Research on Stereo Matching Algorithm Based on Improved Steady-State Matching Probability

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Abstract. Aiming at the hole phenomenon generated by steady-state matching probability (SSMP) stereo matching algorithm in the test graph where the disparity is large, and the problem of correct disparity loss in the left disparity map caused by the error disparity in the right disparity map after using that algorithm. A stereo matching algorithm based on SSMP and semi-global matching (SGM) is proposed. Using the consistency detection method of the disparity maps obtained by SSMP and SGM are presented to fill the disparity map and the filling criterion based on hill-climbing algorithm is introduced. The experimental results demonstrate that the average bad pixels rates of the improved SSMP algorithm is reduced from 5.38% to 5.23% on the Middlebury benchmark. And the proposed algorithm can deal with the above problems well, improve the matching accuracy effectively and robustness.

1. Introduction
As one of the hot spots in the field of machine vision, stereo matching can be divided into two categories: local algorithms and global algorithms. Global algorithms include graph cut (GC) [1], dynamic programming (DP) [2], believe propagation (BP) [3], etc. Global algorithms have high precision but slow speed and local algorithms have fast speed but low precision.
In 2011, Rhemann used color graph as the guide filter to aggregate matching cost quickly [4]. Yang pioneered the cost aggregation using the minimum spanning tree method in 2012 [5]. In 2014 Ham proposed the SSMP to obtain disparity map with high accuracy [6]. However, the SSMP often leads to the loss of correct disparity information because of the occlusion. The hill-climbing algorithm is used to segment images based on the consistency of color, using the disparity of the same label page to fill the disparity inconsistency pixels and solving the hole problem of the disparity map. And the disparity consistency between the disparity map obtained by using the SSMP and another one derived by using the cost aggregation method in the SGM is used to solve the problem of the correct disparity loss in the left disparity map due to the inaccuracy of the right disparity map.

2. SSMP
The process of the SSMP is shown in figure 1. First, the initial matching cost function is constructed by using GRD. Then, using the RWR and winner takes all (WTA) to aggregate the matching cost and get an initial disparity map. And finally the refined disparity map is obtained by the empty pixels filling and median filtering.
Figure 1 The flow chart of SSMP algorithm

2.1. Matching cost computation
The matching cost is constructed by using the combination of intensity and gradient information. For any pixel point \( p(x, y) \) in the left image, the corresponding disparity is \( d \), and in the right image \( pd(x-d, y) \) is the corresponding matching point of \( p \). The initial matching cost function is as follows:

\[
C^0(p, d) = \delta \cdot \min\{\|\psi(p, d)\|, \tau_1\} + (1 - \delta) \cdot \min\{\|\nabla_x \psi(p, d)\|, \tau_2\}
\]

Where \( \psi(p, d) \) is the color difference between \( p \) and \( pd \); and the gradient difference between \( p \) and \( pd \) along the X direction is \( \nabla_x \psi_x(p, d) \); \( \delta \) is weight coefficient; \( \tau_1 \) and \( \tau_2 \) are cut off value.

2.2. Cost aggregation
Firstly, the initial matching probability of the pixel point can be determined by its initial matching cost:

\[
P^0(p, d) = \frac{1}{Z(p)} \exp\{-\nu C^0(p, d)\}
\]

\[
Z(p) = \sum_x \exp\{-\nu C^0(p, d)\}
\]

Where \( P^0(p, d) \) can be calculated with an initial matching cost \( C^0(p, d) \); \( \nu \) is the positive factor that controls the growth of the matching probability.

And then, the RWR is used to obtain the stable matching probability:

\[
P^{t+1}(p, d) = (1-\alpha) \sum_{q \in N_p} w(p, q) P^t(q, d) + \alpha P^t(p, d)
\]

Where \( t \) is the number of iterations. \( N_p \) denotes the 4-neighborhood of \( p \). \( w(p, d) \) is an edge weight between \( p \) and \( q \).

\[
w(p, q) = \exp\left(-\frac{\|I_i(p) - I_i(q)\|_2^2}{\gamma_c}\right)
\]

Where \( \gamma_c \) represents the bandwidth parameter, typically set to the intensity variance.

After \( t+1 \) iteration, the matching probability reaches a stable state \( P^{t+1}(m, d) = P^t(m, d) \). At this pixel point, \( P^t(m, d) \) is the stable matching probability when the disparity is \( d \).

2.3. Disparity computation
Using the WTA to derive the disparity:

\[
d = \arg \max \{P(p, 1), P(p, 2), ..., P(p, d_{\text{max}})\}
\]

Where \( d_{\text{max}} \) represents the Parallax search range; \( \arg \max \) is the value of \( d \) when \( P(p, d) \) takes the maximum.

3. Proposed algorithm

3.1. Algorithm structure
Firstly, the SSMP is used to obtain the initial disparity map, and the filling criterion based on color similarity is added. Then, using SGM[7] to obtain another disparity map, and the consistency disparity information of the left disparity map obtained by the SSMP and the SGM is used to fill left disparity map.
which contains empty pixel points. Finally, the refined disparity map is obtained by the empty pixel points filling and median filtering of the SSMP. In figure 2, there is the diagram of the proposed algorithm and the dotted line area is the improvement of the SSMP.

![Figure 2: The improved SSMP algorithm diagram](image)

3.2. The cost aggregation method in the SGM algorithm

The energy function is as follows in term of the cost aggregation algorithm of the SGM.

\[
E(D) = \sum_p C(p, d_p) + \sum_{q \in N_p} P_1 T[d_p - d_q = 1] + \sum_{q \in N_p} P_2 T[d_p - d_q > 1]
\]  

(7)

Where \( C(p, d_p) \) is initial matching cost; \( P_1 \) and \( P_2 \) are constant penalties, and \( P_2 \) should be far greater than \( P_1 \).

\[
L_r(p, d) = C(p, d) + \min_{i} \left( \begin{array}{c}
L_r(p - r, d), \\
L_r(pr, d - 1) + P_1, \\
L_r(p - r, d + 1) + P_1, \\
\min_{k} L_r(p - r, i) + P_2
\end{array} \right)
\]

(8)

Where \( L_r(p, d) \) is along a distance \( r \) of the pixel \( p \) at disparity \( d \).

3.3. Filling criteria based on hill-climbing algorithm

Segment color image by using hill-climbing algorithm[8]. Establish 3D color histogram and count the number of pixels in each color at first. Then, select a number of pixels greater than 0 from the color histogram to start climbing the mountain, and count the number of pixels of the adjacent color. If the number of pixels in the adjacent color is different, then the neighbor as the current point, continue to climb the mountain of adjacent color pixels. When the mountain climbing can no longer be carried out, it is considered to be the peak. Then, select the number of other pixels more than 0 and have not been climbed, repeat the climb process until every color is climbed. The number of peaks selected represents the initial number of clusters. All colors which can climb to the same peak are classified as a class to segment color image.
After the image segmentation is completed, the different classes of the pixels after the segmentation are labeled with different labels. The label page of any point \( p \) in the original image is expressed as \( L_p \), \( q \in N_p \), \( q \) is a point in eight neighborhood pixels of. The label page of \( q \) is represented as \( L_q \). When the disparity \( d_p < 1 \), filling \( d_p \) with the following steps:

a) Initialization: \( n = 0 \), \( S = 0 \)

b) When \( d_q > 1 \) and \( \sum S + d_q \)

\[ d_p = \begin{cases} d_p & n < 3 \\ \left[ \frac{S}{n} \right] & 3 \leq n \leq 8 \end{cases} \]

4. Experimental results and analysis

The experiments of tsukuba, venus, teddy and cones on the Middlebury benchmark are carried out so as to demonstrate the effectiveness of the proposed algorithm. MATLAB programming language is used to realize the proposed algorithm. Computer hardware configuration for experiment is Intel(R)Core(TM)i7-6700HQ CPU@2.60GHz. Using the percent of bad pixels to evaluate the matching accuracy of the proposed algorithm. And the parameter values are set as follows:

\[ \{\delta, \tau_1, \tau_2, \gamma, v, \alpha, P_1, P_2\} = \{0.11, 15/255, 2/255, 50, 3000, 0.003, 0.01, 1000\} \]

Figure 3 shows that the overall effect of the disparity map obtained by the SSMP is significantly better than the disparity map obtained by the SGM, but the SSMP has obvious cavity phenomenon in teddy and cones. The proposed algorithm has some improvement on tsukuba and venus, and the effect of teddy and cones are obviously improved. So as to compare the SSMP and the proposed algorithm better, the local magnification of the disparity maps are shown in figure 4.
Figure 4: Local disparity map; (a) standard disparity map; (b) SSMP; (c) proposed

It is apparent that the difference between the SSMP and the proposed algorithm from figure 4, the proposed algorithm not only increases the correct information of the disparity map, but also can solve the hole problem well. With the purpose of comparing the proposed algorithm with others better, the bad pixels rates of different stereo matching algorithms are shown in table 1.

Table 1: Bad pixel rates of different stereo matching algorithms evaluated in all region (%)

| Algorithm | Tsukuba | Venus | Teddy | Cones | Average |
|-----------|---------|-------|-------|-------|---------|
| Proposed  | 1.87    | 0.36  | 11.1  | 7.60  | 5.23    |
| SSMP      | 1.97    | 0.38  | 11.5  | 7.92  | 5.38    |
| NL        | 1.88    | 0.42  | 11.6  | 8.45  | 5.48    |
| ST[9]     | 2.76    | 0.60  | 15.2  | 7.86  | 6.82    |
| SGM       | 3.96    | 1.57  | 12.2  | 9.75  | 7.50    |
| BP        | 3.40    | 1.90  | 13.2  | 11.6  | 7.69    |
| GC        | 4.12    | 3.44  | 25.0  | 18.2  | 11.4    |
| DP        | 5.04    | 11.0  | 21.6  | 19.1  | 14.2    |

As shown in figure 3 and table 1, the SSMP has obvious advantages over traditional global algorithms on some images (such as the tsukuba and venus), but the advantages on some other images (such as teddy and cones) are less obvious. On the basis of SSMP, the proposed algorithm not only keeps the advantages of the SSMP, but also significantly reduces the false matching points in the teddy and cones. Therefore, from the average bad pixels rates of the above algorithms, the effect of the proposed algorithm is better than others, and the matching accuracy is improved.

5. Conclusion

An improved SSMP stereo matching algorithm is proposed. Hill-climbing segmentation algorithm based on color similarity and the consistency detection method of the disparity map obtained by SGM and SSMP are used to add more accurate disparity to the disparity map. The experimental results show that the proposed algorithm reduces the average percent of bad pixels of the images on the second version of Middlebury benchmark from 5.38% to 5.23%. It can solve the problem of missing Correct disparity in the left disparity map because of the inaccuracy of the right disparity map well, and effectively improve the matching accuracy. And further optimization will be made for the details area and edge in future research.

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