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Image Segmentation of Ovitraps for Automatic Counting of Aedes Aegypti Eggs

Carlos A. B. Mello, Wellington P. dos Santos, Marco A. B. Rodrigues, Ana Lúcia B. Candeias, Cristine M. G. Gusmão

***Abstract*—The *Aedes Aegypti* mosquito is the vector of the most difficult public health problems in tropical and semi-tropical world: the epidemic proliferation of dengue, a viral disease that can cause human beings death specially in its most dangerous form, dengue haemorrhagic fever. One of the most useful methods for mosquito detection and surveillance is the *ovitraps*: special traps to collect eggs of the mosquito. It is very important to count the number of *Aedes Aegypti* eggs present in ovitraps. This counting is usually performed in a manual, visual and non-automatic form. This work approaches the development of automatic methods to count the number of eggs in ovitraps images using image processing, particularly color segmentation and mathematical morphology-based non-linear filters.**

I. Introduction

Dengue is a disease caused by a virus and transmitted by the *Aedes aegypti* mosquito. The *Aedes Aegypti* appeared in Africa (probably in the northeast region) and it was spread there to Asia and Americas, mainly through the maritime traffic. In Brazil, it arrived in the 18th century with the boats that carried slaves, since the eggs of the mosquito can resist without contact with the water for up to one year.

The *Aedes Aegypti* mosquito is a domesticated species, whose life along side man is favored by the utilization of containers in residences suitable for breeding their immature forms. The containers could be as simple as flower pots, small cisterns and discarded tires and cans. These mosquitoes are responsible for one of the most difficult public health problems in tropical and semi-tropical world: the epidemic proliferation of dengue, a viral disease that, in its most dangerous form, dengue haemorrhagic fever, can even cause death of affected human beings [1]. The main strategy of control of dengue proliferation is centered on the reduction of potential breeding containers by the involvement of vector control personnel, several public administration sectors, social organizations, productive sectors that indirectly contribute to the increased number of breeding containers and the general community involved in this social and health problem [1, 2]. The routinely employed method to monitor *Aedes Aegypti* population in Vector Control Programs of Brazilian states is larval surveillance in potential breeding containers, which enables the attainment of entomological indicators such as the Premise, Container and Breteau Indexes [2]. In non-infected municipalities, this Program recommends the use of larvitraps, mat-black containers (in fact, sections of tires) containing 1 liter of water that are checked on a weekly basis, aiming at detecting foci of *Aedes Aegypti* [2].

One of the most important methods available for mosquito detection and monitoring is the use of *ovitraps*, which consist of black containers that are partially filled with tap water holding vertical wooden paddles with one rough side. Ovitraps are sensitive, fast, and economic to determine the presence of egg-laying females of *Aedes Aegypti* [2, 3].

To generate important statistics and furnish government agencies and vector control programs information enough to project official actions and programs to develop and increase the control of dengue mosquitoes, it is very important to count the number of *Aedes Aegypti* eggs present in ovitraps. This counting is usually performed in a manual, visual and non-automatic form. To aid the control of dengue proliferation and the eradication of its more dangerous form to human beings, dengue haemorrhagic fever, this work approaches the development of automatic methods to count the number of eggs in ovitraps images using image processing, particularly color segmentation and mathematical morphology-based non-linear filters.

In Recife, Brazil, the research on dengue is made mainly by the The Aggeu Magalhaes Research Center (CPqAM). This research is part of a project called SAPIO, granted by FINEP, that aims the development of new technologies for dengue control, surveillance and information dissemination.

This paper is organized as follows: next Section describes the images acquired and the algorithms developed to perform automatic counting of *Aedes Aegypti* eggs in ovitraps. Following, the results are related and analyzed in Section III. In Section IV it is presented conclusions and performed some commentaries on our results.

II. Materials and Methods

For this experiment, a digital camera was used. The camera has: 7.2 Megapixels resolution, LCD 2.5'', 4.5 times Optical Zoom and LEICA DC Vario Elmarit lens. The ovitrap was digitized with about 700 dpi resolution and 4 times optical zoom. This process generated a true color digital image of 3,072 *versus* 2,304 pixels. This image was

C. A. B. Mello, W. P. dos Santos and C. M. G. Gusmão are with Department of Computing and Systems, University of Pernambuco, Recife, Brazil, 50720-001 (e-mails: {carlos, wellington, cristine}@dsc.upe.br, Phone: +55 81 2119-3842).

M. A. B. Rodrigues is with Department of Electronic and Systems, Federal University of Pernambuco, Recife, Brazil, 50670-000 (e-mail: benedetti@ufpe.br).

A. L. B. Candeias is with Department of Cartographic Engineering, Federal University of Pernambuco, Recife, Brazil, 50740-530 (e-mail: analucia@ufpe.br).

split into sub-images for the experiments. The amount of eggs in each one of these sub-images is acquired by visual inspection allowing an easy comparison with our new proposal. Fig. 1 presents some sample sub-images used in the tests and the amount of eggs in each one of them. The same figure also presents a zooming into some *Aedes Aegypti* eggs. The images are digitized in RGB color system.

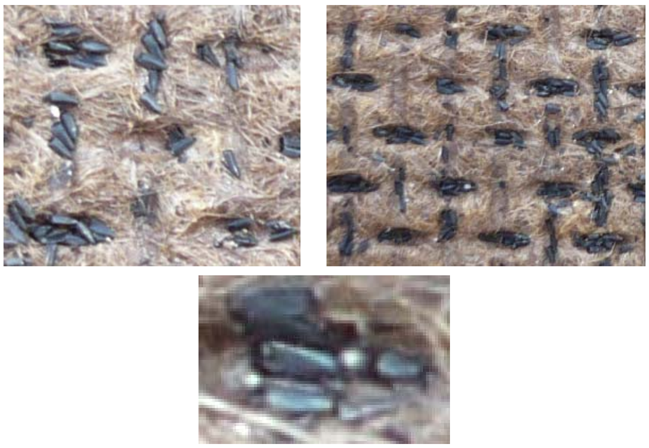

Fig. 1. Samples of an ovitrap: (top-left) a region with 34 eggs, (top-right) 111 eggs and (bottom) a zooming into a group of three eggs.

One of the problems of an automatic counting method is the segmentation of the images [4]. A segmentation algorithm divides an image into its objects or relevant parts. As the objects can vary from image to image, this is not a simple task. Classical segmentation algorithms can be found as watershed [5] and quadtree decomposition [6]. These techniques however are well-known to produce over-segmentation, *i.e.*, they find more objects than it is needed. Fig. 2 presents the segmentation of the image presented in Fig. 1 top-left using watershed and quadtree decomposition.

Other texture based methods groups areas that are considered similar based on some feature as texture anylisis. As before, the idea is to break the image into its components but now these components are merged into one unique area if they are similar. This technique was previously presented in [7] for mammographic image analysis and it uses a fidelity index to merge each sub-region. Fig. 3 presents the 36 different areas found in the sample image of Fig. 1 top-left based on texture features. A different color is used to represent each different area; similar areas must appear in different regions of the image. Again, the problem of over-segmentation can be noticed.

Two methods are proposed for the automatic counting. Each one of them is based on a different color space model. Next, we detail both of them.

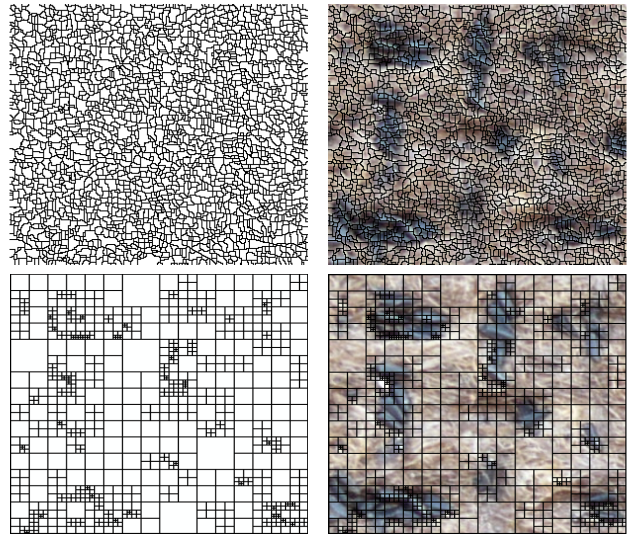

Fig. 2. (left column) Segmentation results using (top) watershed and (bottom) quadtree decomposition. (right column) Overlapping of the segmentated regions and the original image, detailing the oversegmentation.

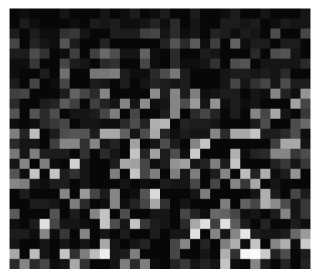

Fig. 3. Segmentation of image of Fig. 1 top-left using a fidelity index to merge similar regions (each different color represents a different region).

A. First Method

In this case, the RGB color model does not contain useful information for segmentation. Because of this, the images are converted into HSL color model (*Hue*, *Saturation* and *Lightness*). One can see in Fig. 4 the HSL components of the image shown in Fig. 1 top-left.

From these three components, the hue is the one that contains information about the color tone. For example a hue value of 240 is related to several blue tones. It is evaluated as [8]:

$$hue = \cos^{-1}\left(\frac{(((r-g)+(r-b))/2)}{\sqrt{(r-g)^2+(r-g)(g-b)}}\right) \tag{1}$$

where r, g and b are the values of the red, green and blue components for a given color. As can be seen in Fig. 2 (top-left), the hue does not retain information about most part of the ovitrap itself.

The hue image is then binarized using Huang thresholding algorithm [9]. Other thresholding algorithms [10] were tested but Huang's and Li-Lee's algorithms produced the best results. We have opted by Huang's algorithm as it has a lower time processing. Fig. 3-left shows the bi-level version of the hue image of Fig. 2 top-left. There are still several parts considered objects in the image as they are converted into white.

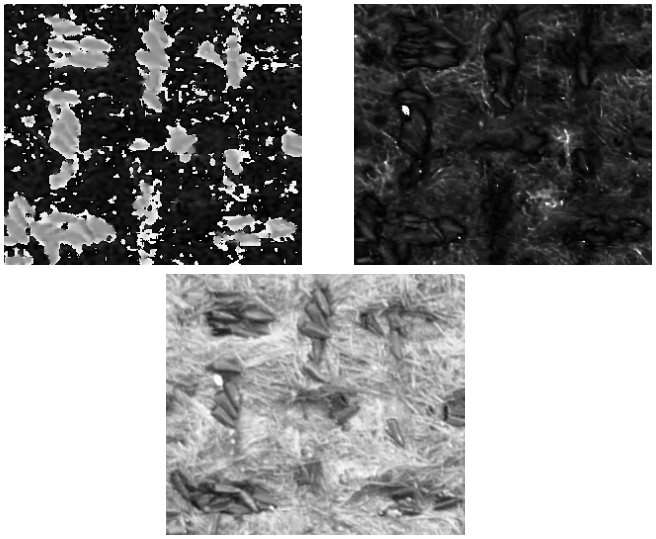

Fig. 4. HSL components of the image in Fig. 1 top-left: (top-left) Hue components; (top-right) Saturation and (bottom) Lightness.

With the bi-level image, a connected components algorithm is applied to label the connected regions of the image [11]. This algorithm puts a different label at each connected white area of the image. With this labeling, it is possible to evaluate each connected area. Small areas can be deleted as it could not contain an egg. Our experiments defined that every area with less than 100 pixels should be deleted. This can be seen in Fig. 5 (right) where it is presented the image of Fig. 5 (left) after the reduction of its white areas.

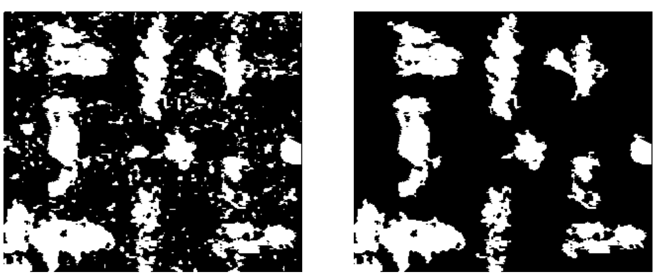

Fig. 5. (left) Hue image after binarized by Huang's thresholding algorithm. (right) bi-level hue image after elimination of small connected areas.

After this, the image is filtered using the morphological operation of closing [4]. For this purpose, a structural element is defined in the form of an egg. As the eggs are disposed in different positions along the ovitrap, it was selected a sample egg with average size and with a small inclination angle. To avoid the loss of small eggs in the counting process, the image used as structural element has its original size reduced from 18 x 30 pixels to 8 x 13 pixels. Fig. 6 presents the original image (left-top) and the final structural element (left-bottom).

The result of the closing operation applied to the image presented in Fig. 5 (right) is shown in Fig. 6 (right). The areas with eggs are now more delimited.

Fig. 6. (left-top) Average egg that was used to define (right-bottom) the structural element. (right) Image of Fig. 5-right after application of the closing operator with the structural element of Fig. 6-right.

For the final stage, we considered that an egg occupies an area of 170 pixels. So, the number of eggs is the total amount of white pixels divided by this average area. In this case, the method registered an amount of 33 eggs against the correct value of 34 eggs that the image contains.

B. *Second Method*

The second approach used in this work is based on converting RGB sub-images to YIQ ones and, finally, segmenting band I and counting mosquitoes eggs using a standard labeling algorithm [11]. YIQ color base transformation is given as follows [12]:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.275 & -0.321 \\ 0.212 & -0.523 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \cdot \qquad (2)$$

The segmentation of band I can be performed in two ways: 1) using limiarization with a fixed threshold of 200; 2) binarization using k-means clustering method [13], with 3 inputs, 4 classes, learning rate of 0.1 and a maximum of 200 iterations. To perform eggs counting, it is considered an average-sized mosquito egg of 220 pixels. Such a difference of size (220 pixels against about 250 of the first method) is due to different segmentation methods and the absence of the application of mathematical morphology-based filters in this method, once there is no structural element.

Fig. 7 (top-left) presents an RGB color sub-image of a determined ovitrap, where Fig. 7 (top-right) shows the RGB composition of its YIQ version. Fig. 7 (bottom-left) presents segmentation results using the fixed threshold approach, whereas Fig. 7 (bottom-right) shows the k-means based method. It can be seen in Fig. 8 and Fig. 9, respectively, the gray level version and histogram of band I of the image presented in Fix. 7 (top-right). In this example, the proposed algorithm counted 34 eggs, exactly the same number of eggs got by the visual non-automatic counting process.

III. Discussion and Results

In Table I, it is presented the results of the two methods applied to another six samples, including an image without eggs. The image labeled as '5' in Table I is the image previously presented in Fig. 1 (top-right) with 111 eggs.

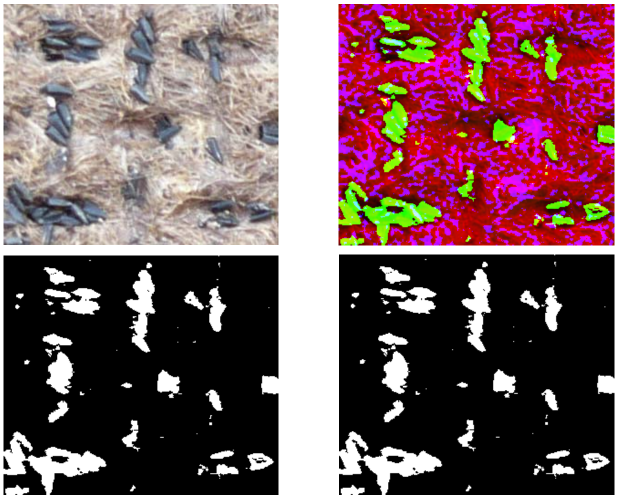

Fig. 7. RGB color sub-image of an ovitrap (top-left), RGB composition of its YIQ representation (top-right), and segmentation of its band I with a fixed limiar of 200 (bottom-left) and a k-means classifier (bottom-right).

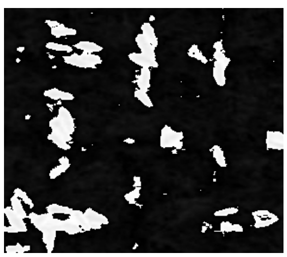

Fig. 8. Band I of YIQ version of sub-image on Fig. 5 (top-left).

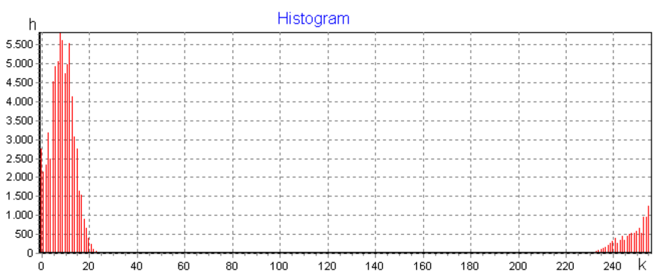

Fig. 9. Histogram of Band I of the RGB sub-image presented in Fig. 7 (top-left)

TABLE I
COUNTING RESULTS USING THE PROPOSED METHODS

Image	Correct Amount of Eggs	Estimated Amount of Eggs by the Proposed Algorithms		
		Method 1	Method 2 Fixed Threshold	Method 2 k-Means
1	22	25	29	20
2	8	10	10	6
3	111	111	113	107
4	30	26	32	28
5	19	19	21	19
6	0	0	0	0

The first method reached a maximum error of 25% in the second image where there is a difference of two eggs. But in average the error was about 6.66% which is acceptable in comparison with a non-automatic method.

The version of the second method with segmentation based on unsupervised classification of the YIQ image furnish better results than the other, based on binarization of band I with a fixed threshold of 200. This result is due to the use of all 3 bands of YIQ image, despite the fact that band I is perfectly feasible to be used as an input to segmentation algorithm, as can be observed in Fig. 7 and Fig. 8. The second method using a fixed threshold value for binarization achieved an average error rate of 7.33%, while the use of k-Means produced an average error of 7.84%.

Both methods achieved very satisfactory results. Other color spaces must be tried in search for better responses.

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REFERENCES

[1] M.J. Perich, A. Kardec, I.A. Braga, I.F. Portal, R. Burge, B.C. Zeichner, W.A. Brogdon, R.A. Wirtz, “Field evaluation of a lethal ovitrap against dengue vectors in Brazil”, Medical and Veterinary Ontomology, vol. 17, p. 205-210, 2003.

[2] M.R. Dibo, F. Chiaravalloti-Neto, M. Battigaglia, A. Mondini, E.A. Favaro, A.A.C. Barbosa, C.M. Glasser, “Identification of the best ovitrap installation sites for gravid Aedes (Stegomyia) aegypti in residences in Mirassol, state of São Paulo, Brazil”, Mem. Inst. Oswaldo Cruz, vol. 100, n. 4, p. 339-343, 2005.

[3] R.A. Gama, A.E. Eiras, M.C. Resende, “Efeito da ovitrampa letal na longevidade de fêmeas de Aedes aegypti (Diptera: Culicidae)”, Revista da Sociedade Brasileira de Medicina Tropical, vol. 40, n. 6, p. 640-642, 2007.

[4] J.R.Parker. *Algorithms for Image Processing and Computer Vision*, John Wiley and Sons, 1997.

[5] E.R.Dougherty, R.A.Lotufo. *Hands-on Morphological Image Processing*, SPIE Press, 2003.

[6] R.C.Gonzalez, R.Woods. *Digital Image Processing*, Prentice-Hall, 3rd Edition, 2007.

[7] C.A.B.Mello, A.A.Mascaro. “Image Fidelity Index Applied to Digital Mammography Texture Segmentation”, Conferencia Latinoamericana de Informática (CLEI), Chile, p. 1-6, 2006.

[8] D.H.Ballard and C.M. Brown. *Computer Vision*. Prentice-Hall, 1982.

[9] L.K.Huang and M.J.Wang. “Image Thresholding by Minimizing the Measures of Fuzziness”, Pattern Recognition, vol 28, p. 41-51, 1995.

[10] M.Sezgin and B.Sankur, “Survey over image thresholding techniques and quantitative performance evaluation.” Journal of Electronic Imaging, vol. 1, pp. 146-165, 2004.

[11] L.Shapiro and G.C.Stockman. *Computer Vision*. Prentice Hall, 2001.

[12] H. Pedrini, W.R. Schwartz, *Análise de Imagens Digitais: Princípios e Aplicações*, Thomson, 2008.

[13] S. Haykin, *Neural Networks: A Comprehensive Foundation*, Prentice Hall, 1998.