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Infrared small moving target detection method based on graph matching

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We apply graph matching method to detect infrared small moving targets using image sequences. Candidates (interest points) detected in the first frame form one graph and the same candidates in the last frame form another one. The real moving targets are extracted by matching these two graphs. Experimental results demonstrate that the proposed method is robust and efficient to the translation and rotation of the background.

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The ability to detect moving targets in infrared images or videos has a major impact on the areas of pre-warning, precision guide, and so on. Yang et al. used an adaptive Butterworth high-pass filter to detect small target. Wang et al. proposed a small target detection method based on the cubic facet model. Deshpande et al. provided a moving target detection method based on max-mean and max-median filters. Zhang et al. presented an algorithm for detecting dim moving point targets under the condition of constant false-alarm ratio. Bae used spatial bilateral filter and temporal cross product of temporal pixels to detect moving targets. The performances of the abovementioned methods are good when the background is static. To enhance the efficiency of small moving target detection, we propose a new method based on graph matching which is robust to the translation and rotation of the background. The experiments reflect the method as being efficient and robust.

Infrared small targets look like small bright dots, so they can be detected by difference of Gaussian (DOG) filters. The candidates are called as interest points in this letter. The difference of two Gaussians with different standard deviations forms a DOG filter.

\[
\text{DOG}(x, y, \sigma_1, \sigma_2) = G(x, y, \sigma_1) - G(x, y, \sigma_2)
\]

\[
= \frac{1}{2\pi} \left( \frac{1}{\sigma_1^2} \exp \left( -\frac{x^2 + y^2}{2\sigma_1^2} \right) - \frac{1}{\sigma_2^2} \exp \left( -\frac{x^2 + y^2}{2\sigma_2^2} \right) \right),
\]

where \(\sigma_1 \in \{2, 3, 4\}, \sigma_2 \in \{3, 4, 5\},\) and \(\sigma_1 < \sigma_2,\) which is similar to the center surround mechanism of human visual system.

A group of feature maps with different scales are obtained after filtering the first frame of image sequence using DOG filters. All of these feature maps are combined together to get the saliency map. The rule of the combination of feature maps is given as

\[
\text{Sali}(x, y) = \max_{\sigma_1, \sigma_2} \{I(x, y) \ast \text{DOG}(x, y, \sigma_1, \sigma_2) \} \quad \sigma_1 < \sigma_2, \quad (2)
\]

where \(I(x, y)\) stands for the input image and the symbol “\(\ast\)” denotes the operation of convolution.

Then the estimated position of the \(n\)th interest point is described as follows,

\[
\hat{a}^n_{i-1} = \frac{v^n_{i-1} - v^n_{i-2}}{t},
\]

\[
\hat{a}^n_{i-1} = \frac{v^n_{i-1} - v^n_{i-2}}{t}. \quad (3)
\]

where \(I^n_{i-1}\) is the detected position of the \(n\)th interest point in the \((i-1)\)th frame using

\[
I^n_{i} = I^n_{i-1} + v^n_{i-1} \cdot t + 0.5 \cdot a^n_{i-1} \cdot t^2 + \tilde{e}, \quad (4)
\]

where \(I^n_{i-1}\) is the detected position of the \(n\)th interest point in the \((i-1)\)th frame and \(\tilde{e}\) is the estimated error.

Step 2: A local region (the area is \(w \times w\)) centered at \(\hat{I}^n_i\) in the \(i\)th frame of the original image is filtered using DOG filters. Then the local saliency map of the \(n\)th interest point is obtained.

Step 3: A Gaussian window centered at \(\hat{I}^n_i\) is added in the local saliency map to reduce the influences of points away from the center. The point with maximum saliency value in the local region is treated as the real interest point in the \(i\)th frame, the detected position is \(I^n_{i} \).
In this process, these interest points are tracked for L frames, and an interest point is eliminated if it deviates from the field. After this process, two graphs are formed. Interest points in the first frame, being treated as dots, and the distances between each other, being treated as the edges, form the first graph. Those of the last frame form the second graph. The moving targets are detected using the graph matching method.

Suppose that the rotation angle and the translation between the backgrounds of the first and the last frames, and where considering the scale changes is established as

\[ X^i_n - X = W_j^i(\Delta \theta)(X^i_n - X - \Delta X), \]

\[ W_j^i(\Delta \theta) = \begin{bmatrix} \cos \Delta \theta & -\sin \Delta \theta \\ \sin \Delta \theta & \cos \Delta \theta \end{bmatrix}, \]

\[ \|X^i_n - X^i_n\|_2 = \|W_j^i(\Delta \theta)(X^i_n - X - \Delta X) - W_j^i(\Delta \theta)\|_2 = \|W_j^i(\Delta \theta)(X^i_n - X^i_n)\|_2 = \|X^i_n - X^i_n\|_2, \]

where \( W_j^i \) is the transformation matrix of the coordinate systems from the first frame to the last frame, and \( X^i_n \) and \( X^i_c \) are the positions of the \( n \)th background points of the first and the last frames, respectively.

Equation (6) explains that the values of 2-norms of the difference of two background points are equal, that is, the length between two background points does not change. Let us consider the graphs shown in Fig. 2.

The dots in these graphs stand for interest points. The distance between two interest points forms the edge of the graph. Graphs \( b \) and \( c \) are formed through rotating graph \( a \) by 90° counterclockwise. Otherwise, the interest point \( A'' \) in graph \( c \) has a motion of translation. Figure 2 illustrates that the relative positions of two points in graph \( b \) do not change comparing with those in graph \( a \). If there is a moving target, such as point \( A'' \) in graph \( c \), the relative positions between point \( A'' \) and others are changed. In light of this regulation, a novel small moving target detection method based on graph matching is proposed. We use the difference of relative positions in the construction of the metric which is formulated as

\[ E(n) = \sum_{m=1}^{N} \left( \|X^i_n - X^i_f\|_2 - \|X^i_n - X^i_f''\|_2 \right)^2, \quad n = 1, 2, \ldots, N \]

where \( n \) stands for the \( n \)th interest point. The larger the \( E(n) \), the more likely the \( n \)th interest point is the moving target. The criterion of the moving targets is given as

\[ \text{The } n \text{th point is } \begin{cases} \text{the target point } & E(n) \geq s \cdot \max(E), \\ \text{the background point } & \text{else}, \end{cases} \]

where \( s \) is a parameter. This factor makes this method detect not only one moving target but also more targets.

Figure 3 gives the detection result of moving targets in Fig. 1 using graph matching. Figure 3(a) shows the \( E \) values of different points and Fig. 3(b) shows the detected moving targets.

To evaluate the target detection performance, the proposed methods are compared with other five sophisticated methods: high-pass filter method\(^8\), max-median method and max-mean method\(^9\), Zhang’s method\(^4\), and Bae’s method\(^5\) by using a mass of image sequences.

In this letter, we present only the results of four sequences (Seq1–Seq4): not only one moving target exists in Seq1, the background of Seq2 has a rotational motion, the background of Seq3 has only a translation motion, and Seq4 has a static background. Three parameters are needed in our algorithms. Threshold \( \text{th1} \) is needed when detecting the interest points. The total number of the frames \( L \) is needed in tracking process. Different sequences have different thresholds in our method. Table 1 gives the best threshold of each sequence. The last parameter \( s \) is an important parameter of graph matching. Results of many experiments...
A ROC curve plots the true positive ratio, TPR as a function of FPR, the false positive ratio in sequence, given by

\[ \text{TPR} = \frac{N_{TT}}{N_{TT} + N_{FT}}, \quad \text{FPR} = \frac{N_{FT}}{N_{FT} + N_{TC}}. \]  

(10)

where \( N_{TT} \) and \( N_{FT} \) are the quantities of true targets and false targets detected in images, respectively, and \( N_{TC} \) and \( N_{FC} \) are the quantities of true clutters and false clutters detected in images, respectively. The TCR values of these sequences obtained by different methods are shown in Table 2 where symbols (b)–(g) stand the same as Fig. 4. These results are still their best performances. From the data in Table 2, we have the same conclusion.

Table 1. Parameters Used in Experiments

<table>
<thead>
<tr>
<th></th>
<th>Seq1</th>
<th>Seq2</th>
<th>Seq3</th>
<th>Seq4</th>
</tr>
</thead>
<tbody>
<tr>
<td>th1</td>
<td>0.059</td>
<td>0.035</td>
<td>0.035</td>
<td>0.200</td>
</tr>
<tr>
<td>L</td>
<td>10</td>
<td>20</td>
<td>10</td>
<td>10</td>
</tr>
</tbody>
</table>

Sometimes, it is not enough to mention that the method with better best performance is more efficient and more accuracy than the method with worse best performance. We need to compare the results under different conditions such as different false-alarm rates. So the performance of these algorithms is evaluated by a receiver operating characteristic (ROC) using Seq1 further.

Table 2. Comparison Results of TCR of Six Image Sequences Obtained by Different Methods

<table>
<thead>
<tr>
<th></th>
<th>Seq1</th>
<th>Seq2</th>
<th>Seq3</th>
<th>Seq4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TCR</td>
<td>0.315</td>
<td>0.090</td>
<td>0.087</td>
<td>1.000</td>
</tr>
<tr>
<td>(b)</td>
<td>0.332</td>
<td>0.078</td>
<td>0.085</td>
<td>1.000</td>
</tr>
<tr>
<td>(c)</td>
<td>0.338</td>
<td>0.084</td>
<td>0.096</td>
<td>1.000</td>
</tr>
<tr>
<td>(d)</td>
<td>0.407</td>
<td>0.093</td>
<td>0.159</td>
<td>1.000</td>
</tr>
<tr>
<td>(e)</td>
<td>0.431</td>
<td>0.085</td>
<td>0.141</td>
<td>1.000</td>
</tr>
<tr>
<td>(f)</td>
<td>0.910</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>(g)</td>
<td>0.910</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

These values are obtained by adjusting the thresholds of these methods. Figure 5 shows the ROC curves. According to the properties of ROC curve, the proposed method is much better than others.

In conclusion, sophisticated methods are sensitive to the translation and rotation of the background. So we propose an infrared small target detection method based on graph matching to conquer this shortcoming. Experimental results verify that the proposed method...
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References