Small Moving Target Detection based on the Concept of Entropy Flow

Zhonghua Wang, Jianguo Liu, He Deng


Small Moving Target Detection based on the Concept of Entropy Flow

Zhonghua Wang, Jianguo Liu, He Deng

1, First Author and Corresponding Author, Institute for Pattern Recognition & Artificial Intelligence, Huazhong University of Science and Technology, Wuhan, 430074, People’s Republic of China; School of Information Engineering Nanchang Hangkong University, Nanchang, 330063, People’s Republic of China, E-mail: wangzhonghuawzh@126.com

2, Institute for Pattern Recognition & Artificial Intelligence, Huazhong University of Science and Technology, Wuhan, 430074, People’s Republic of China, E-mail: jgliu@ieee.org and dengcrane@163.com
doi:10.4156/jdcta.vol5. issue4.29

Abstract

The detection of small moving targets under motorial background is very difficult. In order to solve this issue, a novel detection algorithm is presented in this paper, which is based on the concept of entropy flow. Firstly, the concept of entropy flow is used to measure image motion; Secondly, 2-dimensional histogram of flow field is applied to estimate the background motion; Finally, the targets are obtained by using pipeline filtering in difference image. The experiment results demonstrate that the proposed algorithm is appropriate to detect small targets under moving backgrounds, and the algorithm provides an instructive approach to the detection of small targets.

Keywords: Entropy Flow, Image Motion, Target Detection, 2-dimensional Histogram

1. Introduction

It is a challenging task to detect, identify and track small targets, since there is no shape, size, texture and other information can be used [1]. For the detection of the small moving target, many methods such as neural network [2], double-plateaus Histogram method [3], machine learning classifier and image feature selection-based method [4], eigen space-based method [5] and hausdorff trace transform-based method [6]. However these methods have poor detection performance in each application environment since the targets are small and background clutter is significant.

In order to detect small targets under moving background, this paper presents a novel approach to estimate the background motion, which is on the basis of the concepts of entropic map and entropy flow [7]. The concepts come from the visual mechanism of flying insects that rely on cues derived from image motion to avoid lateral obstacles, to control their speed and height, to cruise and land effectively and precisely, regardless of their relatively small brains and nervous systems. For the detection, recognition and tracing of small targets, such insects are assumed that they utilize relative motion cues to achieve this goal. Since there exists motion cue of small target in image sequence, it provides a possibility to detect small target according to those cues.

Entropy flow is a descriptor of image motion, and the computational method of entropy flow is based on the constancy assumption of instantaneous entropy value [7]. In this paper, the concept of entropy flow is applied to detect small moving target under moving background. We adopt the variational method to compute entropy flow field instead of the constancy assumption of motion vector in a local window. And we utilize the strategy of 2-dimensional histogram of entropy flow field to estimate the background motion, i.e. global motion, rather than the auto-selecting algorithm of assessment threshold.

In general, the compensation of background motion is an important process in the detection of small targets under moving background. So in this paper, the detection algorithm of small moving targets under moving background contains three important steps: Firstly, the computational approach of entropy flow field is chosen. Secondly, the establishment of the 2-dimensional histogram of entropy flow field is used to estimate the background motion. Thirdly, an appropriate threshold method is utilized to segment small targets.
The remainder of this paper is organized as follows: In section 2, we review the general method of small targets detection, and introduce the concept of entropy flow as well as the computational approach of entropy flow field. The variational method to the calculation of entropy flow field is presented in Section 3. The framework of the detection of small moving target based on entropy flow is described in Section 4, and Section 5 validates that entropy flow is suitable for the detection of small moving targets. Section 6 gives a summary and an outlook to future work.

2. The concept of entropy flow

2.1. The general approach to the detection of small targets under moving background

Target detection and tracking are becoming increasingly recognized as important algorithms in many vision systems. Especially, they are widely applied to surveillance systems. Due to complex moving backgrounds and varied luminance and contrast conditions, motion compensation is the basic part of the technique, especially for moving background video[10,11]. It compensates the background motion of image, and through this way, it makes the moving objects more obvious and the detection of target easier. There are two kinds of approaches adopted, one is feature-based methods, and the other is flow-based methods[12,13,14]. Feature-based methods extract features and match them between image frames to fit the global motion model of image sequence. Feature extraction and matching are prepared for image registration. The image registration that implements frame-to-frame registration of the image sequence is the key point of motion compensation. However, it is difficult to choose appropriate feature parameters, which relate to computational complexity and efficiency. Flow-based method can update local image information and help to form the trajectory of tracked objects.

2.2. The concept of entropy flow

Flying insects such as honeybees use 'visual flow' generated by their own motion for many purposes, including navigation, mating and identification of food sources [8,9]. Flying insects have high visual acuity owing to their compound-eye configuration, which are composed of tens of thousands of ommatidia. An eye must reconstruct its spatial environment from an array of intensity measurements, each measurement provided by an individual ommatidium. Information entropy is used to depict that intensity measurements, thus the concepts of entropic map and entropy flow are proposed [7], which characterize topographic features and measure the motion of an image respectively.

Optical flow is a convenient and useful approximation of image motion, defined as the projection of 3-D velocities of surface points onto the image surface-from spatiotemporal patterns of image intensity, and the movement of the image is reflected by its changes of brightness patterns [15]. Since the spatial environment of compound eyes is reconstructed from an array of intensity measurements, an entropic map is founded since the array of intensity information is represented by information entropy. Then the changes of brightness patterns become the changes of entropy patterns. Not surprisingly, a kind of entropy motion is approximate to the image motion, which is called entropy flow, described as the projection of the 3-D motion onto the entropic map plane.

2.3. A differential approach to the computation of entropy flow

In analyzing the motion within adjacent frames of an image sequence, temporal constancy has to be imposed on certain image features. The most frequently-used feature in this context is the image brightness, i.e. the grey values of image objects in adjacent frames do not change over time, then it conduces that the instantaneous entropy values in entropic map sequence stay the same over time.

The constraints on constancy and affine deformation of image motion are typically applied over local regions through a minimization. This assumption is not true across the entire image, while for small image regions, it provides an adequate approximation. Assume that in a small neighborhood Ω, the motion vectors remain constant, then entropy flow is obtained by minimizing the following energy
Small Moving Target Detection based on the Concept of Entropy Flow
Zhonghua Wang, Jianguo Liu, He Deng

where $W(x)$ represents a window function, $\nabla T$ is the spatial entropy value gradient and $V=(u, v)$ is denoted as entropy flow. The solution $V$ will be obtained through the least square method.

### 3. The computation of entropy flow

Optical flow and entropy flow are two descriptors of image motion, and the successful methods in the computation of optical flow are variational strategies [15]. As a result, we compute entropy flow field from a variational perspective that is we recover the entropy flow field $v$ as a minimum of a suitable energy functional, which contains data and regularizing smoothness terms. The proposed variational model is described as:

$$E(v) := \beta_1 \cdot E_{\text{data}}(v) + \beta_2 \cdot E_{\text{smooth}}(v)$$  \hspace{1cm} (3.1)

where $E(v)$ is the energy functional, and the weighting parameters $\beta_1, \beta_2$ are positive constant. Larger value for $\beta_2$ results in a stronger penalization of large flow gradient thus leading to smoother flow field.

Assume that $H: \Omega \subset \mathbb{R}^3 \rightarrow \mathbb{R}$ means a rectangular entropic map sequence with two spatial and one temporal dimension at points $\mathbf{x} := (x, y, t)^T$, $\Delta := \Delta_2 = a_{xx} + a_{yy}$ indicates Laplacian operator, and $\nabla := \nabla_3 = (a_x, a_y, a_t)$ denotes partial derivatives with respect to spatiotemporal case. In this case, we resort to a variational model to determine the entropy flow field $v: \Omega \subset \mathbb{R}^2 \rightarrow \mathbb{R}^2$.

#### 3.1. Variational model

It is not enough to compute the two unknown variables $u$ and $v$ (aperture problem), similar to the optical flow. It is only possible to determine the normal flow that is normal to entropic map edges. Then another constancy assumption is necessary. We assume that motion vectors remain constant in a small neighborhood of size $\delta$, similar to Lucas & Kanade which yields the best results in comparison [16]. Therefore, the data term is described as follows:

$$E_{\text{data}} := \int_{\Omega} G_\delta \left( H_x u + H_y v + H_t \right)^2 \, dx \, dy$$  \hspace{1cm} (3.1.1)

where the standard derivation $\delta$ of the Gaussian serves as an integration scale.

In order to obtain dense entropy flow field, the filling-in effect may happen in flat regions where the entropic map gradient vanishes. Then additional assumption is necessary, which usually forms the smoothness term of energy functional. The simplest regulariser is homogeneous regularization, and a more general model in smoothness term is presented in [17]. We accept that idea, and modify that model, then the regularizing smoothness term is described as:

$$E_{\text{smooth}} := \int_{\Omega} \left( \lambda_g + \lambda_l \cdot b(VH) \right) \left( |V u|^2 + |V v|^2 \right) \, dx \, dy \quad \text{where} \quad b(VH) := N \left( \sqrt{H_x^2 + H_y^2 + H_t^2}; \sigma_e \right)$$  \hspace{1cm} (3.1.2)

where $N$ denotes a non-normalized Gaussian function, and $\lambda_l$ and $\lambda_g$ are the local and global smoothness parameters respectively, which are positive constant.

Therefore, the entropy flow field is the solution of the following energy functional:
arg min \( E(v) \) = arg min \( \beta_1 \cdot E_{data}(v) + \beta_2 \cdot E_{smooth}(v) \)

\[
= \arg\min_{v,\nu} \beta_1 \int \int_{\Omega} G_s \ast (H_u + H_v) \cdot dxdy + \beta_2 \cdot \int \int_{\Omega} (\lambda_g \ast b(|\nabla H|))(\nabla u^2 + \nabla v^2) \cdot dxdy
\]

\[\text{(3.1.3)}\]

### 3.2. Algorithm implementation

The solution of the equation (3.1.3) is not trivial. The frequently-used approach is iterative strategy for solving the corresponding Euler-Lagrange equation (elliptic approach). Then the corresponding Euler-Lagrange equation of the equation (3.1.4) is shown as:

\[
\begin{align*}
\left( \lambda_g + \lambda_u \cdot b(|\nabla H|) \right) \Delta u &= -\frac{\beta_1}{\beta_2} \left( G_s \ast (H_u^2) u + G_s \ast (H_u H_v) v + G_s \ast (H_v H_u) \right) = 0 \\
\left( \lambda_g + \lambda_v \cdot b(|\nabla H|) \right) \Delta v &= -\frac{\beta_1}{\beta_2} \left( G_s \ast (H_u H_v) u + G_s \ast (H_v^2) v + G_s \ast (H_v H_u) \right) = 0
\end{align*}
\]

The equation (3.2.1) is linear with respect to the unknown variables \( u \) and \( v \). Finite difference methods afford a powerful tool for obtaining approximate numerical solutions, though their analytic solutions are not known. Gauss-Seidel or successive over-relaxation (SOR) iterations are good compromise between simplicity and efficiency, and these algorithms are appropriate to solve a linear system. The initialization is not critical in SOR iteration, since the method is globally convergent. So we adopt SOR iteration to recover the entropy flow field. Then the finite difference approximation of the equation (3.2.1) is described as:

\[
\begin{align*}
\left( \lambda_g + \lambda_u \cdot b(|\nabla H|) \right) \sum_{j \in R(i)} {\frac{u_j - u_i}{h^2}} \frac{\beta_1}{\beta_2} \left( G_s \ast (H_u^2) u_i + G_s \ast (H_u H_v) v_i + G_s \ast (H_v H_u) \right) &= 0 \\
\left( \lambda_g + \lambda_v \cdot b(|\nabla H|) \right) \sum_{j \in R(i)} {\frac{v_j - v_i}{h^2}} \frac{\beta_1}{\beta_2} \left( G_s \ast (H_u H_v) u_i + G_s \ast (H_v^2) v_i + G_s \ast (H_v H_u) \right) &= 0
\end{align*}
\]

(3.2.2)

This sparse linear system may be solved iteratively by using SOR method. If the upper index denotes the iteration step, the iterative solution of the equation (3.2.2) will be written as:

\[
\begin{align*}
u^{i+1} &= (1 - \omega) v^i + \omega \sum_{j \in R(i)} {\frac{v_j - v_i}{h^2}} \frac{\beta_1}{\beta_2} \left( G_s \ast (H_u^2) u_i + G_s \ast (H_u H_v) v_i + G_s \ast (H_v H_u) \right) \\
u^{i+1} &= (1 - \omega) v^i + \omega \sum_{j \in R(i)} {\frac{v_j - v_i}{h^2}} \frac{\beta_1}{\beta_2} \left( G_s \ast (H_u H_v) u_i + G_s \ast (H_v^2) v_i + G_s \ast (H_v H_u) \right)
\end{align*}
\]

(3.2.3)

where \( \omega \in (0, 2) \) has a strong influence on the convergence speed: the values of \( \omega > 1 \) are used to speed up convergence of a slow-converging process, while the values of \( \omega < 1 \) are often used to help establish convergence of a diverging iterative process.

### 3.3. The performance

The proposed entropy flow is appropriate to estimate image motion. In order to test our proposed computational approach of entropy flow, we compare the descriptive performance of image motion of the presented method with the global method (Horn & Schunck), local method (Lucas & Kanade) [15]. Some of those comparisons are given as the average and standard deviation of the angular errors (Av. Err. and St. Dev.), whose motive is to better interpret our results. We focus on some synthetic
image sequences - Sphere, Office, Yosemite without cloud sequences, since their ground-truth flow fields are known. The qualitative performance of image motion field is authenticated by the quantitative evaluation, i.e. measuring in terms of the error measure [15], namely the angular error between the correct image motion $u_0$ and the estimated entropy flow $u_e$ via $\phi_e := u_0 \cdot u_e / \| u_0 \| \| u_e \|$, where $\phi_e$ is the angular error.

The rotational motion is dominating in the synthetic Sphere sequence, whose images are color, and the size is 200×200×3. The estimation of entropy flow in color image sequence is out of our scope in this paper. So we firstly convert them into grayscale images, and present the 7th frame in Figure 1 (a). The ground-truth flow field between frame 7 and 8 is known previously, and it is shown in Figure 1 (b). The computed flow field based on Horn & Schunck, Lucas & Kanade approaches, and our method are shown in Figure 1 (c), (d) and (e) respectively. All the flow fields are shown in the same criteria for visualization.

![Figure 1. The flow field contrasts. (a) The 7th frame of the Sphere sequence. (b) Its ground-truth flow field. (c), (d) and (e) are the computed flow fields according to different computational approaches.](image)

From Figure 1, we can see that the performance of the presented method is superior to that of other approaches, and the computed entropy flow field is more approximate to the ground-truth flow field. The same conclusion is also obtained from Table 1. The computed Av. Err.s and St. Dev.s of Sphere, Office and Yosemite without cloud based on Horn & Schunck, Lucas & Kanade approaches, as well ours are presented in Table 1 respectively.

<table>
<thead>
<tr>
<th>Sequences</th>
<th>Methods</th>
<th>Horn &amp; Schunck</th>
<th>Lucas &amp; Kanade</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sphere</td>
<td>Av. Err.</td>
<td>5.1329°</td>
<td>4.7487°</td>
<td>3.4470°</td>
</tr>
<tr>
<td></td>
<td>St. Dev.</td>
<td>9.6226°</td>
<td>8.8341°</td>
<td>7.4419°</td>
</tr>
<tr>
<td>Office</td>
<td>Av. Err.</td>
<td>13.7660°</td>
<td>12.4387°</td>
<td>9.0488°</td>
</tr>
<tr>
<td></td>
<td>St. Dev.</td>
<td>10.6899°</td>
<td>12.6790°</td>
<td>8.1590°</td>
</tr>
<tr>
<td>Yosemite</td>
<td>Av. Err.</td>
<td>18.4379°</td>
<td>15.1573°</td>
<td>12.9484°</td>
</tr>
<tr>
<td></td>
<td>St. Dev.</td>
<td>17.8891°</td>
<td>15.3506°</td>
<td>13.1430°</td>
</tr>
</tbody>
</table>

The motion in the above synthetic sequences is rigid, the performance of the presented method is superior to that of Horn & Schunck, Lucas & Kanade approaches in both qualitative and quantitative comparisons. While for nonrigid, this conclusion may be right or not? And then we resort to MiniCooper sequence, which descrip t a man closing the trunk cover. The 10th frame is shown in Figure 2 (a). We also displayed the computed magnitudes of flow fields based on Horn & Schunck, Lucas & Kanade approaches, as well our method in Figure 2 (b), (c) and (d) respectively. In the same criteria for visualization, that conclusion obtained from the rigid motion is also right for nonrigid motion.
Small Moving Target Detection based on the Concept of Entropy Flow
Zhonghua Wang, Jianguo Liu, He Deng

Figure 2. The magnitude contrasts. (a) The 10th frame of the MiniCooper sequence. (b), (c) and (d) are the computed magnitudes of flow field based on the different approaches.

4. Small moving targets detection based on entropy flow

Based on the optical flow field, there are two methods for detecting moving objects. One way is to find discontinuities in the flow field; the other is a histogram-based algorithm [18]. In this paper, we want to use the analogue histogram-based approach to detect small targets, which is on the basis of entropy flow field.

4.1. The framework of the detection algorithm

The proposed small targets detection algorithm originates from the idea of Russo et al. [18], who suggest to build a 2-dimensional histogram of flow field, and then they recognize that the main peak in the histogram would correspond to background and clutter motion, and the smaller local peaks would likely correspond to moving objects. This result is true in the small target detection, since the motions of moving targets are noticeably different from background and clutter motion and their individual sizes (areas) is significantly smaller than that of the background.

We want to use the concept of entropy flow to estimate the image motion, and assess the background motion from the 2-dimensional histogram of entropy flow field (EFH), thus a residual image that contains small targets is obtained. The proposed small targets detection approach consists of the following steps, and the framework of the algorithm is shown in Figure 3.

1) Compute entropy flow field using a variational method, according to Section 3;
2) Construct 2-dimensional histogram of entropy flow, and determine the main peak in the histogram, i.e. ascertain the motion field of the background;
3) Compensate the background motion, and obtain a difference image that contains small targets;
4) Segment the small targets through a threshold.

Figure 3. The framework of detection algorithm based on entropy flow

4.2. Discussion

The choice of threshold is vital in small targets detection. However, in the separation of real targets, it is unavoidable to bring some false targets. The pipeline filtering technique [19] is applied to ascertain real targets and abandon pseudo candidates, since pipeline filter is a spatial-temporal filter which is to reduce the effect of noise in the time sequence. When some noise pixels with high intensity levels are distributed close together both spatially and temporally in the pipeline, their effect on the temporal window summation is significant and can result in false detection. Notice that these
pixels do not have to be continuously distributed in adjacent frame while the continuity and smoothness constraint of target trajectory restricts the pixels in adjacent frames to stay within a small neighborhood of each other. In this paper, we adopt the following simple principle: If a candidate appears $m$ times and its location changes $k$ times in continuous $n$ frames, it will be verified as a real target. Otherwise, it will be considered to be a noise.

The 11th, 18th and 51st frames of three small target image sequences under sky background (selected randomly in the sequences) are shown in Figure 4 (a1), (b1) and (c1) respectively. The target is a fighter plane in each image, while they all have in the form of bright spots. The cloud motion has great effect on the detection effectiveness. The corresponding entropic maps according to [10], the computed entropy flow fields between them and their respective subsequent frames, 2-d histograms of entropy flow field and the detection results are shown in Figure 4 (a2) ~ (c5) respectively.
Small Moving Target Detection based on the Concept of Entropy Flow
Zhonghua Wang, Jianguo Liu, He Deng

Figure 4. The experimental results. (a1) ~ (c1) represent one frame of different small target sequences. (a2) ~ (c2) are the corresponding entropic maps. (a3) ~ (c3) display the computed entropy flow fields. (a4) ~ (c4) are 2-d histograms of entropy flow fields. (a5) ~ (c5) are the detection results.

5. Experiments

5.1. Dataset description

In order to test our algorithm on the detection of small moving targets under moving background, we have done many experiments on small target image sequences, which are under sky background. The target in each image is a fighter plane, which is expressed in the bright spot. The complexity of image backgrounds is different, and some single-frame images of these three image scenes are shown in Figure 4. Without doubt, the moving cloud has a great influence on the detection result, even it is impossible to detect the plane when it submerges in the cloud. Then pipeline filtering approach is used to confirm real targets. In this paper, if a candidate appears 4 times and its location changes 3 times in continuous 5 frames, it will be verified as a real target. There is one image sequence in every data set, each image sequence contains 50 frames, and the image size is 460×620. The subsequent experiments were implemented by matlab R2008a on a computer with AMD Athlon II X2 240 2.80-GHz CPU, 1.75-G RAM, and Microsoft Windows XP operating system

5.2. Performance evaluation

The qualitative norms are the probability of detection ($P_{\text{detect}}$) and the probability of false alarm ($F_{\text{false}}$), which represent the probability of detection of target in multiframes where targets exist, and the probability of false alarm of targets in multiframes where targets do not exist respectively. In this paper, the false-alarm rate $F_{\text{false}}$ and the detection probability $P_{\text{detect}}$ are defined as following.

$$F_{\text{false}} := \frac{M_{\text{false}}}{M_{\text{total}}} \times 100\% \quad P_{\text{detect}} := \frac{N_{\text{detect}}}{N_{\text{total}}} \times 100\%$$

(5.2.1)

where $M_{\text{false}}$, $M_{\text{total}}$, $N_{\text{detect}}$ and $N_{\text{total}}$ denote the number of false detections in the whole sequence, the number of frames of the whole sequence, the number of true detections, and the number of true targets in the whole sequence respectively.

The detection probabilities and false-alarm rates of above three sequences are shown in Table 2. Since the computational process of entropy flow field involves the iterated operation, the average overhead time of the detection procedure may consume much time. In this paper, the iterations are 10. The average overhead time of three sequences are shown in Table 2 as well.

Table 2. The detection probabilities, false-alarm rates and time consumings on each sequence including 50 frames.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Figure 4 (a1)</th>
<th>Figure 4 (b1)</th>
<th>Figure 4 (c1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elapsed time (s) (50 frames)</td>
<td>7.1573</td>
<td>6.9543</td>
<td>6.9616</td>
</tr>
<tr>
<td>Detection probability</td>
<td>94%</td>
<td>85%</td>
<td>82%</td>
</tr>
<tr>
<td>False-alarm rate</td>
<td>6%</td>
<td>20%</td>
<td>26%</td>
</tr>
</tbody>
</table>
6. Summary and Conclusion

In this paper, we have employed the concepts of entropic map and entropy flow to detect small moving targets under moving background. We have presented a variational method to compute entropy flow since entropy flow is approximate to image motion, then we have used a 2-dimensional histogram-based approach to eliminate the motions of non-target objects, the pipeline filter has been used to confirm real target finally. Aiming to estimate target motion, the presented method is superior to that of the optical flow approach. Detecting and tracking the target, the presented method also has good performance under background clutter. However, other methods may be explored to weed spurious motions better, which are the focus of our further research.

7. Acknowledgements

This work is supported by the Project of the National Natural Science Foundation of China under Grant No.61071136 and the Project of the National Youth Science Foundation of China under Grant No.40801164. The authors would like to thank the anonymous reviewers for their valuable comments and advice.

8. References


