with HMMs usually occurs through the creation of an HMM for each class of problem. To classify a given sample among the known classes, the probability of each HMM generating this sample is calculated. Finally, the sample is classified as belonging to the class associated with the HMM that presents the highest probability of generating it (most likely HMM).

In [6], Wang describes a classification approach that uses a combination of HMM with the technique of k nearest neighbors (KNN) in order to minimize the misclassification present in traditional approach, which appears especially when the difference between the values of the probabilities of the most likely HMMs is small. On this basis, they propose the use of a KNN classifier in a second classifying round for the cases where the difference mentioned above is not significant. According to the authors, this combination adds little computational cost and increases the accuracy rate of the classifier, which was increased from 82.1% to 88.3% in the recognition of facial expressions. Other works, such as [7, 2], also use similar combinations.

In this paper, we used an approach of combining HMM with machine learning techniques similar to that used in [6]. However, different machine learning algorithms, such as decision trees, support vector machines and neural networks, were used, besides KNN. When evaluating a sequence of observations, the probability of generating this sequence for each HMM's is calculated. If the difference between the highest probability and any other probability is below a certain threshold, the second level classifier is called. Otherwise, it assumes that the sample belongs to the class of the HMM that produced the higher score.

3. Experiments, Results and Analysis

The experiments in this study were conducted using sequences of images of larvae in small containers containing some liquid substance. Briefly, the aim of these experiments is to automatically identify certain behaviors of the animals in these sequences. The behaviors to be identified are alive and death. Initially, the images of larvae were captured and later processed, so that relevant information can be extracted. Then, this information was provided to the classifiers in training and classification modes.

3.1. Acquisition and image treatment

Three videos with 1300 frames each containing the image of one larva in a container with a liquid substance were produced. Two of them correspond to images of dead or dying larva and the other one to images of live larva. Because there are multiple occurrences of the behaviors in the three videos, smaller shots have been produced from the original videos, 24 shots for dead and 10 for live larva. Each shot is made up of 100 frames, approximately (the shots have different sizes). Two thirds of the shots, for each class (dead/live), were used to train and one third to test, in all experiments. Images were semi-automatically segmented using a combination of background subtraction, machine learning and manual manipulation.

Thirteen features were extracted from each segmented frame. Three of them are the X and Y coordinates of the center of mass of the larva and the first moment of Hu, which was obtained by means of statistical moments. Other six correspond to the values of a 6-bin histogram of the angles of the larva shape, which are calculated using the k-curvature algorithm. The last four are the shape descriptors: aspect ratio, form factor, roundness and compactness. Exploratory experiments showed that the shape descriptors alone were sufficient to produce good discrimination, and so, the other nine have been discarded for subsequent experiments. In order to produce a discrete sequence of symbols to feed the HMM, each frame was mapped, using a machine learning algorithm, to two states: stretched or curved larvae.

3.2. Methodology for training and classification

Traditionally, to classify a given sequence of observations, a classifier based on HMM compares the odds of generating the sequence of observations in each model. Therefore, the sequence is classified as belonging to the class whose model showed the highest probability of generating it. In the experiments, a combination of HMM and other classifiers have also been tested. A set of feature vectors composed of the output of each HMM, together with the class information (dead or alive), is used to train another classifier.

Several experiments have been conducted in order to evaluate the best configuration of the HMM for this problem, including HMM initialization and stopping strategies. Three different initialization strategies were analyzed: (1) random, (2) pre-computed automatically and (3) pre-computed manually; together with three different stopping criteria: (1) fixed number of iterations, (2) threshold and (3) output stability. In the experiments with probabilities pre-computed automatically, tests have also been used to find the best number of HMM internal states.

In the case of random initialization, an uniform distribution is assumed for the initial states, transition and emission matrices. For the ''pre-computed automatically' case, initial states and transition also assume an uniform distribution, however the cluster algorithm K-Means is used to initialize the emission matrix, using the strategy described in [1]

Finally, the initialization called "pre-computed manually' is based on direct estimates of all the parameters but requires the manual preparation of a training set that includes a mapping from each frame (observation) to an internal state. In this case, the internal states corresponds to larva in two groups of shapes that are relatively easy to be identified by visual observation: stretched and curved. Figure 1(a) illustrates an example of larva stretched and Figures 1(b) and 1(c) illustrate examples of curved larvae. These shapes may happen in both dead and live larvae.

(a) Stretched (b) Curved (c) Curved

Figure 1. Images of larvae in different postures.

The Baum-Welch iterative algorithm has been used to learn the parameters for each HMM. Some experiments have been conducted in order to find the stopping criteria for the problem. The first criterion stops iteration when the probability of the training set given the current HMM parameters is not greater than the probability given the previous parameters [8]. The second criterion stops iteration when the difference between the probability using the current and previous iteration parameters is smaller than a pre-defined threshold (in the experiments, these thresholds ranged from 10^{-1} to 10^{-6}). The third criterion uses a fixed number of iteration. The values 9 (default for JAHMM[1]), 50, 100, 500 and 1000 iterations were tested. The JAHMM's default value has been used as a baseline performance in the experiments.

Additionally, we analyzed the hit rates for this application using a combination of HMM and other classifiers. In these experiments, a second level classifier is called whenever the difference between the values returned by each HMM was bellow a predefined threshold. Decision trees (J48), k-Nearest Neighbor (IBK), support vector machines (SVM) and neural networks were tested as the second level classifier. These same classifiers have also been used directly, without HMM. As these classifiers require a fixed size attribute vector, and the sequences of frames have different sizes, the training and test set had to be preprocessed. At first, we counted the occurrences of each posture, stretched (S) or curved (C) in the sequence of frames, producing in this way two new attributes. Another four attributes were produced by counting the number of occurrences of all possible pair of postures: SC, CS, SS and CC. One last attribute corresponded to the number of times that the larvae changed its posture in the sequence.

1 JAHMM is a free open source library which contains HMM algorithms implementations.

3.3. Experiments configuration

The experiments performed in this work can be classified into four different groups: (1) initialization strategies, (2) stopping criteria, (3) combination of HMM and second level classifiers and (4) classifiers without HMM. Hit rates were produced for all the experiments and area under the ROC curves (AUC) for some of them.

3.3.1. Initialization Strategies Table 1 presents the hit rate and AUC values for all the initialization strategies. It was observed that, according to Rabiner [5], the HMM's whose initial parameters are calculated from the training set, manually or automatically, showed better results compared to HMM's with random initial probabilities. Even in this regard, the HMM's with initial probabilities precomputed automatically presented hit rates that are even higher than those computed manually. This information shows that in some cases, the manual calculation of the initial probabilities (which can be exhaustive and impractical) becomes unnecessary, given the existence of automatic mechanisms for obtaining these probabilities.

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

Table 1. Hit Rate and AUC for different initialization strategies

3.3.2. Stopping Criteria As described earlier, we used three new criteria to compare against the standard criteria of JAHMM (which uses a fixed number of iterations equal to nine). Next, we present the results obtained considering each of the initial models. All stopping criteria were combined with all initialization strategies, as they could be dependent. With random initial probabilities, few changes were found. Using the first criterion (stop when no increase in probabilities happens), there was an increase in hit rate of 12% (in relation to JAHMM default criterion). However, this is not a significant increase, because all instances were classified as belonging to the class alive. Because this class has more instances in the training set, the final probability increased. In the second criterion (stop when difference in probability is bellow threshold), no change in hit rate were produced. The same occurred with the third criterion when the number of iterations was less than 500. From this, all instances were also classified as belonging to the class alive, as happened with the first criterion.

Whereas initial probabilities were precomputed manually, it was noticed a small change in the hit rates in two stop criteria. The first showed no changes. In the second, considering a threshold of 10^{-1}, an increase of 3% in accuracy was achieved. With thresholds equal to 10^{-2} and 10^{-3}, the increase was 12%. When the thresholds were under these values, the increase was 6%. The third criterion produced an increase of 6% in all variations of iterations. Finally, the hit rates when initialization were precomputed automatically (with two states) was reduced with stopping criteria. With the second criterion, the reduction was 17% and, with the first and third criteria of 3%. Considering all tests, the maximum increase recorded was 12% with the second stopping criterion and initial probabilities precomputed manually. However, these increase must be considered with care, as it seems that it results from overfitting the training set, which is biased toward alive larvae.

3.3.3. Combination of HMM and second level classifiers In all experiments with the combination of HMM and a second level classifier, using the best initialization strategy and stopping criteria found in the other experiments, there was no increase in hit rates, indicating that for this problem, a second level classifier is useless

3.3.4. Classifiers without HMM For comparison with previous experiments, the results of experiments performed with fixed-attribute-vector-length machine learning algorithms, using the same training and data set, are presented below . The algorithms used were IBK, J48, SVM and MLP with the three sets of features described earlier. The default parameters value from Weka[2] were used, except from IBK, which was fine tunned to a better K value.

The best results were obtained with the algorithm IBK, with a maximum AUC of 0.9792 and the worst results were obtained with the SVM algorithm, with AUC of 0.5 in all cases. This poor result with SVM may be related to the use of the default parameters in Weka. Both J48 and MLP presented better results (hit rates and AUC) than the HMMs. Although these classifiers were not initially designed to deal with temporal information, as it is the case of HMM, in these experiments, they presented much better results.

4. Conclusions and Future Work

Several experiments were performed in this work with images of larvae in recipients containing larvicides extracted from plants to evaluate the applicability of hidden Markov models to assist counting process of live and dead larvae. In the experiments, first, we analyzed the set of initial probabilities of the models. According to literature, these probabilities may significantly interfere in the training process and hence the classification. We analyzed three sets of probabilities, consisting of 1) uniform and random, 2) manually precomputed, and 3) automatically precomputed probabilities. Based on these experiments results, we conclude classifiers with models whose initial probabilities were precomputed obtained better results than those with random models. Moreover, it was observed that the results obtained with models precomputed automatically were close to those obtained with manually precomputed models, which indicates that the onerous task of obtaining initial probabilities may be unnecessary in some cases. Different stop criteria for training algorithm, Baum-Welch, were also analyzed. These experiments were used to check if the stopping criterion used in previous experiments was appropriate. In fact, few substantial changes were observed in these experiments with respect to previous ones. Thus, we can infer that, considering the computational cost and classification performance, the criteria previously used (nine iterations) was appropriate for the application.

Finally, considering classifiers using HMM's, last experiment examined the combination of such HMMs classifiers with machine learning algorithms. Such combination can improve the performance of these classifiers. In this work, the classifiers were combined with four algorithms – decision trees, k-Nearest Neighbor, support vector machines and neural networks. The parameter used for activation of the algorithms was based on the probabilities difference. In some circumstances, the auxiliary algorithms perform the final classification. No improving was detected in any experiments involving combined classifiers when the threshold used was less than 82%. In other cases, all rates were lower than those obtained with isolated classifier. For these experiments, classifiers were used with models with initial automatically precomputed probabilities with three states. These results may come from no relevant variations in the images used, especially in the images of dead larvae.

According to obtained results with classifiers based only on learning algorithms used in combinations, it was observed that the performance of classifiers based on HMM's obtained considerable mortality rates, but lower than some classifiers. Probably, this result is related to the pattern of behaviors existing in database, which might be better classified using finite numbers of features, ignoring temporal patterns in some cases. Another possible cause is the existence of noise in the entries, which may have been smoothed favoring some classifiers. Future work suggestions which can scientifically help with this application are given below.

The analysis of a larger set of different samples of live and dead larvae could find temporal patterns which can be identified by HMMs classifiers. Other algorithms for parameter reestimation may allow identification of behavior not considered by the algorithm Baum-Welch. Finally, it is also appropriate to analyze the performance of classifiers

2 Weka is a free open source library with machine learning algorithms.

based on machine learning algorithms (such as J48, IBK and MLP, which showed good results) in samples with different patterns. Additionally, the performance of other classifiers (or combinations of classifiers) in this problem can be analyzed.

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