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# A Dynamic Programming Stereo Matching Method Combining Adaptive Weighting

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**Abstract:** Traditional stereo matching algorithms based on dynamic programming only consider the disparity smoothing constraint of adjacent pixels in the row direction of the image, but ignore the disparity smoothing constraint of neighboring pixels in the column direction, resulting in a solution also known as the epipolar optimal solution.This matching method ignores the smoothness constraint in the column direction, resulting in a high mismatch rate in the column direction, resulting in clear disparity stripes on the resulting disparity map.In response to this issue, this article proposes a stereo matching algorithm based on row row bidirectional dynamic programming, which improves the matching effect to a certain extent.In the process of minimizing the energy function, the dynamic optimization method is first used in the row direction to provide the energy minimization value of the disparity map. Then, based on the solution result of the row dynamic programming, the corresponding data items in the energy function are updated. Finally, the dynamic programming optimization is performed in the column direction to obtain a dense disparity map.

**Keywords:** Dynamic programming; Row and column bidirectional; Energy function; Parallax map

## 1. Introduction

Stereo matching is based on epipolar constraints, which means that during the matching operation, it is assumed that the matching points on the left and right images are on an epipolar line, and the matching operation is carried out sequentially on different epipolar lines to find the best matching point pair on each epipolar line. The strategy adopted in dynamic programming research is phased optimization, which provides new research tools for solving stereo matching problems.The traditional dynamic programming based stereo matching method is based on epipolar constraints, dividing the stereo matching process into sub processes of finding the best matching point pairs on each epipolar. By sequentially searching for the minimum cost path of each epipolar matching point pair, the final disparity image is generated. This method has high computational efficiency and good matching accuracy, but the disadvantage is that the matching process ignores the constraint of disparity between each epipolar, resulting in stripe defects in the disparity image.

## 2. Improved stereo matching algorithm based on row row double dynamic programming

In the improved stereo matching algorithm based on bidirectional dynamic optimization, the variables calculated on each epipolar line are the disparity values $d = x_l - x_r$ of the matching point pairs, i.e;The selected cost function is an adaptive weighted cost function;By defining the global energy function, establish the connections between each matching sub stage, and finally achieve dynamic optimization by minimizing the global energy function.

The algorithm process is shown in Figure 1. Firstly, the weighted cost function is used to calculate the disparity value on each polar line. Secondly, a global energy function is constructed to establish the connection between each sub process. During the dynamic optimization process in the row direction, a reward value is set to constrain the data items of the energy function. Then, a second dynamic optimization is performed in the column direction to obtain the minimum value of the energy function and generate a dense disparity image.

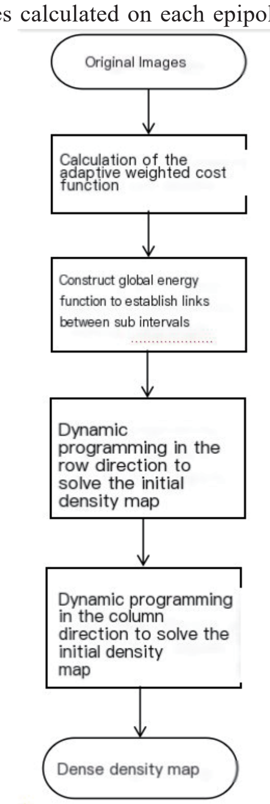


**Fig.1Flowchart of the Paper**

2.1 Calculation of Adaptive Weighted Cost Function

This paper proposes a new similarity cost function, which is a weighted accumulation cost function. To verify the effectiveness of this cost function in disparity discontinuous regions, the disparity matching strategy of WTA (Winner take all) is used, and equation (1) is the adaptive weighted cost function:

$$C(p,\overline{p_d})=\frac{\sum_{q\in N_p,\overline{q_d}\in N_{\overline{p_d}}} w(p,q)w(\overline{p_d},\overline{q_d})e(q,\overline{q_d})}{\sum_{q\in N_p,\overline{q_d}\in N_{\overline{p_d}}} w(p,q)w(\overline{p_d},\overline{q_d})} \tag{1}$$

Among them, point p represents the pixel points to be matched in the reference image, point $\overline{p_d}$ represents the pixel points of the target image, $C(p,\overline{p_d})$ is the cost function, $w(p,q)$ and $w(\overline{p_d},\overline{q_d})$ represents the weights of the windows in the reference image and target image, respectively, q and $\overline{q_d}$ represents the initial cost function of the corresponding pixel points and in the two matching windows.When using the absolute distance SAD function for calculation, its expression is as follows (2):

$$e(q,\overline{q_d})=\min\left\{\sum_{C\in\{r,g,b\}}\left|I_C(q)-I(\overline{q_d})\right|,Th\right\} \tag{2}$$

In equation (2), $I_C$ is the color brightness, Th is the truncation threshold, that is, the minimum disparity value is obtained when the brightness difference is greater than the truncation threshold.When selecting the disparity optimization strategy for WTA, the calculation of disparity results is shown in equation (3).

$$d_p^* = \arg\min_{d \in S_d} C(p, \overline{p_d}) \quad (3)$$

The calculation method for weight $w(p,q)$ is shown in (4):

$$w(p,q) = \exp\left[-\left(\frac{\Delta c_{pq}}{\gamma_c}\right)+\left(\frac{\Delta g_{pq}}{\gamma_p}\right)\right] \quad (4)$$

The variables $\Delta c_{pq}$ and $\Delta g_{pq}$ are represented as the Euclidean distance between the color and image coordinates of the pixel q in the matching window and the center pixel p in the window, respectively.The two parameters of the weight function $\gamma_c$ and $\gamma_p$ are selected as half of the matching window.

2.2 Global Energy Function

The global energy function includes two terms: data term and smooth term. Equation (5) is the global energy function:

$$E(d) = \sum_p D(p, \overline{p_d}) + \sum_{\text{(p,q) are adjacent points}} V(d_p, d_q) \quad (5)$$

The first term is the data term of the energy function, and the second term is the smoothing term of the energy function.This article selects the adaptive cost function of equation (1) as the data term of the energy function;The smoothing term of the energy function adopts an improved Potts function, and the classic Potts function model is shown in equation (6)

$$V(d_p,\ d_q) = \begin{cases} 0 & d_p = d_q \\ g_f(\Delta f) & else \end{cases} \quad (6)$$

The function $g_f(.)$ is a piecewise function with gradients as variables, where the function $\Delta f$ represents adjacent pixels p and q in the image

The specific expression of the function $g_f(.)$ for the gradient between is shown in equation (7).

$$g_f(\Delta f) = \begin{cases} p * s & \Delta f < T \\ s & else \end{cases} \quad (7)$$

The above equations $p$、$t$、$s$ are all threshold parameters, which are constant throughout the entire stereo matching process. P is used to constrain changes at small gradients, and s is used to smoothly constrain changes at large gradients. In this algorithm, a more stringent smoothing threshold is used instead of equation (7), and the specific expression is (8).

$$g_f(\Delta f) = \begin{cases} p * |d_i - d_j| & \Delta f < T \\ s * \ |d_i - d_j| & else \end{cases} \quad (8)$$

2.3 Bidirectional Dynamic Optimization Solution for Rows and Rows

After defining the global energy function of the transfer equation between variables, the problem of stereo matching is transformed into solving the problem of minimizing the global energy function, that is, the process of obtaining the optimal disparity value $d^*$ through full process optimization, as shown in equation (9).

$$d^* = \arg\min\ E(d) \quad (9)$$

The traditional strategy of using dynamic programming based stereo matching algorithms to solve stereo matching is to first divide the process of stereo matching into matching operations on different epipolar lines, then match and operate each pixel on each epipolar line, find the disparity value of the path, record it, and finally combine the disparity values on each epipolar line to generate a dense disparity map. The path here is not a general distance, but a sum of similarity function and smoothing function, which is equation (10):

$$D(p, \overline{p_d}) + V(d_p, d_q) \quad (10)$$

Figure 2 shows the dynamic optimization process of stereo matching in the row direction. The minimum cost path from the leftmost to the rightmost on the corresponding epipolar line can be obtained through matching operations. The length of each path is shown in equation (10). Finally, the disparity image of stereo matching can be obtained by fusing the disparity values of each epipolar line.

This paper proposes a new matching strategy that can compensate for the shortcomings of this traditional algorithm.The new matching strategy first dynamically optimizes in the row direction, obtains the initial disparity map, and records it. The disparity map solved based on row dynamic programming is an optimal solution on the epipolar line, and the true probability of the disparity value is high, which can guide dynamic optimization in the column direction.Under this strategy, this article introduces a reward and punishment method that guides dynamic optimization in the column direction by reducing the value of the matching cost function corresponding to the initial disparity value $d^*$. That is, the initial disparity map obtained by dynamic optimization in the row direction is taken as a result, and then an update is given to the data item corresponding to this disparity result. Other data items remain unchanged during this process. Equation (11) represents the update of the data item.

$$D(p, \overline{p_{d^*}}) \leftarrow D(p, \overline{p_{d^*}}) - r \quad (11)$$

In equation (11), the parameter r is a non negative number, with a range of positive values relative to the cost function.The value of r in this article is 3.

After updating the data items in the energy function based on the initial results of the row dynamic optimization strategy, dynamic optimization can be performed in the column direction, which only considers the disparity constraint of adjacent pixels in the column direction. The operation process is consistent with the dynamic optimization process in the row direction.The disparity map obtained through the bidirectional dynamic optimization process of rows and columns contains a small number of obvious noise points. These isolated points can be removed through some simple post-processing. The method is: if the disparity of pixels in the left and right neighborhoods of a pixel is equal in the row direction, the disparity value of pixels in the left and right neighborhoods is assigned to that pixel;If the disparity between pixels in the upper and lower neighborhoods of a pixel in the column direction is equal, assign the disparity value of its upper and lower neighboring pixels to that pixel;In other cases, keep the disparity value of the disparity map unchanged.

## 3. Experimental results and analysis

To verify the effectiveness of the algorithm, an experiment was conducted using Matlab 2016a on an HP Pro Tower computer. The experimental images were taken from Tsukuba provided in the Middlebury database,Venus, Teddy, and cones are four images. Figure 3 shows the disparity map generated by this algorithm, and the disparity result map is uploaded to the Middlebury website for testing. Through the generated disparity map, it can be seen that this algorithm has achieved ideal matching results in flat disparity areas, discontinuous areas, and occluded areas. Through the cones map, it can be seen that compared to the traditional two dynamic programming algorithms, the disparity map based on this algorithm has significantly reduced black areas at the boundaries and greatly suppressed the phenomenon of disparity stripes. The experimental parameters used in the algorithm are as follows: $\gamma_c$ =5, $\gamma_p$ =18.5,Th =40,T =20, P =3, s =1, r =1.


**Fig.2 Comparison of Results of Different Algorithms**

At the same time, this article also compared with dynamic programming algorithms that use the SAD function as the initial matching function. The dynamic optimization strategies are row dynamic optimization (DP1 algorithm) and row row bidirectional dynamic optimization (DP2 algorithm), respectively.Table 1 shows the data of three algorithms fed back through website testing, where nonocc represents the percentage of errors in non occluded areas, a11 represents the percentage of errors in all areas, and disc represents the percentage of errors in non continuous areas of disparity. From the table, it can be seen that when using the bidirectional dynamic optimization strategy, the error percentage of the disparity result graph solved by the weighted adaptive cost function is significantly lower than that when using the traditional SAD function as the cost function;When the selected cost functions are all SAD functions, the strategy based on row row bidirectional dynamic optimization proposed in this paper is superior to the traditional one-way dynamic optimization strategy. The algorithm reduces the error matching rate and improves the matching effect.

**Tab. 1 The Comparison of Different Algorithms**

| Algorithms | Tsukuba | | | Venus | | | Teddy | | | Conesde | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Nonocc | All | Disc | Nonocc | All | Disc | Nonocc | All | Disc | Nonocc | All | Disc |
| DP1 | three point three two | 4.19 | thirteen point one | seven point seven seven | eight point nine six | nineteen point nine | ten point one eight | nineteen point four | twenty point one | six point one six | fifteen point one | nineteen point three |
| DP2 | three point five three | five point four eight | fourteen point seven | five point six eight | four point three eight | twenty-two point seven | ten point three eight | eighteen point eight | twenty-one point two | eight point nine five | nineteen point six | twenty-two point seven |
| This Paper | one point five nine | three point four five | six point one one | zero point four nine | two point one seven | four point three seven | nine point five two | eighteen point eight | nineteen point two | four point eight seven | fourteen point nine | nine point seven two |

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