A BEHAVIOR-BASED EVALUATION OF PRODUCT QUALITY

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ABSTRACT

In the pharmaceutical industry, quality is often measured by the impact of a product on a population. Knowledge about the behaviour of mosquitos responding to a repellent is a case in point in helping to improve the effect of insect repellent. It is ideally carried out using 3D videos which require a stereoscopic apparatus. To do so using 2D video and effectively evaluate the repellent is an difficult problem as is known in the biotechnology research field. In this paper, we propose a general framework for the swarm motion analysis of multiple mosquitos based on 2D videos. The effectiveness and robustness of our algorithm are verified by multiple 2D videos capturing mosquitos behavior in different experimental conditions.

***Index Terms*—** Target tracking, saliency, motion statistics, efficacy evaluation

1. INTRODUCTION

The study of mosquito motion has been covered in many fields, e.g. entomology, biology, neuroscience and agriculture. The research varies primarily along three veins: the number of mosquitos, the goal and the methodology employed. Most of the research is focused on the characterization of the kinematics of a insect: from biology directly through study of the anatomy [1], aerodynamic models [2, 3, 4, 5, 6, 7] consider the appendages of the mosquito (particularly the wings) moving through air, wing speed via the sounds produced as they flap [8, 9, 10], and 3D video [11, 12, 6]. [13] propose a three-tier behavioral model for automatic tracking and behavior analysis of bees.

There are currently few efforts similar to the goal we have set, i.e. the description of the coarse motion of a group of mosquitos. In [14], the work is centered on the kinematic description of a group of mosquitos. High-speed and high-resolution video (2D) are utilized to document the paths of the mosquitos and their head orientation for comparison and further description of their aeronautic capabilities. However, the data collection required the intervention of an expert to locate the mosquitos and the landmarks thereon. As a result, this work, while employing video to describe group mosquito motion, was neither fully automatic in method nor concerned with the mosquitos responses to the stimuli.

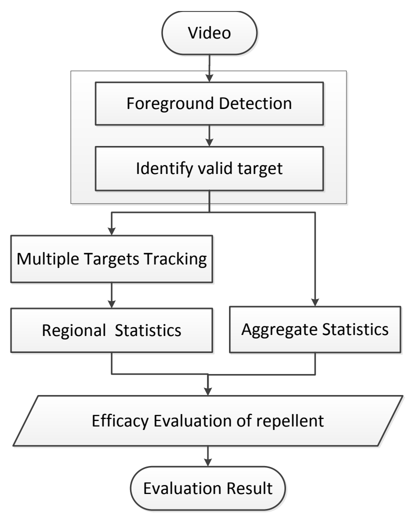

Fig. 1. Process flow of the system.

In [15], a fairly complete description of a swarm of mosquitos was provided. The goal of their effort was to compare various mosquito traps. 3D video data was produced from a stereoscopic apparatus. Then the video was automatically analyzed via some proprietary software to produce paths of the mosquitos in three dimension space. These trajectories were further analyzed for duration, acceleration, heading and position of the mosquitos. The resulting statistics were utilized to describe how effective each trap was for attracting and containing mosquitos. Our proposed effort distinguishes itself from others by regional statistics and global statistics which describe regional and global motion state. Additionally, our work does not require the processing nor the hardware associated with 3D reconstruction of the scene.

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In this paper, we propose a framework for target detection, target tracking, motion statistics and efficacy evaluation of the repellent which is illustrated in Figure 1. In Section 2, we build foreground model and background model by Gaussian Mixture Model (GMM) to detect the targets. spatio-temporal context is used to identify the valid targets. In Section 3, a Kalman filter is utilized to track interacting targets. Morphology optimization algorithms are used to locate the split or occluded targets. In Section 4, we illustrate an efficacy evaluation model based on the swarm motion of the mosquitos. In Section 5, we present experimental results to substantiate our algorithm. Section 6 summarizes the main conclusions and highlights our future directions of research.

2. TARGET DETECTION

In order to separate the mosquitos in the foreground from the noisy background, we propose a two-stage processing. In the first stage, a temporal statistical analysis is carried out for foreground candidates; this is followed by a spacial analysis to remove false positives, due to possible environmental lighting condition changes over time.

2.1. Foreground Detection

For each pixel, we need to classify it into either foreground or background. We propose to use Gaussian mixture model for the foreground-background modelling. The EM algorithm is utilized to learn the model from training frames. For each pixel (x, y), denote the value function at time t as $f_t(x, y)$. Let $N(\mu^f(x, y), \delta^f(x, y))$ and $N(\mu^b(x, y), \delta^b(x, y))$ be the foreground and background normal distribution at (x, y) with component weights ϕ_f and ϕ_b respectively. The foreground detection mask $\Upsilon_t = \Upsilon_t^{(1)} \cup \Upsilon_t^{(2)} \cup \Upsilon_t^{(3)}$ where

$$\Upsilon_t^{(1)} = \{(x, y) : |f_t(x, y) - \mu^f(x, y)| \leq |f_t(x, y) - \mu^b(x, y)|\},$$
$$\Upsilon_t^{(2)} = \{(x, y) : |f_t(x, y) - \mu^b(x, y)| \geq \alpha * \delta^b(x, y), \phi_f = 0\},$$
$$\Upsilon_t^{(3)} = \{(x, y) : |f_t(x, y) - \mu^f(x, y)| \leq \beta * \delta^f(x, y), \phi_b = 0\}.$$

Here α and β is the chosen positive factor for the desired statistical confidence interval.

Then we apply the so-called *8 connected-component labeling* algorithm to Υ_t to detect connected regions in the binary images. We call each connected region a *blob* in the sequel.

2.2. Target Validation

In order to remove false positive blobs, let $A(\cdot)$ denotes the average of pixel values over a given region, we propose a spacial saliency measure $S = A(R^b \backslash R^f)/\max\{A(R^b), A(R^f)\}$ to identify the true mosquito blobs, where R^f denotes the blob and R^b denotes the region difference of the minimal bounding box over R^f and the circumscribed disk over the above minimal bounding box. We pick blobs as valid foreground when S is higher than a threshold.

3. MULTIPLE TARGETS TRACKING

In tracking the mosquito swarms, we use Kalman filter [16] to track all the targets. Furthermore, the Hungarian Algorithm [17] is used to assign targets' IDs to all the valid blobs. One big challenge in correctly tracking lies in the observational non-Gaussian noise for the mosquitos; this problem leads to mis-detections (mistakenly splitting one target into false pieces or occlusion of several true targets), resulting in failed tracking. We propose the following strategy to address such issues.

3.1. Matching Rule

In order to estimate correctly the occlusion and split of true targets, we consider two essential ingredients for target matching: the Transition Matching(TM) and the Overlap Matching(OM). TM describes the probability of matching an identified target at time $t-1$ with the observational blob at time t. OM describes the probability of matching two observational blobs at time t.

Suppose the location of a blob is defined as the center of its circumcircle. $d(s_1, s_2)$ denotes the Euclidean distance between centers of two disks s_i with radii r_i. We define $\nu(s_1, s_2) = d(s_1, s_2)/(r_1 + r_2)$. Denote the i-th observation blob at time t as o_t^i and the j-th identified target at time t as τ_t^j. The predicted center of τ_t^j is denoted as $\overline{\tau_t^j}$. $S(\cdot)$ denotes the center of its circumscribed disk of a blob. We define for TM

$$p(o_t^j|\tau_{t-1}^i) = f(\nu(S(\overline{\tau_{t-1}^i}), S(o_t^j))),$$

and for OM

$$p(o_t^i, o_t^j) = f(\nu(S(o_t^i), S(o_t^j))),$$

where f is the *pdf* for the exponential distribution $Exp(\lambda)$ with $\lambda = 1$.

3.2. Merge for Split Target

This part is to estimate and merge the split blobs of target based on the TM and OM. For each target, if mis-detected as splitting, we use the following algorithm recursively to estimate which blobs are from the same target. Denote $p(o_t^m, o_t^n|\tau_{t-1}^i) := p(o_t^m|\tau_{t-1}^i)p(o_t^n|\tau_{t-1}^i)p(o_t^m, o_t^n)$ and δ as a positive threshold. We find split pairs o_t^m and o_t^n matched with τ_{t-1}^i as the

$$\begin{aligned} &\underset{o_t^m, o_t^n}{\text{argmax}} && p(o_t^m, o_t^n|\tau_{t-1}^i) \\ &\text{subject to} && p(o_t^m, o_t^n|\tau_{t-1}^i) > \delta \end{aligned}$$

3.3. Separation for Occluded Targets

For each blob of possible occlusion of true targets, denote $p(o_t^m|\tau_{t-1}^i, \tau_{t-1}^j) := p(o_t^m|\tau_{t-1}^i)p(o_t^m|\tau_{t-1}^j)$, the following algorithm is used to estimate the occluded targets $\tau_{t-1}^i, \tau_{t-1}^j$.

$$\begin{aligned} \underset{\tau_{t-1}^i, \tau_{t-1}^j}{\text{argmax}} \quad & p(o_t^m|\tau_{t-1}^i, \tau_{t-1}^j) \\ \text{subject to} \quad & p(o_t^m|\tau_{t-1}^i, \tau_{t-1}^j) > \delta \end{aligned}$$

In order to locate the occluded targets, we propose the following method to locate the positions of the occluded targets.

$$\begin{aligned} \underset{\{R_i\}_{i=1}^M}{\text{argmin}} \quad & Area(\cup_{i=1}^M R_i \setminus B) + \sum_{i=1}^M Area(R_i) \\ \text{subject to} \quad & Area(B) - Area(\cup_{i=1}^M R_i \cap B) = 0 \\ & Area(R_i) > 0, i = 1, 2, ...M \end{aligned}$$

where R_i is the bounding box of target i, B is the occluded blob, and M is the number of the occluded targets.

4. EFFICACY EVALUATION MODEL

Here we proposed the Aggregate Quantitative Statistics and Spatially Selective Statistics to characterize the motion of targets. Based on these statistics of motion, Global Evaluation Model and Spatially Selective Evaluation Model are built to measure the impact of repellent on the mosquitos.

4.1. Aggregate Quantitative Statistics

The following features are used to describe the overall distribution of the targets at each time which characterizes the impact of repellents on the targets. The mosquitoes are put into a jar whose width and height are represented by W and H respectively as shown in Figure 2(a).

- Maximal Height (MH)

This parameter measures maximal vitality of targets which is represented by the maximal vertical coordinate of the targets.

$$MH(t) = \max_{i=1,2,\dots,N} (H - CY_t(i))/H,$$

where $CY_t(i)$ is vertical coordinate of centroid of target i.

- Area of Polytope (AP)

This parameter measures the crowding level of targets.

$$AP(t) = \frac{Poly(\bigcup_{i=1}^N B_t(i))}{W \times H}$$

where the function $Poly(.)$ is to calculate the area of the polytope of all the valid blobs.

- Height of Aggregate Centroid (HAC)

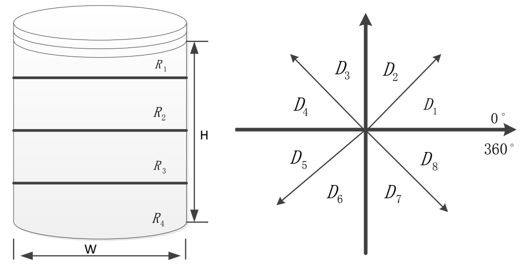
This parameter describes the vertical height of aggregate centroid of all valid blobs.

$$HAC(t) = \frac{H - CY(t)}{H},$$

where $CY(t)$ is vertical coordinate of aggregate centroid.

4.2. Spatially Selective Statistics

In this part, we use the distribution of position and distribution of velocity over time to characterize the motion of targets.



(a) Region Division (b) Direction Division

Fig. 2. Region and Direction Divisions

- Position Distribution (PD)

Position distribution depicts the change of number of targets in different subregions over time. The whole observation region is split uniformly into 4 subregions as shown in Figure 2(a). The statistics of the position $PD(t)$ is described as follows:

$$\begin{aligned} PD(t) &= \sum_{k=1}^K \alpha_i PS_t(k)/(N \max\{\alpha_k\}_{k=1}^4), \\ PS_t(k) &= \frac{1}{N}\sum_{i=1}^N \Theta(\tau_t^i, R_k), \\ \Theta(\tau_t^i, R_k) &= \mathbb{1}(\tau_t^i \in R_k), \end{aligned}$$

where α_i is the weight coefficient. K is the number of divisions of observation region. N is the number of tge targets. $\mathbb{1}(\cdot)$ is the indicator function.

- Velocity Distribution (VD)

Velocity distribution measures the motion state of targets. The direction of motion is uniformly quantized into J bins as shown in Figure 2(b).

$$VD(t) = \frac{1}{2}(1 + \sum_{j=1}^J \beta_j VS_t(j)),$$

$$VS_t(j) = \sum_{i=1}^{N} \Phi(A_t(i), D_j) V_t(i) / (\sum_{i=1}^{N} \Phi(A_t(i), D_j)),$$
$$\Phi(A_t(i), D_j) = \mathbb{1}(A_t(i) \in D_j),$$

where β_j is the weight coefficient. J is the quantization number of direction of motion. $A_t(i)$ is the moving direction of target i at time t. D_j is the quantized bin of direction. $V_t(i)$ is the velocity of the target i at time t.

4.3. Evaluation Model

4.3.1. Global Evaluation Model (GEM)

Global Evaluation Model is used to evaluate the efficacy of repellent based on the aggregate quantitative statistics.

$$E_g = \frac{1}{(T-1)^3} \sum_{t=1}^{T-1} \omega_{mh}(t) \sum_{t=1}^{T-1} \omega_{ap}(t) \sum_{t=1}^{T-1} \omega_{hac}(t),$$
$$\omega_{mh}(t-1) = \mathbb{1}(MH(t) - MH(t-1) < 0),$$
$$\omega_{ap}(t-1) = \mathbb{1}(AP(t) - AP(t-1) < 0),$$
$$\omega_{hac}(t-1) = \mathbb{1}(HAC(t) - HAC(t-1) < 0),$$

4.3.2. Spatially Selective Evaluation Model (SSEM)

Spatially Selective Evaluation Model is used to evaluate the efficacy of repellent based on the regional quantitative statistics.

$$E_r = \frac{1}{(T-1)^2} \sum_{t=1}^{T-1} \omega_p(t) \sum_{t=1}^{T-1} \omega_v(t),$$
$$\omega_p(t-1) = \mathbb{1}(PD(t) - PD(t-1) < 0),$$
$$\omega_v(t-1) = \mathbb{1}(VD(t) - VD(t-1) < 0),$$

4.3.3. Evaluation Fusion Model

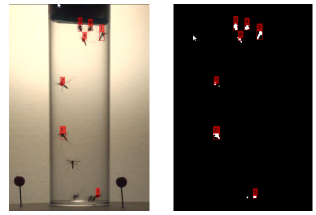
The final result Υ of efficacy evaluation is calculated using the global evaluation E_g and spatially selective evaluation E_r.

$$\Upsilon = \alpha \times E_g + (1-\alpha) \times E_r,$$

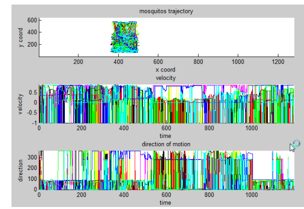
where α is the weight coefficient.

5. EXPERIMENTAL RESULTS

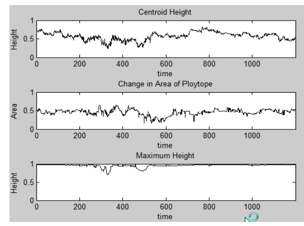
In order to analyze the behavior of "hungry" mosquitos in an enclosed environment, with a single food source, affected by a chemical stimulus, we perform multiple experiments which are captured in 4 videos of similar duration under the different illumination. Each video corresponds to one stimulus scenario of interest and with the same number of mosquitos. Figure 3(a) shows tracked targets in original image and binary image. Figure 3(b) shows the tracking information (Trajectory, Velocity and Direction). The global statistics (MH, AP, HAC) are shown in Figure 3(c). Figure 3(d) shows regional statistics of position and velocity (PD, VD). Table 1 shows experiment results. The result is calculated on the basis of 60 seconds of video after applying the repellent. It is shown that the 3rd is the most effective and the 1st is the worst. Intuitively the evaluation results are in agreement with human observation.



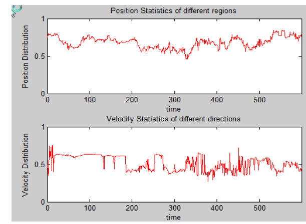
(a) Target Tracking



(b) Motion Information



(c) Global Statistics



(d) Regional Statistics

Fig. 3. Tracking and the statistics information

Table 1. Evaluation Results

Repellent ID	1	2	3	4
Num of Mosquitos	10	10	10	10
Time Length(sec.)	60	60	60	60
Detection Accuracy	0.288	0.479	0.42	0.373
Track Accuracy	0.391	0.606	0.297	0.668
Track Precision	0.657	0.528	0.612	0.576
Evaluation Result	0.065	0.243	0.27	0.194

6. CONCLUSION

In this paper, we proposed a general analysis framework of insect behavior for external stimulus using 2D video, and unveil the multiple targets detecting and tracking, behavior statistics and efficacy evaluation under different external stimulus. For the target detection algorithm, we utilized spatio-temporal context to detect and identify the valid targets. In the tracking algorithm, we proposed a morphology optimization algorithm to locate the occluded targets. Finally the efficacy evaluation model is built to analyze the influence of stimulus on group motion of the targets. We verify the effectiveness of our algorithm by conducting the experiments. The experimental results have shown that our approach is effective and robust when faced with changing experimental conditions. Future work will focus on adaptive model and introducing more efficient metric space to track intersecting targets.

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