Application Research of Moving Target Detection Based on Optical Flow Algorithms

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Abstract. After many years of research, optical flow algorithm has achieved good results in detecting moving objects in simple scenes, but the detection effect in some complex scenes is not ideal, for example, in scenes with changing illumination and large displacement, the accuracy of moving objects detection is low. In order to solve this problem, this paper proposes texture decomposition of images, and applies texture image and pyramid technology to Lucas-Kanade optical flow algorithm. Relevant experiments show that this method can achieve better detection results for moving objects in static scenes.

1. Introduction
Moving object detection technology is the basis of high-level vision understanding. It is to extract moving object from video image sequence, so how to extract the whole moving object quickly and accurately is a difficult problem in moving object detection.

At present, the most commonly used methods are background subtraction, frame difference and optical flow. The frame difference method has the advantages of low computational complexity, easy implementation, strong adaptability to the environment and high stability, but it is usually difficult to obtain the complete contour of moving objects, which is prone to "hollow" phenomenon. Background subtraction is to build a background model by learning the video frames, the foreground object is obtained by subtracting the background model from the input video sequence[1]. The algorithm is sensitive to the change of illumination, and the extracted foreground has shadow. Optical flow algorithm can know not only the location of moving object, but also its velocity and direction. At the same time, optical flow method does not need background modeling and background updating, and the resulting moving object will not appear "holes" and "ghosts", so it is widely used.

In order to solve the problem of moving object detection in complex scenes, an improved optical flow algorithm is proposed. The image texture decomposition and image pyramid techniques are applied to the Lucas-Kanade light flow algorithm to reduce the interference of illumination variation and large displacement to moving target detection.

2. Lucas-Kanade Optical Flow Algorithm

2.1. Optical flow field
Optical flow field is the instantaneous motion vector of all pixels. If the Pixel brightness of the object remains the same while the object is moving, then the instantaneous velocity of the brightness is the optical flow, and the light flow of all the pixels in the image constitutes the optical flow field. The concept of optical flow dates back to 1950, when it was first proposed by psychologist Gibson[2].

The optical flow algorithm assumes that:
(1) The brightness of the pixels is constant between two adjacent frames;
(2) The motion between two frames of the same time and within two frames is smaller;
(3) All the pixels of the same object have the same trajectory, that is, the same space.

2.2. L-K algorithm
Lucas-Kanade (L-K) algorithm is a classical algorithm of sparse optical flow method. It was proposed by Lucas and Kanade in 1981. L-K algorithm mainly calculates the motion information of the corresponding pixels between two frames, and calculates the information of the pixels in the small target, so as to get the optical flow vector[3].

Assuming that in the small neighborhood $\Omega$ of $(x, y)$, the optical flow of all the pixels is basically the same, which can be roughly approximated to $(u,v)$. Then, different weights are given to each point in the region. According to the weights and $(u,v)$, the accurate optical flow at point $(x,y)$ is calculated. Let there be $n$ pixels in the neighborhood of $\Omega$, and $(u,v)$ corresponding to each pixel should satisfy the basic equations $n$ of formula (1):

$$I_{x_i}u + I_{y_i}v + I_o = 0 \quad i = 1, 2, ..., n$$

The basic constraint equation of optical flow is equation (2):

$$E_e(u,v) = \int \int [I_{x_i}u + I_{y_i}v + I_o]^2 \, dx \, dy$$

In the neighborhood of $\Omega$, the error of the Lucas-Kanade light flow is formula (3):

$$E_{LK}(u,v) = \int \int W^2(x,y) \, (I_{x_i}u + I_{y_i}v + I_o)^2 \, dx \, dy$$

Among them, $W(x,y) = \{w_i | i = 1, 2, ..., n\}$ is the weight of each point in the neighborhood of $\Omega$, and its distribution characteristics are that the more deviated from the center, the smaller the corresponding weight value.

By discretizing formula (3), the L-K optical flow at the point can be obtained as follows:

$$\begin{bmatrix}
\sum_{i=1}^{n} w_i^2 I_{x_i}^2 \\
\sum_{i=1}^{n} w_i^2 I_{y_i}^2 \\
\sum_{i=1}^{n} w_i^2 I_{x_i} I_{y_i}
\end{bmatrix}
\begin{bmatrix}
u \\
v
\end{bmatrix}
= -\begin{bmatrix}
\sum_{i=1}^{n} w_i^2 I_{x_i}
\sum_{i=1}^{n} w_i^2 I_{y_i}
\sum_{i=1}^{n} w_i^2 I_{x_i} I_{y_i}
\end{bmatrix}$$

Among them, $I_{x_i}$, $I_{y_i}$, $I_o$ are the gradient values of $i$ pixels in the neighborhood of $\Omega$ along $x$, $y$, $t$ directions, and $w_i$ is the weight of the point. If the order formula (5) holds:

$$A = \begin{bmatrix}
I_{x_1}...I_{x_n} \\
I_{y_1}...I_{y_n} \\
\end{bmatrix}^T, W = \text{diag}(w_1, w_2, ..., w_n), b = [I_{x_1}, I_{x_2}, ..., I_{x_n}]^T$$

Then formula (4) can be expressed as formula (6):

$$A^TW^2A \begin{bmatrix}
u \\
v
\end{bmatrix} = A^TW^2b$$

The solution of formula (6) can be written as formula (7):

$$\begin{bmatrix}
u \\
v
\end{bmatrix} = (A^TW^2A)^{-1}A^TW^2b$$

3. Algorithm in This Paper
3.1. The decomposition technology of structural and texture
The purpose of image decomposition is to decompose the image information that people need from the
input image. Because the texture image only contains the details of the image and does not contain the geometric information sensitive to the change of light, the input image is divided into the structural part and the texture part. Then the optical flow field of the input image is calculated by using texture image instead of the input image, so that the deviation caused by the change of light can be avoided.

The structure texture decomposition of an image is to decompose the image into a structure and a texture\[4\], which can be mathematically expressed as formula (8):

\[
I(x, y) = I_s(x, y) + I_f(x, y)
\]

Where \(I(x, y)\) represents the known input image, \(I_s(x, y)\) represents the image structure part, \(I_f(x, y)\) represents the image texture part.

That is, the texture component \(I_f(x, y)\) is:

\[
I_f(x, y) = I(x, y) - I_s(x, y)
\]

### 3.2. Image pyramid technology

In the basic constraint equation of optical flow, it is assumed that the two frames are moving in small displacement, but in the real scene, the motion speed is faster and the displacement of the two frames is quite different, which makes the assumption not valid. We can use image pyramid technology to satisfy the basic constraints of optical flow by reducing image resolution.

In this paper, the Gauss pyramid is used to downsample the image, that is, to reduce the image. It works like this:

1. Assuming the layer \(k\) image is known, now calculate the layer \(k + 1\) image;
2. Have the layer \(k\) image convolution with the gauss kernel, removing all even rows and columns;
3. The resulting image is the layer \(k + 1\) image.

It can be seen that the Gauss pyramid can reduce the image size, reduce the resolution and descend the order from bottom to top. For different pyramid layers, combining LK optical flow method to calculate optical flow can improve the accuracy of optical flow calculation\[4\].

### 3.3. Algorithmic principles and procedures

In order to overcome the inadaptability of optical flow in the condition of illumination variation and large displacement, the image texture-structure decomposition technique and image Gaussian pyramid technique are used in the Lucas-Kanade optical flow algorithm Fig.1 shows the schematic diagram of the improved algorithm.

![Fig.1 The schematic diagram of algorithm in this paper](image-url)
The processing steps of the algorithm are as follows:

Step1: From the input video, select two consecutive frames, frame \( k \) and frame \( k+1 \), with illumination variation or large displacement movement;

Step2: The two frames are preprocessed, that is, the image is reduced to proper size, denoised and grayed to improve the processing speed and reduce the running time.

Step3: The gray-scale image is decomposed into the structure of the main structure of the image and the texture of the image texture information;

Step4: After the decomposition of the texture image instead of the input image for follow-up operation, the size of the image to determine the number of pyramid layer \( L \), The optical flow initialization \( u^0 = 0, v^0 = 0 \);

Step 5: Pass optical flow \((u^k, v^k)\) to layer \( k + 1 \), compute \( I_x, I_y, I_{xx}, I_{yy}, I_{xy}, I_{xt} \) and \( I_{yt} \);

Step 6: Set the iteration number to \( m \) and initialize the \( du^0 = 0, dv^0 = 0 \);

Step 7: According to Lucas-Kanade optical flow algorithm to solve \( u^{k+1}, v^{k+1} \);

Step 8: Post-process the result of step 7 and output the final result;

Step 9: If \( k \neq L - 1 \), go to Step 5, and let \( k = k + 1 \); otherwise, output the result.

4. Experimental Results and Analysis

The experimental environment of this paper is Microsoft Windows 10. The processor is Intel i7-8700, the main frequency is 3.20 GHz, the memory is 8.00GB. The experiment is based on the Matlab R2014a. The experimental data are LASIESTA(Labeled and Annotated Sequences for Integral Evaluation of Segmentation Algorithms) data set[5], and the size of the images are 352*288.

4.1. Moving object detection under varying illumination

In the experiment, 128th frame and 129th frame images of I_IL_01 image sequence in the LASIESTA data set indoor sequence were used, and the illumination of this image sequence changed before and after the light was turned on. Fig.2 shows the experimental results.
It can be seen that the background illumination has not changed much since the light has not been turned on in the 128th frame image, and the above algorithms have successfully extracted moving objects. But the 129 frame is the image after the light is turned on. Compared with the traditional L-K, the algorithm in this paper is less affected by noise, and the detection accuracy is obviously higher.

4.2. Moving object detection under large displacement

In order to simulate the situation of large displacement, the 118th and 122th frame of I_SI_01 image sequence in LASIESTA data set are selected. Fig.3 shows the experimental results.

Fig. 2 The result of moving target detection

(c) The improved algorithm in this paper

Fig. 3 The result of moving target detection

(a) Input image

(b) L-K optical flow algorithm

(c) The improved algorithm in this paper
It can be seen that in the motion scene with large displacement, the traditional LK detection effect is not very good. Some optical flow points have drift. However, the detection effect of this algorithm is not too disturbed. It can still detect the complete moving target, and the detection effect is better.

4.3. Quantitative analysis

To further verify the accuracy of moving object detection, the following quantitative analysis is performed. The most commonly used criteria for optical flow performance are average of angle error (AAE) and average of endpoint error (AEE) [6]. The AAE formula is shown in formula (10):

\[
AAE = \frac{1}{N} \sum_{i=1}^{N} \arccos \left( \frac{u_i \times u_{GT} + v_i \times v_{GT} + 1}{\sqrt{u_i^2 + v_i^2 + 1} \sqrt{u_{GT}^2 + v_{GT}^2 + 1}} \right)
\]  

(10)

The AEE formula is shown in formula (11) as follows:

\[
AEE = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(u_i - u_{GT})^2 + (v_i - v_{GT})^2}
\]  

(11)

In formula (10) and (11), \(N\) is the number of pixels in the image, \((u, v)\) is the computational optical flow field, \((u_{GT}, v_{GT})\) is the real optical flow field.

We select the video frames I_BS_02, I_IL_01, I_SI_01 in the LASIESTA data set, compute the AAE and AEE metrics of LK and algorithm, as shown in Tab.1.

|         | I_BS_02 | I_IL_01 | I_SI_01 |
|---------|---------|---------|---------|
| AAE     | LK      | 9.95    | 5.1     | 7.01    |
|         | Ours    | 8.12    | 3.02    | 3.26    |
| AEE     | LK      | 0.36    | 0.51    | 0.58    |
|         | Ours    | 0.19    | 0.2     | 0.31    |

As can be seen from Tab.1, the AAE and AEE of the improved algorithm under static background are lower than LK.

5. Conclusion

According to the principle of Lucas-Kanade light flow algorithm, the image texture decomposition and image pyramid technique are applied to the detection of moving objects. The robustness and generality of the proposed algorithm are verified by comparing the experimental results with the traditional optical flow algorithm.

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