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Mobile sensing in *Aedes aegypti* larva detection with biological feature extraction

Dia Bitari Mei Yuana[1], Wahjoe Tjatur Sesulihatien[2], Achmad Basuki[3], Tri Harsono[4], Akhmad Alimudin[5], Etik Ainun Rohmah[6]
[1,2,3,4,5]Department of Electrical and Computer Engineering, Politeknik Elektronika Negeri Surabaya, Indonesia
[6]Institute of Tropical Disease, Entomology laboratory Kampus C Universitas Airlangga, Indonesia

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ABSTRACT

According to WHO, Dengue fever is the most critical and most rapidly mosquito-borne disease in the world over 50 years. Currently, the presence and detection of *Aedes aegypti* larvae (dengue-mosquitoes vector's) are only quantified by human perception. In large-scale data, we need to automate the process of larvae detection and classification as much as possible. This paper introduces the new method to automate *Aedes* larvae. We use *Culex* larva for comparison. This method consists of data acquisition of recorded motion video, spatial movement patterns, and image statistical classification. The results show a significant difference between the biological movements of *Aedes aegypti* and *Culex* under the same environmental conditions. In 50 videos consisting of 25 *Aedes* larvae videos and 25 *Culex* larvae videos, the accuracy was 84%.

Corresponding Author:

Dia Bitari Mei Yuana,
Department of Electrical and Computer Engineering,
Politeknik Elektronika Negeri Surabaya,
Jl. Raya ITS, Sukolilo, Surabaya, 60111, Indonesia
Email: diabitari@pasca.student.pens.ac.id

1. INTRODUCTION

Aedes aegypti mosquito is a vector that transmits the Dengue virus from one person to another. The WHO says dengue is the most critical disease and most quickly transmitted through the *Aedes aegypti* mosquito. Due to the rapid spread of Dengue fever, the presence of mosquitoes plays an important role [1]. The difficulty in identifying *Aedes* vector ones is because their physical performance of all mosquitoes is similar [2]. Several studies on mosquito identification have been carried out, such as by molecular identification through DNA, morphological identification by sampling breeding sites [3], physical identification by image processing [4, 5], or by spatial similarity in several regions [6, 7]. However, it is difficult to implement their methods because they are expensive and require special expertise. Meanwhile, to combat Dengue fever, we need to empower ordinary people who don't have much money and are not very skilled in technology [8-10]. Therefore, we need to find a method that is simple in implementation, relatively inexpensive but accurate enough to classify larval [11, 12].

This paper discusses the method for classifying *Aedes aegypti* larvae. As a comparison, we utilize *Culex*, the common mosquito that lives in Indonesia [13]. Both have the same performance but different impacts: *Aedes aegypti* is very dangerous while *Culex* is not [14]. This method utilizes video captured by a standard camera. It is hoped to be useful to increase awareness of vector-borne diseases. We use the optical flow method to detect larval motion. *Aedes* larvae movements can be recognized by the optical flow method. A consistent pattern was analyzed using the optical flow method to detect *Aedes* larvae. Then, we use the Euclidean distance calculation to compare motion of the *Aedes* larvae and *Culex* larvae.

2. RESEARCH METHOD

Larvae are one stage of the mosquito life cycle where mosquito eggs emerge in the water. In this stage, larvae spend most of their time feeding and growing [1]. Larvae can detect quick changes in light and when a shadow is cast on the water, they will defensively dive to the bottom of the water. It can also detect sudden vibrations in the water and will likewise dive down [15, 16].

To get food and grow, the biological behavior of mosquitoes moves from one point to another with a certain pattern. Each species in the mosquito family has a different pattern [17]. Therefore, an important feature for classifying larvae is the pattern of larval movement. In this paper, we focus on analyzing the movement of single larvae. We use video processing to recognize patterns of differences between *Aedes* and *Culex*. Figure 1 shows the diagram block of this method. Using cellular devices mounted on a tripod, the researchers recorded the movement of *Aedes* larvae and *Culex* larvae and then selected 15 frames to process.

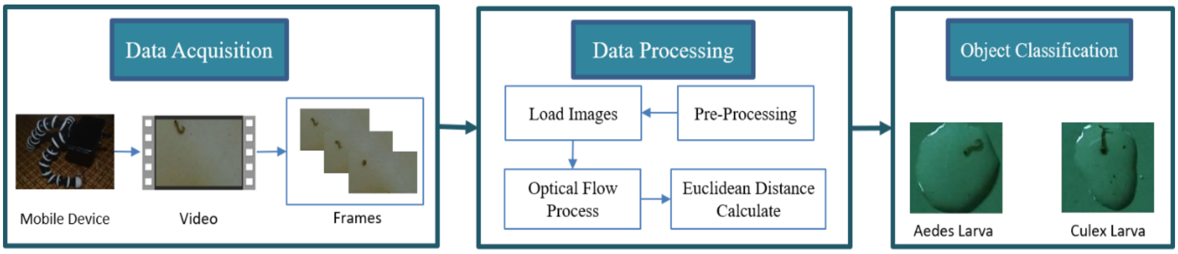
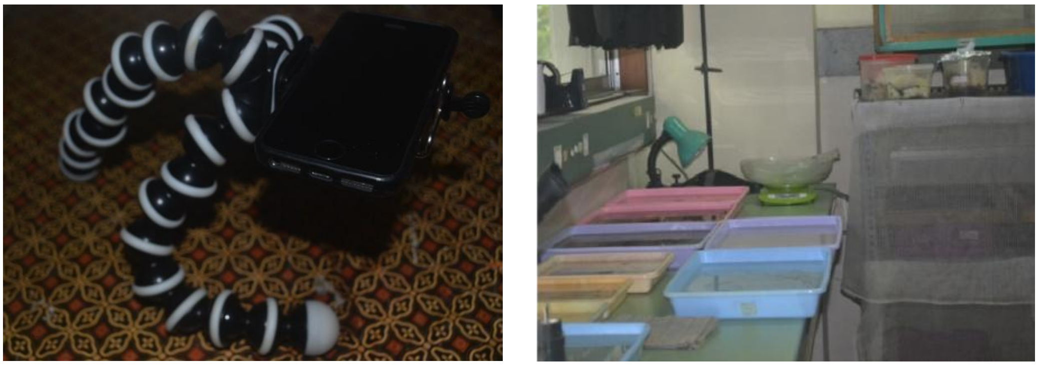


Figure 1. Diagram block of the method

Optical flow method can describe the meaning of motion [18]. To capture the movement, we should process video data. Movement patterns can be captured from moving objects in the video. This pattern is utilized to describe the type of object is moving. Figure 1 shows diagram block of the method to process dataset of *Aedes aegypti* and *Culex*. The dataset is taken using data collection techniques as data acquisition. Furthermore, the data is processed for further processing using the optical flow method. In optical flow, the differences movement patterns of *Aedes* and *Culex* larvae are analyzed. *Aedes* larvae have more consistent pattern compared to *Culex* larvae which unpredictable movement patterns. So, to recognize the movement patterns of *Aedes* larvae or *Culex* larvae, the researcher use the Euclidean distance calculation in the optical flow method.

2.1. Data preparation

To analyze the pattern of larvae motion, we set up the video recording system to collect the data in Entomology Laboratory, Airlangga University Surabaya, Indonesia. The system consists of a smartphone with a flexible tripod stand and larvae container that contains water. Figure 2(a) shows the system for image acquisition. Figure 2(b) shows the larvae container. It is a specific apparatus to sterilize the environment so that the water suitable for larvae during the collecting data process. Two types of mosquito's egg were incubated in two different containers.



(a) (b)

Figure 2. Materials and tools, (a) Image acquisition using mobile device, (b) Experimental setup

Soon after the egg metamorphoses to be larvae, every larva is laid on the tray that contains water. Then we took a video of them during the larvae stage (7 days). Since our purpose is developing this software for people, and many of them are low-income, we use Ovo hand phone's camera: mobile device that low-income people in Indonesia usually have. We also set up the lighting as their home's lighting.

2.2. Preliminary research

Along with the literature study and gathered knowledge from the expert, we also conducted a preliminary study to convince our hypotheses about the biological characteristics of both mosquito types. We record 5 second's video data of *Aedes aegypti* and *Culex*, parsed into 5 frames and analyzed briefly. Figure 3 describes the pattern of motion serially of *Aedes aegypti* and *Culex*. In 5 second, there are differences in motion pattern between *Aedes aegypti* larvae and *Culex* larvae. *Aedes aegypti* larvae tends to move at Figure 3(a)-(e) while *Culex* tends to quiescent at Figure 3(f)-(j) frame 1 to frame 4 then moves in frame 5. This preliminary study leads us to extract their features more

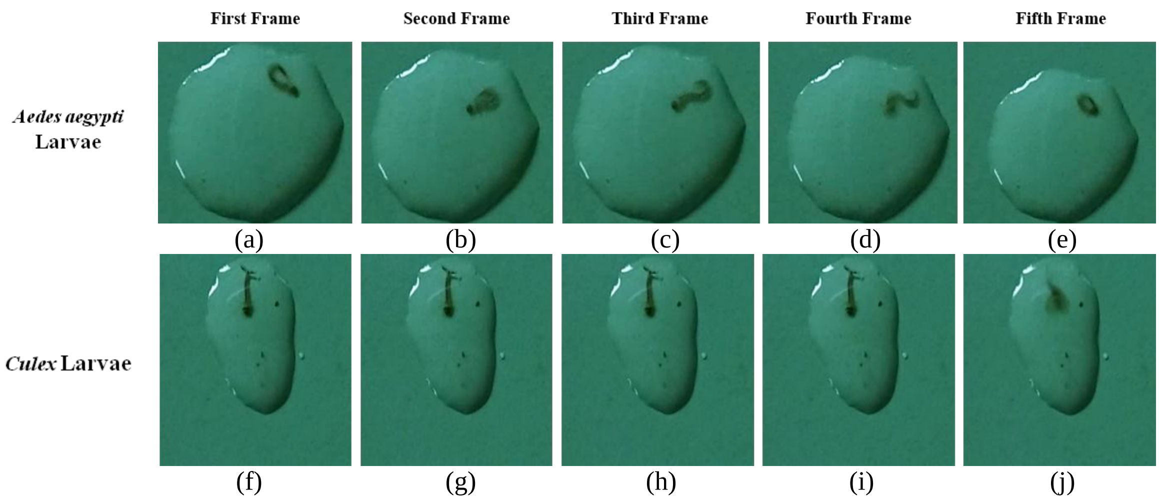


Figure 3. The frame of larva *Aedes aegypti* and *Culex* support, (a) *Aedes aegypti* larvae from first frame, (b) *Aedes aegypti* larvae from second frame, (c) *Aedes aegypti* larvae from third frame, (d) *Aedes aegypti* larvae from fourth frame, (e) *Aedes aegypti* larvae from fifth frame, (f) *Culex* larvae from first frame, (g) *Culex* larvae from second frame, (h) *Culex* larvae from third frame, (i) *Culex* larvae from fourth frame, (j) *Culex* larvae from fifth frame

2.3. Preprocessing data

Preprocessing data consist of parsing video data. In this research, 28 videos of *Aedes aegypti*'s motion and 22 videos of *Culex* motion are captured. They are parsed into 15 frames and analyzed. The raw video data has a big resolution. It is not efficient for training. Therefore, we conducted pre-processing to avoid irrelevant images such as the background. Preprocessing data consist of:

- Converting video data to 15 image frames
- Converting the true color image rgb to the greyscale intensity image or frame
- Converting the image to integer

2.4. Spatial movement pattern

In disease spreading, contracting area and pattern of disease vector are important [18, 19]. To analyze spatial movement patterns, we employed an optical flow method. Optical flow is technique to detect, predict and interpret and compensate the movement of an object [15-20]. In this paper, we explore Lucas Canade algorithm to recognize the pattern of larvae [21, 22]. Larva's video is processed using optical flow. Each video is taken 15 frames for motion detection. The first process is finding the corners of each frame, and then using the Lucas Kanade concept by tracing the position of certain nodes in one frame to the next frame continuously with the image flow (velocity) vector (Vx, Vy) should fulfill (1) [23].

$$\mathrm{I_x}(q_i)V_x + \mathrm{I_y}(q_i)V_y = \mathrm{I_t}(q_i) \tag{1}$$

Where Ix(qi), Iy(qi), It(qi) is partial derivatives to image I respect to the position of x,y to time t based on qi. In that sense, (1) is written in term matrix Av=b as follows.

$$A = \begin{bmatrix} I_x(q_1)I_y(q_1) \\ I_x(q_2)I_y(q_1) \\ \vdots \quad \vdots \\ I_x(q_n)I_y(q_n) \end{bmatrix} v = \begin{bmatrix} V_x \\ V_y \end{bmatrix} b = \begin{bmatrix} -I_{t(q_1)} \\ -I_{t(q_2)} \\ \vdots \\ -I_{t(q_n)} \end{bmatrix} \tag{2}$$

As a result, the vector flow is a transpose matrix as shown in (3).

$$\mathrm{A^T Av = \ A^T Ab} \tag{3}$$

To get the spatial movement pattern, we perform several steps:
- Load image of 15 frames,
- Find the corners: starting from q+2 where q is q is called as an early object definition,
- Apply the Lucas Kanade method, and draw the optical flow vectors.

2.5. Image statistical classification

We employ Euclidean distance to recognize movement patterns of larvae. Value of Eucledian distance will high when the larvae move actively, vice versa. The total value of Euclidean distance was applied to detect the differences *Aedes aegypti* larvae and *Culex* larvae. In this case, we calculated Eucledian distance of every frame has a different matrix, total value of the matrix.

The Optical Flow method produces values of the movement in every frame [24]. Velocity of movement represents differences of motion pattern between *Aedes* larvae and *Culex* larvae. Theoretically, *Aedes* larvae move consistently while *Culex* larvae move inconsistently. Therefore, we can be conclude that the total velocity of *Aedes* larvae is higher than *Culex* larvae in early experimental (15 frame). The next step is calculated Euclidean distance from every frame with (4):

$$\sqrt{(x_{n-}x_{n-1})^2 + (y_{n-}y_{n-1})^2} \tag{4}$$

wherex_n and y_n are total matrix x and y at t=n, and x_{n-1} dan $x_{n-1}$are total matrix x and $y$at t=n-1.

3. RESULTS AND ANALYSIS

In this research, we captured 28 videos of *Aedes aegypti* and 14 videos of *Culex* in Laboratorium Entomology, Institute of Tropical Desease Airlangga University. Beftore analyzed the pattern, all video data were preprocessed as mention in section 2.3. The result is shown in Figure 4. Figure 4 shows a video sample used as test data. In one video that lasts 11 seconds produces 325 frames. However, researchers used 15 frames to be processed using the optical flow method to detect moving objects. After preprocessing, we loaded the image. This process includes removing irrelevant images such as small plankton or water contaminator. Then, find the corner. Every frame has a different matrix depend on the next object. The next step was calculated with Lucas Kanade method by (2)-(3).

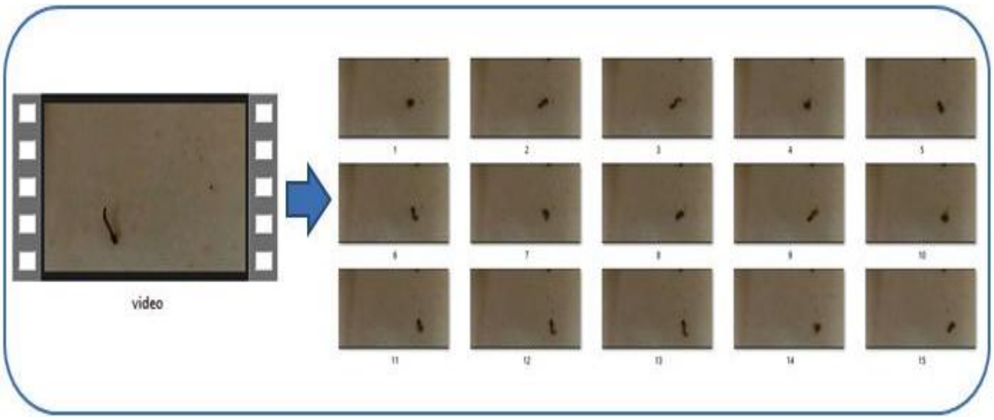


Figure 4. Result of preprocessing

Based on matrix from 14 frames in find corner, process, discard corners was handled near the margins of the matrix frame. Thus, the moving object was reflected in the next frame by the optical flow vector calculated in Lucas Canade method. The result of the Lucas Kanade method is saved as a one-dimensional matrix. Every matrix may different as the number of the matrix in find corner also different. We found the differences vector optical flow that reflecting spatial objects movement from frame 1 to frame 14 of every video. To classify the larvae, Eucludean distance is applied. The distance is calculated from the next frame to the previous frame until 15 frames. From 15 frames, we got 13 values of Eucledian distance. Experiment, the results of different Euclidean distance is calculated.

Figure 5 shows 50 video experiments consisting of 25 *Aedes* Larvae videos and 25 *Culex* larvae videos. The blue color indicates the Euclidean Distance value of the *Aedes* larvae and the red color indicates the Euclidean distance value of the *Culex* larvae. The yellow line is the threshold of *Aedes* larvae and *Culex* larvae based on the average value of Euclidean distance. For *Aedes* larvae, the threshold is not more than one while *Culex* larvae is more than 1. The average Eucledean Distance of both Aedes and Culex was calculated. The result is shown in Table 1.

The Euclidean distance of *Aedes* larvae is 1.181372 while in *Culex* larvae is 0.060723. It shows that the movement of *Aedes* larvae is relatively more consistent than *Culex* larvae. Details of the values of Euclidean distance of *Culex* larvae and *Aedes* larvae in Figure 5 are discussed in Table 2. The video numbers represent each *Aedes* larvae and *Culex* larvae that produce Euclidean distance values. Table 2 shows there are 25 videos with a maximum of 25 *Aedes* larvae videos and 25 *Culex* larvae videos so that the total video trials are 50 videos.

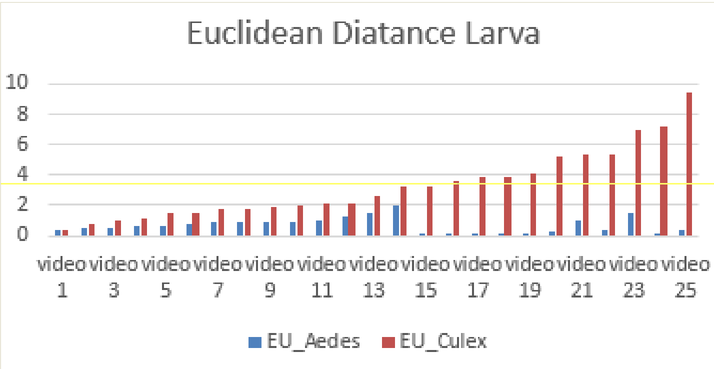


Figure 5. Euclidean distance larvae

Tabel 1. Euclidean distance *Aedes* and *Culex* frame by frame

Frame	*Aedes*	*Culex*
2-3	2,70	0,08
2-3	1,99	0,13
4-5	0,98	0,03
5-6	0,74	0,02
6-7	0,68	0,06
7-8	0,51	0,03
8-9	0,71	0,09
9-10	0,94	0,01
10-11	0,92	0,02
11-12	1,14	0,01
12-13	1,46	0,09
13-14	1,41	0,10
14-15	1,10	0,06
Average	1,181372	0,060723

Tabel 2. Euclidean distance of the larvae's *Aedes*

Larva	EU_Aedes	Result	EU_Culex	Result
video 1	0,389693	TRUE	0,3326	**FALSE**
video 2	0,445714	TRUE	0,70682	**FALSE**
video 3	0,49031	TRUE	0,95355	**FALSE**
video 4	0,667548	TRUE	1,07183	TRUE
video 5	0,676606	TRUE	1,47463	TRUE
video 6	0,771291	TRUE	1,50798	TRUE
video 7	0,827584	TRUE	1,78752	TRUE
video 8	0,850508	TRUE	1,78752	TRUE
video 9	0,884203	TRUE	1,86375	TRUE
video 10	0,927365	TRUE	2,0422	TRUE
video 11	0,992542	TRUE	2,07134	TRUE
video 12	1,19805	**FALSE**	2,14131	TRUE
video 13	1,495861	**FALSE**	2,55891	TRUE
video 14	1,963727	**FALSE**	3,19357	TRUE
video 15	0,058198	TRUE	3,22102	TRUE
video 16	0,088696	TRUE	3,56586	TRUE
video 17	0,126362	TRUE	3,83153	TRUE
video 18	0,150237	TRUE	3,87637	TRUE
video 19	0,165304	TRUE	4,14823	TRUE
video 20	0,299907	TRUE	5,22371	TRUE
video 21	1,05906	**FALSE**	5,32439	TRUE
video 22	0,342779	TRUE	5,32846	TRUE
video 23	1,544764	**FALSE**	7,01613	TRUE
video 24	0,078225	TRUE	7,16964	TRUE
video 25	0,338474	TRUE	9,46401	TRUE

Based on the test results of 50 videos consisting of 25 videos of *Aedes* larvae and 25 videos of *Culex* larvae, there were five "FALSE" in e *Aedes* larvae and three in *Culex* larvae, as shown in Table 2. So, the accuracy of the testing system was 84%. A comparison between both Euclidean distance of the two mosquitoes is shown in Figure 11. Regarding the influence of water quality in mosquito movements, in future research, we will emphasize the application of sensing fusion as applied to coral disease [25].

4. CONCLUSION

The biological feature extraction by using mobile sensing is conducted. The result shows that larvae detection using vision-based perception is powerful to replace chemical and morphological features. The accuracy of the system is 84%. Also, it is easy to handle and user-friendly. However, there several challenges before mobile sensing is launched, such as the influence of water quality and movement patterns of crowd larvae. All should be handling by vision-based perception.

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BIOGRAPHIES OF AUTHORS

DiaBitari Mei Yuana received her first degree from Informatics Engineering and Computer Engineering Department, Politeknik Elektronika Negeri Surabaya (PENS), Indonesia 2017 and now she was a student of Applied Master Degree in Informatics Engineering and Computer Department. She acts as a part of Environmental Research Laboratory member since 2017. She was interested in Image Processing, Video Processing, Object Detection System, and Software development.

Ir. WahjoeTjaturSesulihatien, MT., Ph.D. is currently an teaches in Postgraduate and Electrical Engineering at PENS, Indonesia. She received first dgree from Institut Teknologi Sepuluh November in 1988 and her postgraduated program in 1999. Her PhD. Degree in Keio University, Japan in 2017. Her research interest is Environmental Modelling and Anaysis.

Drs. Achmad Basuki, M.Kom., Ph.D. is currently an teaches in Postgraduate of Computer and Informatics Technology at PENS, Indonesia. He received first degree of Mathematics at Institut Teknologi Sepuluh November in 1992 and master program of Informatics Engineering in 1999. His Ph.D. Degree in Saga University, Japan in 2011. His research interest is Computer Vision, Simulation and Modeling.

Tri Harsono, Ssi., M.Kom., Ph.D received his first degree from the Mathematics FMIPA and master degree from Informatic Engineering in Institut Teknologi Sepuluh Nopember (ITS). Then, he received Ph.D program from Computer Science, Saga University, Japan. The research interest in modelling and simulation. He is currently an teaches in Politeinik Elektronika Negeri Surabaya (PENS)

Akhmad Alimudin, S.ST., M.Kom is a lecturer in Politeknik Elektronika Negeri Surabaya (PENS). He heads the UPT Komputer at PENS.

Etik Ainun Rohmah worked as a researcher in the Entolomology Laboratory of the Institute of Tropical Diseases (ITD) Surabaya, Indonesia in 2011 until now. One of the fields of study focus is a entomology, molecular biology, histology, and ecology. received her first degree from Dept. Biology, Faculty of Science and Technology, and magister of Tropical Medicine, Universitas Airlangga.