Dual Dynamic Programming with Quantization for Disparity Map

Monika Gupta[1], Sapna Malik[2]
Lecturer in Govt. College, Sec- 14, Panchkula, India

Abstract

Intensive research has been done in the field of stereovision to calculate an accurate disparity map, but all the existing methods have some limitations like high execution time, discontinuities, horizontal streaks etc. In this paper we propose an improved disparity map method, Dual dynamic programming with quantization, based on dynamic programming that provides lower execution time and more accurate disparity map. Our method improves the accuracy of stereo matching.

Keywords

Disparity map, Correspondence problem, Stereo matching

I. INTRODUCTION

Stereovision is an area of study that attempts to recreate human vision system by using two or more two-dimensional views of the same scene to derive three-dimensional depth information about the scene. A computer compares the images and tries to find a set of points in one image that can be identified as same points in another image. This is known as correspondence problem [2]. Finding corresponding points in stereovision is the major problem in stereo computation. The spatial displacement between two corresponding pixels in stereo pair is called disparity [3]. Solution to the correspondence problem is estimating a disparity map which is the set of disparity values of all the pixels in a reference image.

The techniques based on intensity difference finds the intensity difference between two points in left and right image and finds the corresponding point by minimizing the difference. In correlation the output of the scanning window is convolved with the first and the location that gives the highest convolution coefficient is the corresponding area. Gradient-based methods or optical flow Horn [5], determines small local disparities between two images by formulating a differential equation relating motion and image brightness. In order to do this, the assumption is made that the image brightness of a point in the scene is constant between the two views. Gradient-based methods can only estimate disparities up to half a pixel since the local derivatives are only valid over that range. Block matching and gradient-based methods have a problemof depth discontinuities. Feature-based methods [6] overcome the problem of depth Discontinuities by limiting the regions of support

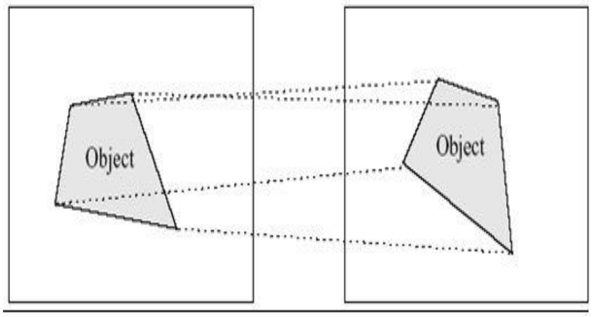


Figure 1: The general correspondence problem

To determine disparities certain constraints are exploited which are further classified as local and global constraints. Local constraints are the simple term referring to constraints on the small number of pixels surrounding a pixel of interest. Similarly global constraints are those on scan lines or on the entire image. Once these constraints are exploited the problem of correspondence is solved and disparity map can be determined. After the determination of disparity map, the three dimensional position of the object can be easily computed by the technique called triangulation.

The rest of the paper is organized as follows section 2 explains existing local and global methods, section 3 explains proposed method and section 4 shows results and outcomes.

II. EXISTING METHODS:-LOCAL AND GLOBAL METHODS

A. *Local Methods*

Local Methods fall into three broad categories: block matching, gradient methods, and feature matching. Disparity is estimated at a point, by comparing small regions about the point with a series of small regions extracted from other image. Two classes of metrics are commonly used for block matching: intensity difference and correlation [4].

to specific reliable features in the images. Due to the need for dense depth maps for a variety of applications feature based methods are rarely used. The most common local methods [7-8] are normalized cross correlation, sum of square differences and sum of absolute differences. Local methods are not able to deal with the problems of occlusion, uniform texture and discontinuities.

B. Global Methods

Global methods adopt the method of optimizing an energy function to estimate disparity. Few important algorithms in this regard are Dynamic programming, graph cut [9] and belief propagation [10]. Dynamic programming is a mathematical method that reduces the computational complexity of optimization problems by decomposing them into smaller and simpler sub problems [11]. A global cost function is computed in stages, with the transition between stages defined by a set of constraints. For stereo matching, the epipolar monotonic ordering constraint allows the global cost function to be determined as the minimum cost path through a disparity space image (DSI). The cost of the optimal path is the sum of the costs of the partial paths obtained recursively. The local cost functions for each point in the DSI may be defined using one of the area-based methods.
This section explains the basic steps for evaluating the DP matrix. As first step, it is necessary to obtain the elements of the matrix. The instructions for accomplishing this are described in pseudo code below, where i as well as j have to be counted from 0 to n-1 separately, in order to cover all elements of matrix A. The value n is representing firstly the width of the input images but also stands for the dimension of the whole DP matrix [refer figure 2]

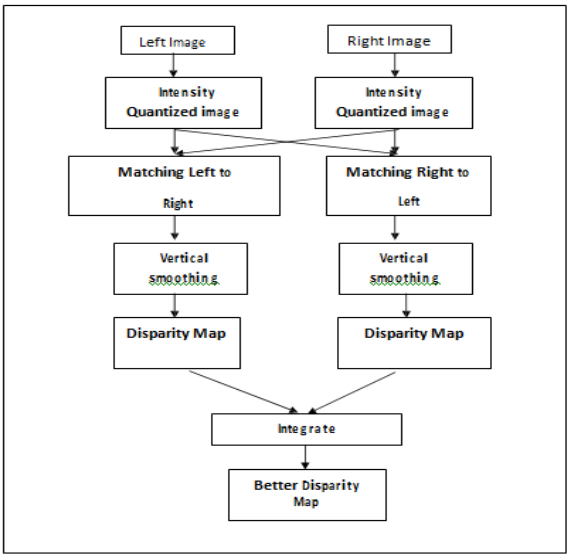
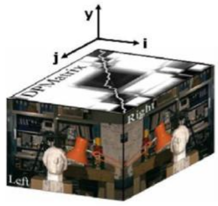


Figure 4: Flow chart of the dual matching

The horizontal strips in the disparity map extend from the foreground object and thus result in ambiguous results in the vicinity of the object where the horizontal strips exist.



Right

Left	S	T	E	R	E	O
S	0	1	2	3	4	5
T	1	0	1	2	2+1	...
R	2	1	1	1+0	1+1	...
E	3	2	1	1+1	1+0	...
O	4	3	2	1+1	1+1	
E	5	4	2+0	2+1	...	

Fig 2:Dp Matrix   Fig 3:Construction of basic DP matrix

C. Pseudo code for the matrix

Minimum = Min(A[i-1,j],A[i,j-1],A[i-1,j-1])
ColorL=LeftImage[i,y]
ColorR=RightImage[j,y]
A[i,j]=Minimum+Dif(ColorR,ColorL)
In the beginning, A [0, 0] has to be initialized with 0. Afterwards, all other elements are evaluated in the order from the upper left to the lower right corner as shown in fig 3.
Global search methods provide global support for local regions that lack texture and would otherwise be matched incorrectly. However the principal disadvantage is the possibility that local errors may be propagated along a scan line, corrupting other potentially good matches. Horizontal streaks caused by the problem may be observed in many of the disparity maps.

D. Proposed method-Dual matching using Dynamic Programming:-

A typical disparity map from dynamic programming [12-13] has the following flaws :
1) It has horizontal strips.
2) It has discontinuities in the vertical direction.
3) The background information is not obtained, foreground objects are present in the disparity map.

In our proposed method we will be generating the two disparity maps and then combining their results. The procedure is enumerated below:

1) Finding the disparity map from the set of images using simple dynamic programming principle by scanning the images from Left to Right.
2) Finding the disparity map from the set of images using simple dynamic programming principle by scanning the images from Right to Left.
3) Combining the results of step 1 and step 2.
4) Applying the quantization principle to obtain a better disparity map.

III. QUANTIZATION

The quantization step is done at the beginning of the process. The quantization is performed on the

The concept used to correct this problem is devised from the strategy that scan lines in a stereo pair read from left to right will produce different path for the minimum cost path in the matrix while using dynamic programming, from the same scan lines read from right to left. This is due to the fact that the minimum cost path is determined using the greedy first algorithm, thus there is always a local search for the minima, not a global search. Thus the disparity map generated from a scan line read in left to right direction will produce a different result from the same scan line read in right to left direction. The points listed above can be combined to reduce the error inherent in the dynamic programming method for disparity calculation. As in both the scan directions the location of the horizontal strips are different and very little background information is present, thus when we mathematically average the disparity of each point, the average error is reduced.This is because the points representing the object have almost similar disparity values in both the disparity maps; thus their averaged result is very close to the original values in the two disparity maps. However the error due to the horizontal strips is reduced significantly as the background has very little information, and the disparity value of the horizontal strips shift more towards the background disparity value.

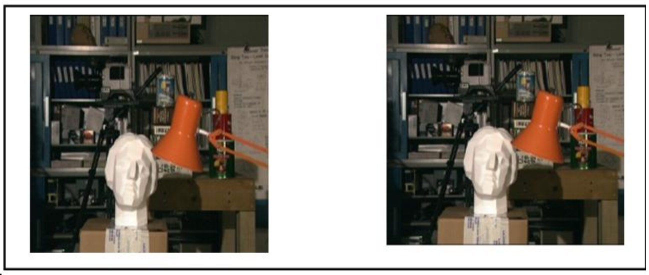


Figure 5: Original stereo Image from the University of Tsukuba provided by Scharstein and Szeliski

Figure6shownbelowistheresult obtained from dual matching in dynamic programming which uses the concept of dual matching quantization and vertical smoothening in dynamic programming. In basic dynamic programming horizontal streaksare obtained (referfigure9). The disparity map obtained by our proposed method is better than the traditional existing local and global methods. The disparity map is obtained in the same time as is obtained by using simple dynamic programming. Also the time taken in obtaining disparity map is less than the time taken by graph cut.

intensity values for the points. The formula for quantization applied is

Floor (intensity/step)*step

Thus the intensity values are rounded to a near multiple of the step value. Quantization is done on the disparity images with step size 20 and step size 50. The quantization factor increases as various new objects come into discrete view in the disparity maps. However at very large values, the amount of loss of information is significant, and thus the results can be ambiguous. It is observed that even the background objects which were not visible at low quantization value come into view with larger quantization value. This is because in a dark background most points have very similar intensities but when they are quantized to step values, the difference among the intensity values is increased. Thus the dynamic programming can now easily use this large difference to provide more information.

IV. VERTICAL SMOOTHING

The traditional dynamic programming technique results in disparity maps with discontinuities along the vertical direction. To smoothen out these discontinuities, the process in volvesa simple interpolation method where it guesses if it can assign two vertically neigh boring pixels with the same disparity value. The result from this, resultsin vertical smoothed out disparity maps. The process is to calculate the fractional change in the disparity value for the point In the image from the point above it. If the fractional change is less than the threshold value then the two points can be assigned same disparity value which is the average of the calculated disparity at the point and the assigned disparity of the above point. The choice of calculated disparity for the point and assigned disparity for the above point is because this ensures that there is significant contribution by the currently calculated value and the averaging it with assigned disparity value of the above point makes the result shift slightly towards the disparities of the above points above the current point in consideration. Thus, this ensures that there is gradual change in disparity for the points in the same object vertically; and ittends to hide the ab normal results that can occurin somes can lines.

V. RESULTS

At a first step, calibrated and rectified images from two cameras are taken and disparity map is calculated by using dual matching dynamic programming; which is our proposed method. The standard rectified image is taken (refer figure 5 shown below).

Fig:6: Result of proposed System

VI. COMPARATIVE ANALYSIS OF PROPOSED APPROACH WITH EXISTING LOCAL AND GLOBAL METHODS

Approach	Uniform/ Repetitive Texture	Low execution Time	Real Time	Disparity Map	Time of execution	
Local methods (SSD,SAD, NCC, Norm alized NCC)	No	SAD and SSD have low execution time but NCC and normalized have high execution time.	Yes	Poor	SSD	11.58 secs
					SAD	10.45 secs
					NCC	29.67 secs
DP	Yes	No	No	Medium with horizontal streaks	39.76 secs	
Dual matching using DP (Proposed method)	Yes	No	No	Good Without any horizontal streaks.	39.78 secs	

VI. CONCLUSION

We have developed a system that uses the principle of stereovision and generates disparity map from a given set of two images, from which depth of objects can be perceived. The system has marked advancement over the existing systems and finds a better disparity map, even in locally ambiguous regions in images (e.g., occlusion regions or regions with uniform texture).

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Disparity map obtained from various local and global methods

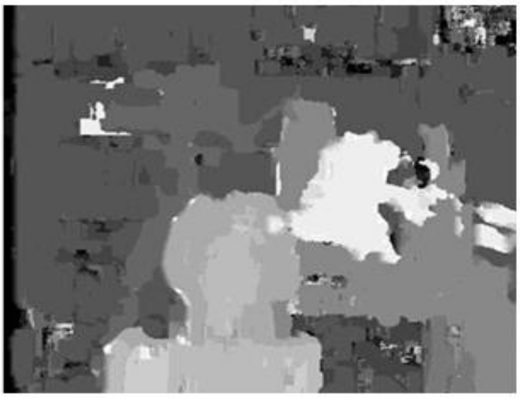

Fig 7: Result of sum of square diff.

Fig 8: Result of NCC

Fig 9: Result of dynamic programming

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