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Mosquito Tracking by Image Segmentation of Optical Flow Field

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Abstract

High speedy Mosquito tracking and a time efficient technique have been presented by considering on image segmentation of the optical flow which has been computed by image successive frames to track the Mosquito of a specific region of interest on the region of field with segmented flow regions. The optical flow has been established by the successive two frames to consider acquiring the image for computing. A fuzzy antagonism index has been indicated as the degree of the consistency of flying Mosquito. The image frames are used to segment the optical flow field. The images have been segmented in flow field with in the different consistency of region of interest. The specific region of interest can be detected in the different region of interest spaces. Therefore, the Mosquito can be tracked from two subsequent images. However, the detected specific region of interest is a sub-region of region of interest. The specific region of interest. It is the facilitating real-time process of Mosquito tracking. In the proposed technique, it has been demonstrated image sequences of moving Mosquito for detection and position tacking.

Keywords: mosquito, time efficient, tracking, segmentation, optical flow

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1. Introduction

Tracking and localization of flying Mosquito detection is the most interesting and funny but challenging research work to save human life from Malaria. This research work has other applications in defense vision analysis. Some conventional methods are presented in the literature [1-3] for tracking of moving from a motion sight. There are some techniques are used with morphological methods. But the inherent problem of these techniques has been used for the morphological operations.

The image flow [4-7] from a 2D perspective specifies the amount of the pixels of an image moves between two adjacent time-ordered frames [8]. The flow field has been considered to refer as the optical flow field [6]. The optical flow is such an efficient and effective technique that suspect object motion with image intensity variations which is computed between two consecutive image frames [9, 10] and the optical flow score is the technique in the literature [11-15]. The optical flow approximation is capability to find in detecting Mosquito's pattern. It is deriving in the 3D motion and structure of the Mosquito in an image frame. The optical flow techniques include real-time multiple Mosquito tracking. The detection of Mosquito is motion of neonatal seizures [16]. It can be segmented of 3D motion [17].

The optical flow assessment method represents the changes in Mosquito's image brightness. The partial derivative constraint equation can be used for time computation. The two similar equations the optical flow constraint equation (OFCE) and the continuity equation of fluid-dynamics can be used [7]. It assumes that the Mosquito's image intensity is stationary due to time reference. There are two computation of optical flow such as regularization and multi-constraint-based approaches. Regularization approached model of the optical flow field estimated as an ill-posed problem [18]. The minimized and regularized has been considered by an appropriately weighted smoothness constraint. In this analysis, the velocity has been evaluated at every point in the Mosquito image. Regularization-based approaches using the OFCE can be found in [19-21]. It has the uniqueness. The regularization processes also help to determine of the Mosquito's shape [20]. Thus it can be helpful to determine the Mosquito's

pattern. The contours of the optical flow can be assessed to detect the flying Mosquito. The image brightness stationary condition is the multi-constraint-based approaches flying-invariant function like contrast, average, variance, entropy, curvature, moments, gradient magnitude of color spectrum, local intensity, images obtained. These methods are intended at formative the inversion or pseudo-inversion of the coefficient matrix of these functions. The equivalent optical flow mechanisms are used to set the constraint for image [21, 22]. To bright of intensity, it is used the second-order partial derivatives to compute the flow mechanism [23, 24]. The main theme of these techniques is in the image pixel neighborhoods similarity of velocity. The neighboring pixels are in a smooth optical flow field [7]. This multipoint method [25] approach is usually involving as,

- a) Sequence of image is pre-filtered to regularize the initial data [21], [24], [26];
- b) Collecting a large number of constraints for large neighborhood [27];
- a) The estimated optical flow fields are used for post-filtering [24];

All are used to smooth out the optical flow mechanism obtained in the multi-constraintbased approaches. It is extended Schunck's method [28, 29] by Nesi et al. [30] to optical flow control (EOFC) equation. It uses the divergence of the flow field of the image brightness. The EOFC has been used to estimate the optical flow mechanism in a motional flying position. The local optical flow estimation methods are relatively faster but less stable and larger than the global estimation methods (GEM).

There are two optical flow components such as Coherent Optical Flow (COFF) regions and incoherent Optical Flow (IOFF) regions. The coherent can be arisen out of actual displacements of flying Mosquito and the incoherent regions can be arisen out of changes in the intensity level. These changes can be occurred due to in surface reflectance and ambient illumination conditions. But the second movements are the non-reflective in the motion or flying scene. There are several regions matching of optical flow techniques have been proposed to get better the precision of the optical flow by eliminating differentiation of image intensities [7].

In this research, the mosquito can be detection from the optical flow field or flying image in the motional flying scene to follow the constraints of spatial coherence over very small time [31]. It can be exploited in the present treatment to focus on a smaller region of the motional flying scene of the Mosquito for the computation of the optical field.

The flow field can be computed the present and next image frames for effective segmentation [7] of the regions of interest (ROI). A specific region of interest is called subregion of interest (SROI). The SROI can be detected based on its coherence constraint, density of the optical flow, subsequent flow field of the ROI's neighborhoods of the detected SROI. Results of these proposed method has been presented on the tracking of image sequences of flying Mosquito. The timing requirements of the proposed method are the main fact to detect Mosquito. Here, the conventional Horn and Schunck's method is also reported.

2. Mathematical Overview

The mathematical overview of the optical flow field, fuzzy neural concepts and logic index of the Mosquito's Image pixel neighborhood has been sketched. There are limitations of the inherent optical flow field method due to Horn and Schunck [6] has been removed. The proposed image segmentation process has been improved the time efficiency and effectiveness of the optical flow to compute by fuzzy theory concepts [32]. The smoothness constraints have been incorporated in the optical flow computation methods to regularize the way by means of smoothness integration of data. The smoothness coherence constraints suppose that the flying Mosquito in the motional image are structurally integral and smooth. The optical flow based flying or moving pattern of the Mosquito is a sequence of time in ordered images causes sequential variations are exclusively due to image motions. Then the sequence of images indicates for the estimation of 2D discrete image displacements or velocities. It can be referred to as the optical field or Mosquito image velocity filed. The intensities of the Mosquito image and its derivatives are used to explain the motional flying parameters of the Mosquito's image scenes. The optical flow explains two mechanism of the motional flying Mosquito of a region feature such as proboscis, head, throat, abdomen or wing in the image [31, 32].

Suppose that $M(\vec{x_{\nu}},t)$ is the image intensity [5], then

 $M(\vec{x_{\nu}},t) = M(\vec{x_{\nu}} + \delta \vec{x_{\nu}},t + \delta t)$

(1)

Where $\delta \vec{x_i}$ is the displacement of the local image region at $(\vec{x_i}, t)$ after time δt . Taylor expansion of the left hand side can expressed as,

$$M(\vec{x_{i}},t) = M(\vec{x_{i}},t) + \nabla M\delta\vec{x_{i}} + M_{t}\delta t + H^{2}$$
⁽²⁾

Where $\nabla M = (M_x, M_y)$ and M_t are respectively, the order partial derivatives of the Mosquito image intensity function $M(\vec{x_v}, t)$ with respect to the space for Mosquito and time and H^2 represents the higher order terms which can be eliminated and the above Equation (2) can rewrite as,

$$\nabla M \delta \vec{x_t} + M_t \delta t = 0$$
Or,
$$\nabla M \frac{\delta \vec{x_t}}{\delta t} + M_t \frac{\delta t}{\delta t} = 0$$
i.e.
$$\nabla M \vec{v_t} + M_t = 0$$
(4)

Where, $\vec{v_l} = (u, v)$ is the velocity of the Mosquito image. The above equation is the OFC equation [5]. The velocity direction of the Mosquito image is the local slope of the intensity function can be computed. It can be referred as the aperture problem. The estimation of the motion at Mosquito image location is enough intensity. The velocity of the Mosquito image can be determined by the Equation (4). To satisfy, it needs some criterion such as uniform illumination, Lambertian surface reflectance, and translation motion parallel to the Mosquito image plane.

It can be used a regularization term to approximate the motions of the neighboring regions with Mosquito's motion. It has been introduced a global smoothness constraint [6] to formalize the image flow constraint [7]. It has been generated an incomplete correlation between the Mosquito's motional domain and the image intensity domain. The error term of the constraint has been defined [5] by,

$$Er = \int_{D} \left[\left((\nabla M \vec{v} + M_t)^2 + \lambda^2 tr((\nabla \vec{v})^T)(\nabla \vec{v})) \right) + \varepsilon \right] dx$$
(5)

Where, $\vec{v_i} = (u, v)$ is the Gauss-Seidel equation in the domain D, λ is the term of weight, and ε is the error term.

The optical flow based techniques has another problem. This technique is highly sensitive towards to the smaller intensity variations in the consecutive Mosquito images frame. In the incoherent optical flow field regions, the Mosquito actually cannot be detected in the movement situation. These uneven vectors are contributed to by minor variations as changes in illumination, little movements in the background, and use the differential eq. in the optical field for computation. Thus, the OFF comprises an allocation of incoherent flow regions in the sense of the intensity variations and coherent flow regions are actually significant travels of the Mosquito in motional picture. This can be distributed as a map of motion vectors. The map indicated as an intensity structure, it can be represented as a binary image scene which can be comprised as the coherent and incoherent flow fields. The intensity can be dark levels and which is directly proportional to the degree of movement pictured by the motion vectors. Thus in the coherent situation for the problem of tracking of the moving or flying Mosquito in a motion scene eliminate problem of Mosquito image segmentation. The coherent and incoherent regions are the representation of the motion vectors for the segmentation of the intensities [7]. The segmented motion scene can be used for extracting the coherent regions. It can be depicted in the Mosquito's motional picture.

In [33], the membership function has been defined as $\pi_M(x_i)$, i = 1,2,3,...,n where the fuzzy set, $M = \{x_1, x_2, x_3, ..., x_n\}$. $\pi_M(x_i)$ lies in [0,1]. This function reflects the degree of control of the rudiments within the fuzzy set. The higher value of a component, the greater is the containment of the component within the fuzzy set and lower value indicates a weaker control [32]. According to Zadeh's notation [33], a fuzzy set *M*, then the modified equation can be expressed as,

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$$M = \sum_{i} \frac{\pi_M(x_i)}{x_i} + \varepsilon, i = 1, 2, 3, \dots, n$$
(6)

Where, *n* is the number of the components in the fuzzy set and \sum_i expresses a set of components, ε is the error of the field.



Figure 1. Pixel Intensity Information of OFF

The OFF can be visualized as a 2D fuzzy 0 or 1 intensity plot. The denser region is darker in the intensity plot. But, in the IOFF region reflects brighter and sparser intensity. The degree of COFF and IOFF in the computed OFF is known by the uncertainty in the intensity in the neighborhoods of a flow region. The distribution and density of the darker pixels in the computed OFF depict the attendance in the neighborhood of a particular optical flow region [7]. A pixel neighborhood can be measured of the amount of homogeneity/heterogeneity of the neighborhood of the candidate pixel which is in the fuzzy hostility [32, 34]. The pixels in the neighborhood are more homogeneous then the fewer pixels are in the antagonism to its neighborhood that indicating more COFF neighborhood region. However, a pixel in an IOFF neighborhood region is more antagonism to its neighborhood geometry, the antagonism index (ε) of the second-order neighborhood can be defined as [34],

$$\varepsilon = \frac{3}{8} \sum_{i=1}^{8} \frac{\left| \pi_p - \pi_{q_i} \right|}{\left| \pi_p + 1 \right| + \left| \pi_{q_i} + 1 \right|} + c \tag{7}$$

Where π_p is the candidate pixel and π_{q_i} , i = 1, 2, 3, ..., 8 is the fuzzy membership value of neighbors in the second order neighborhood fuzzy subset and c is the fuzzy errors. The (ε) lies in [0,1], maximum index is $\varepsilon = 1$, minimum index is $\varepsilon = 0$, the higher value of ε then the higher index in the candidate pixel in the neighborhood. The fuzzy index of the pixel in a neighborhood flow is mentioned of COFF or IOFF in the computed flow regions in a motion image which can be used between the COFF and IOFF.

In Figure 1 shows the distribution of the pixel intensity levels in 2^{nd} order neighborhood OFF region, Figure 1a, and Figure 1b are not perfectly homogeneous but Figure 1c, Figure 1d, and Figure 1g are perfectly homogeneous which has least index ($\varepsilon = 0$), Figure 1e, Figure 1f, and Figure 1h are perfectly heterogeneous and the index is ($\varepsilon = 1$), Figure 1i-1p shows the threshold [35] region of homogeneous optical flow regions. However, OFF regions comprise only darker regions indicating the homogeneous regions that are the essential logical regions for actual motions [7] between the COFF and IOFF.

3. Proposed Algorithm

The Mosquito detection and tracking by using fuzzy theory has been segmented of OFF to accomplished in Figure 2 that has presented in the following ways,

- a) Time-ordered image frames can be extracted from a video sequence using standard library routines and then the extracted Mosquito for the computation of OFF.
- b) The OFF between the initial two image frames which can be computed for intensity between Mosquito image frames. The OFF is computed by using Equation (4) along with Horn and Schunck regularization term which has given in Equation (5). The flow vectors are measured at each pixel location along with the X and Y directions put in to the Mosquito image velocities. It can be summarized as (i) denser flow regions corresponding to the moving or flying Mosquito and (ii) sparser flow regions equivalent to the ambient luminance changes between frames and any noises. It may move stealthily in during the attainment of the video sequence.
- c) It can be determined the optical flow on ROI using pixel antagonism index which is useful segmentation of the OFF into COFF and IOFF regions is the most significant phase for the removal of the IOFF regions and subsequent removal of the COFF regions. It can be considered the computed OFF to be a fuzzy intensity map of IOFF or COFF regions, the fuzzy antagonism index (ε) of each flow region neighborhood pixel is computed by using Equation (7) and then the OFF is thresholded [35] at a antagonism index which value of $\varepsilon = 0.5$. It corresponds to the outer line between the IOFF and COFF distributions. All of fuzzy indexes are $\varepsilon > 0.5$ that can be comprised the filtered which is out from the flow field [7], [35]. It can be treated as random disturbances of incoherent regions in the OFF which are rarely clustered jointly. Whereas, a pixel which is antagonistic sufficient in its neighborhood. It can be unspecified to be a part of the incoherent regions only. It can be made coherent regions form the ROIs for further calculation of the OFF of the video succession [36].
- d) The SROI on ROI by detecting highest density optical flow regions by a pixel position (x, y) of interest on the extracted coherent ROIs for able to Mosquito detection and its position tracking. The position can be laid on the moving or flying ROI. At first, the ROI must be minimum size which should be spatial coherence constraint and secondly the pixel position on the ROI must be the maximum neighborhood attention of optical flow. The sharp noise in the OFF must be in the hostility index based filtering process. The SROI on ROI of Mosquito image which have maximum absolute [7, 31] OFF. It means that the tracking the fastest moving or flying region. In the first one can achieved in neighborhood OFF attention of each pixel is measured. However, $m \times n$ neighborhood averaging of the OFF is done for minimum size (3 × 3) in coherently for flying Mosquito. Thus, the summation of the absolute value of the

OFF vectors in its 3×3 in Figure 1c to Figure 1l or 2×2 in Figure 1m to Figure 1p neighborhood in the X and Y directions. At last, the pixel with the maximum value of computed summation is taken as SROI on a ROI. It can be estimated in a SROI on a desired ROI even in those motion images. It can be comprised multiple moving or flying Mosquito with different velocities of the Mosquito because of the faster speedy Mosquito turn out stronger OFF which is applied for the highest optical flow strength to pertain the high-speedy Mosquito.



Figure 2. Mosquito Detection and position Tracking Algorithm

e) Optical flow can be computed in the neighborhood of SROI in subsequent image frames contain the moving regions that can constitute the background. A small position or SROI can be tracked on a moving region which is equivalent to tracking the whole region which can reduce the time complexity of the tracking technique. Then it can be obtained the flying or moving Mosquito. It is noted that time-ordered frames can be processed to track which can be estimated the spatial coherence constraint and it can be ensured the integrity of the moving or flying Mosquito SROI. The first two time ordered frames OFF and a SROI on the moving or flying Mosquito is detected and the position is tracked in the neighborhood point that constitutes the

ROI for operation in the subsequent frames to be processed. Tracking of the moving or flying Mosquito then synonymous to shifting the ROI in agreement with the OFF can be detected SROI.

5. Results and Discussions

The proposed algorithm has been applied for detecting and position tracking of the Mosquito. The experiments have been conducted by the time series of the image frames [7], [36] in the live video sequences by GigE 4900C camera in Figure 3 and Figure 4 which corresponding the Mosquito image frames along with the tracked SROI. The algorithm has been implemented on Keyence controller around the detected SROI. In assumption, the targeted point of the Mosquito can shoot by LASER that cause the Mosquito should be destroyed successfully. The mentioned algorithmic technique has less complexity. Table 1 shows the computational times in seconds required by the proposed technique. The table shows evident for the proposed technique. In the proposed technique which becomes more famous as the numbers, less time consuming, and dimensions of flying sequences can rise. In finally, it can be concluded that the proposed technique out performs the optical flow computation technique which takes into reflection the entire image frames.



Figure 3. Original Images Frames of the Mosquito



Figure 4. Detection and Position Tracking of the Mosquito

Table 1. Positions and their Execution Time								
	Position (x,y)	Time elapsed 1	Time elapsed 2	Time elapsed 3	Avg. Time (ms)			
1	(187,133.5)	0.0345326	0.0340094	0.0343725	0.034305			
2	(180,230.5)	0.034277	0.0342373	0.0336188	0.034044			
3	(169,368.5)	0.0348935	0.0347315	0.0335772	0.034401			
4	(180,246)	0.0327388	0.0308947	0.0314708	0.031701			

able 1.	Positions	and their	Execution	Time

6. Conclusion

Mosquito detection and position tracking algorithm through the computation of Optical Flow Field has been explained in this research paper. The main aim of this paper has been proposed to segment the optical flow field regions computed between successive Mosquito image frames of live video sequences into coherent optical flow field and incoherent optical flow field by using fuzzy index of the flow regions. Time reducing to attain by the selection of a region of interest and a specific region of interest among the coherent optical flow field and specific region of interest computation in optical flow field followed by segmented optical flow field over selected neighborhood of specific region of interest. This technique is efficient and effective of fast detection and tracking process.

Acknowledgements

Warm expression and sincere thanks to Fuzhou Jufeng Elect Ltd. Co., 268 Gushanzhou, zhoutou, Tongkou cun, Minghoujingxizheng, Fuzhou, China especially to Li Zhangdong for his support to accomplish the experiment and special thanks to Xiamen University, China 863 project (2014AAQ00283), Project Number 2, China for supporting the project.

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