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Q-Learning for Stereo Vision

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Abstract— computer Stereo Vision is an efficient method of extracting three dimensional features from a two dimensional image, utilizing a stereo image set. In order to obtain accurate three dimensional features such as depth, a crisp disparity map is required. A disparity map may be hindered by various problems such as occlusion and ambiguous matching. Thus to solve these problems and obtain a crisp disparity map, this project seeks to apply reinforcement learning, especially Q-Learning. Q-Learning is an optimizing technique that has been used to fine tune certain standard algorithms of stereo vision. Q-Learning have been used to optimize the window size of a Block Matching algorithm. The effectiveness has been tested of the algorithms using quality metrics such as Bad Pixel Matching. After the development of the algorithm, the algorithm has been applied for visual servoing of a wheeled robot along the depth axis. Thus the paper provides a robust Machine Learning technique to fine tune Block Matching algorithm of Stereo Vision.

Keywords— Computer Stereo Vision, Disparity Map, Block Matching, Q-Learning, Window size, Wheeled Robot, Visual Servoing, Minoru stereo camera.

I. INTRODUCTION

Stereo Vision can be defined as the technique of perceiving depth in a two dimensional image using the projection of the image from two different vantage points. This technique is used by the humans effectively to perceive depth and essentially witness the environment around them in three dimension. The human eyes are displaced by a distance of six centimeter, on an average. The two different projections are processed by the brain and humans can inherently estimate three dimensional parameters such as depth, thickness etc. Computers have been readily trying to mimic this ability of humans, which has given rise to the field of Computer Stereo Vision. For the estimation of depth and other three dimensional parameters from a two dimensional image, the construction of a disparity map is crucial. Disparity refers to the displacement between the pixel position in reference image (left image) and the corresponding pixel position in the matching image (right image). When Disparity is calculated for all the pixels in one image, it is known as a disparity map. Disparity calculation faces many challenges. Few of challenges are occlusion, ambiguous matching, rectification of images, etc. Occlusion is the phenomenon of one pixel being obstructed or occluded by another pixel, which may happen in case of three dimensional images. Ambiguous matching refers to a problem wherein a similar intensity pixel is selected in the matching image instead of the pixel which was formerly selected in the reference image. These problems are collectively called as Stereo Correspondence problems. There are many algorithms available for solving this problem. O. Faugeras et al used a cross correlation [10] based technique to find disparity maps. Q. Tian and M. N. Huhns used sub-pixel registeration [11] for solving the correspondence problems. : Emmanouil Z. Psarakis and Georgios D. Evangelidis then evolved the earlier algorithms into enhanced normalized cross correlation technique to improve the disparity map quality. E. Klingbeil et al [1] developed algorithms for servoing of robots using stereo vision. M.C. Nguyen [5] et al developed learning methods to be used in stereo vision. In the paper, authors seek to fine tune the Block Matching algorithm using Q-Learning technique. The stereo pairs have been acquired from the Middlebury datasets. Block Matching is applied to search the corresponding pixel of the reference image in the matching image. Next the disparity map thus obtained is measured for its quality using percentage of bad pixel matching as its quality metrics. Then the block size in the block matching algorithm is varied using Q-Learning and based on the performance with respect to the aforementioned quality metrics, it is assigned a particular reward or penalty. After a number of iterations, the rewards and penalties are accumulated and the optimized block size is obtained. Thus a higher quality disparity map is obtained using this algorithm. After a tuned algorithm is obtained, it is used for the visual servoing of a wheeled robot. The robot consists of two motors and a castor wheel. It is controlled by Atmega 328 from ATMEL. The position of the robot is observed by Minoru stereo camera and is processed in the MATLAB platform. Based on its position, the robot is commanded to reach to the closest object. The command transfer is done through serial communication of MATLAB with the Atmega328 board. In subsequent sections the software and hardware involved in the development of this paper are explained in detail.

II. DISPARITY

The reference image has been taken as the left image of the stereo pair and the matching image as the right image of the stereo pair. For calculation of disparity, a pixel is chosen in the reference image and the corresponding intensity pixel is searched in the matching image. Once the corresponding pixel is found, the displacement of the pixels is calculated using either sum of absolute distances, sum of squared distances or normalized cross correlation. The authors have used the sum of absolute distances. Let 'L' denote the reference image and 'R' denote the matching image.

$$L[i,j] = I[i,j] \quad (1)$$

$$R[i,j] = I[i,j] + d \quad (2)$$

Here I is the pixel intensity and d is the distance between the referenced and matched pixel. For i and j ranging throughout the size of the image, by plotting the values of 'd' the disparity map of the given stereoscopic set has been obtained.

A. Block Matching Technique

A region or block of pixels is selected in the reference image, this is known as the template and the matching region is searched in the matching image. During the search, the algorithm starts looking in the matching image from the same coordinate from where the template is chosen. When searching the matching image, the algorithm starts at the same coordinates as the template and searches to the left and right up to some maximum distance. The closest matching block is selected and the disparity is just the horizontal distance between the centers of the two blocks.

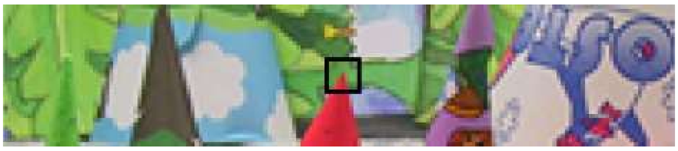

Figure-1: Block chosen in Left Stereo Image

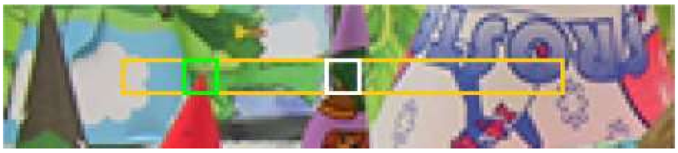

Figure-2: Search in Right Stereo Image

The direction of the search is only in the left or right direction. This is because the datasets obtained from Middlebury are rectified, that is the epipolar line on both the left and right images is same. Hence the matching block is searched only on the left or right direction limited by a disparity range. To compute the sum of absolute differences between the template and a block, each pixel is subtracted in the template from the corresponding pixel in the block and take the absolute value of the differences. Then sum up all of these differences and this gives a single value that roughly measures the similarity between the two image patches. A lower value means the patches are more similar.

B. Distance Calculation

The distance formula is applied to compute the distance between the centers of the template block and the matched block. This distance provides us the disparity.

$$S=\sqrt{((x2 - x1)^2 + (y2 - y1)^2)} \quad (3)$$

Here S denotes the distance between the centers of reference block and the matched block, x1, y1, represent the coordinates of center of the reference block and x2, y2, represent the coordinates of the centers of the matched block.

C. Quality Metrics

The quality of the disparity map can be calculated using various quality metrics. These quality metrics determine the level of accuracy of the algorithm used to obtain the disparity map. The quality metrics compare the obtained disparity map with the ground truth disparity map. A ground truth disparity map is obtained by using laser range finders and provides the exact displacement of the matching image's pixels with respect to the reference image's pixels. The two most prevalent quality metrics are Root Mean Squared error (RMS) and percentage of Bad Pixel Matching.

$$\text{RMS} = (\frac{1}{n} \sum_{x,y}(dc(x,y) - dt(x,y))^2)^\wedge ½ \quad (4)$$

Where, N is the total number of pixels in the image, dc is the computed disparity map, and dt is the ground truth disparity map.

$$\text{Bad Pixels} = (\frac{1}{n} \sum_{x,y}(|dc(x,y) - dt(x,y)| > \rho) \quad (5)$$

where, N is the total number of pixels in an image, dc is the computed disparity map, and dt is the ground truth disparity map, and ρ is the threshold for evaluating bad matched pixels (usually attains the value of 1.0).

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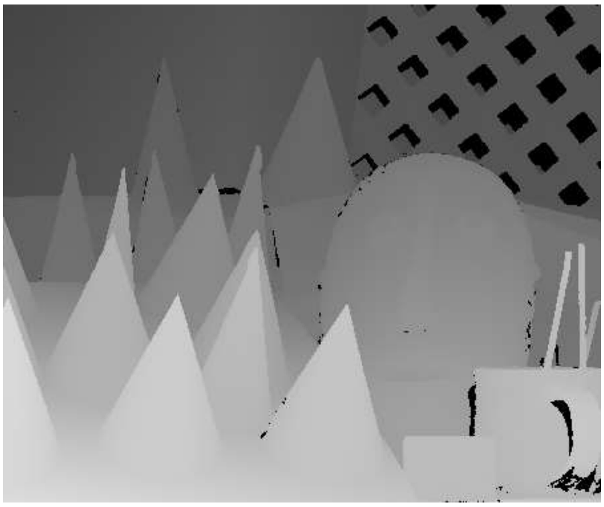

Figure-3: Ground Truth Disparity Map

Figure-4: Left Image

Figure-5: Right Image

C.Quality Metrics

Now, the Block Matching technique has been used to find the disparity map of the stereo set of images named "Cones" taken from Middlebury. By manually varying the window sizes and varying quality of the disparity maps is obtained. The disparity maps are compared on the basis of the percentage of bad pixel matching that is obtained. Thus, looking at the figures 6,7 and 8, it can concluded that an optimized window size can provide us with a high quality disparity map. Hence it is seeked to achieve this with the help of Q-Learning.

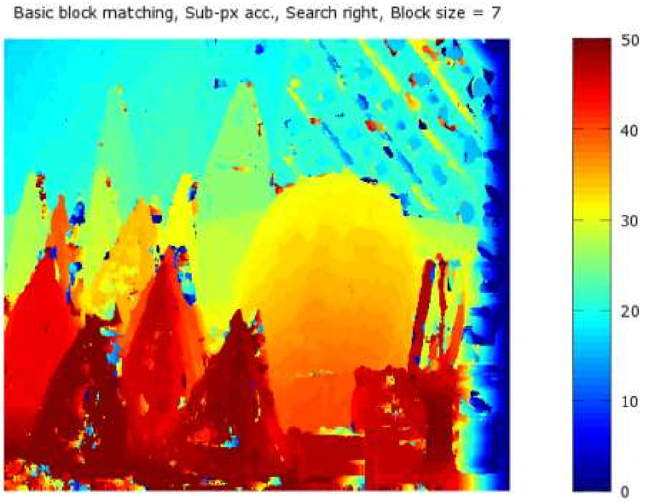

Figure-6: Disparity Map with Block size=7

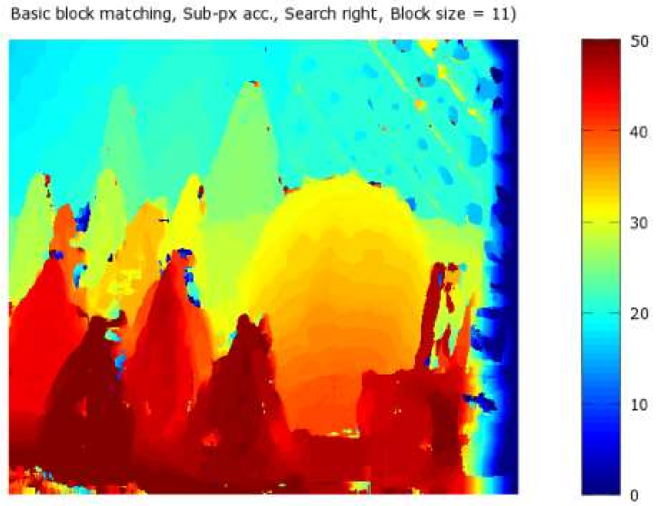

Figure-7: Disparity Map with Block size=11

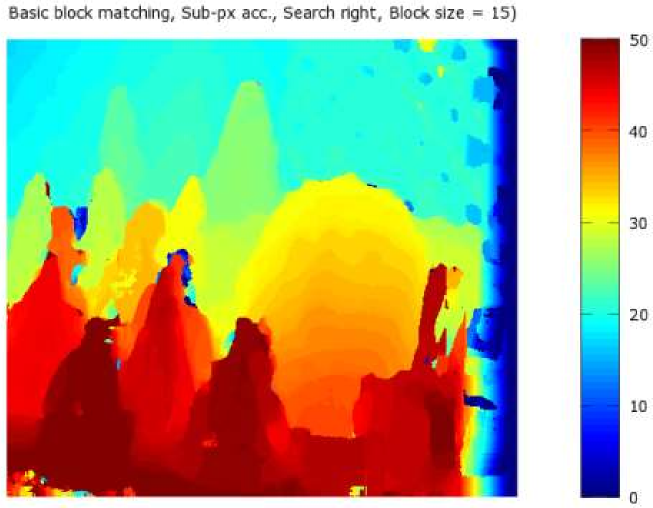

Figure-8: Disparity Map with Block size=15

D. Q-Learning

A form of Reinforcement Learning, Q-Learning belongs to the superclass of Machine Learning. A computer system is said to learn from a data set denoted by 'D' to perform the task denoted by 'T', if after learning, the system's performance on T improves, as measured by a performance measurement index, denoted by 'M'. Trial and error method is utilized by Reinforcement Learning to learn. Random actions are considered to make a system achieve its goal and then, a feedback is obtained in the form of rewards or penalties that determine whether the action taken was correct or incorrect. Therefore, after a number of iterations the algorithm comes to know which steps are beneficial and which are not with respect to the goal to be achieved. In this paper, Tabular Q – Learning Technique is utilized to optimize the window size used for the disparity calculation using Block Matching technique. To implement the Q-Learning, the cost function taken is a function of the quality metrics used. A reward function has been generated which is essentially the quality metrics: percentage bad pixel matching. Based on the performance of the Block Matching algorithm at a particular window size, the window size has been attributed a corresponding reward on penalty as judged by the quality metrics. Based on this reward or penalty the window sizes are varied to obtain an optimized size which gives the least number of bad pixels. The Q matrix was initialized by all zeroes. The states are denoted by 's' and actions by 'a'. Now for a multiple iterations, the Q matrix is altered using the following equation:

$$Q\ (s, a) = R\ (s, a) + \gamma .\ \mathrm{Max}\ (Q\ (\text{next } s, \text{all } a)) \tag{6}$$

Figure-9 depicts the changing values of bad pixels as Q-Learning iterates.

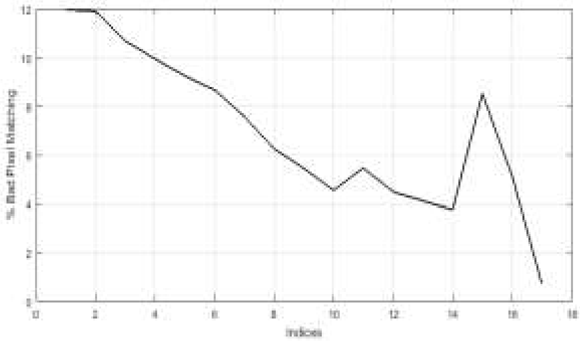

Figure-9: Bad Pixel Percentages

IV. RESULTS AND DISCUSSIONS

The Q-Learning algorithm starts from a randomly selected window size. Then the performance of the Block Matching algorithm with that particular window size is evaluated using the quality metrics. Based on this rewards and penalties are attributed and the value of window size is changed again. This happens iteratively. After a fixed number of iterations, twenty in this case, one can be able to observe minimized values of bad pixel matches. After twenty iterations it is observed that the bad pixel percentage was 0.74 for the window size 23. From the figure-3 it can be observed the robustness of the algorithm. The bad pixel matching percentage keeps on decreasing mostly, but two peaks in the otherwise linear graph. These peaks are because of the unexpected behavior of certain window sizes. But even when so happens, the Q-Learning algorithm varies the window size in such a way that in the immediate next step there is a decrease in the bad pixel percentage. Thus the unexpected behaviors of certain window sizes are effectively countered by the Q-Learning.

V. IMPLEMENTATION

A. Problem Statement

The problem statement can be defined as follows: To process the acquired scene and analyze which object is the closest to the camera and to drive a wheeled, skid steering based robot to the nearest object by taking constant feedback from the stereo cameras.

B. Hardware Requirements

The first requirement is a stereo camera that can take images of the same scene from two vantage points, separated by a constant distance. For this an off the shelf camera has been taken, Minoru 3D Web-camera. It consists of two individual cameras, displaced by a distance from each other.

They take the picture simultaneously and can be connected to the personal computer using USB 2.0 port. It consists of a VGA CMOS Sensor. Its Maximum resolution is 800×600. Camera baseline length is 6 .cm. Maximum frame rate is 30 frames per second. Our wheeled robot is based on a metal chassis and has ATMEGA8 as its microcontroller. It consists of two motors which have a maximum rating of 12V and 900 mA. A differential drive has been used to move the robot in left, right and forward directions. The camera feeds back the position of the robot and after the analysis on MATLAB in the PC, the appropriate commands are given to the robot via serial communication between the COM ports of the computer and the serial port of the ATMEGA8 controller.

Figure-10: Minoru Stereo Camera

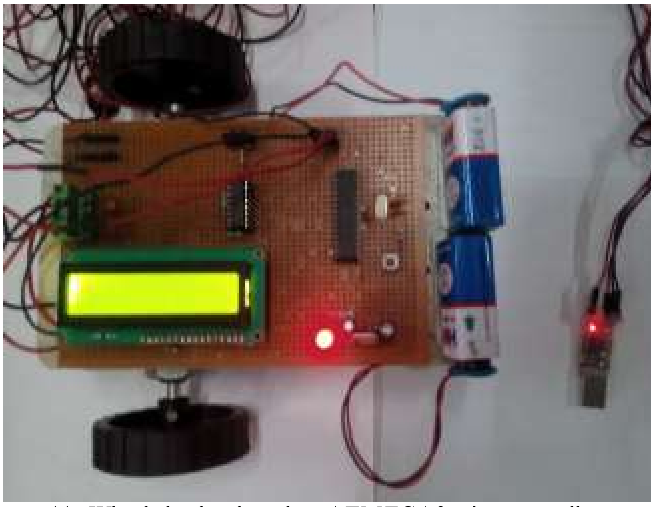

Figure-11: Wheeled robot based on ATMEGA8 microcontroller

C. *Modus Operandi*

First the disparity of the scene without the robot is being calculated. The object having the maximum disparity is selected and its coordinates are extracted. Next, the robot is introduced into the scene. The robot has a circular marker attached to it. The robot is tracked using this circular marker. Now the disparity at the coordinates obtained in the previous step is again calculated and it is matched with the disparity of at the position where the circular marker is detected. If the disparity of the robot is more it is moved forward and if it is more it is rotated and moved backwards. This continues till the disparity of the nearest object and that of the robot is not equal, in this way the robot is able to traverse in the direction of the line joining the plane of the camera and that of the object, that is in a three dimensional direction.

IV. CONCLUSION AND FUTURE SCOPE

It can be concluded from the paper that the Q-Learning technique was able to tune the Block Matching algorithm in an effective manner and that it provided us a robust algorithm that can be used effectively for any rectified image set, to obtain crisp disparity maps. The future scope of this paper is that, Q-Learning can be used along with algorithms such as Graph cut or enhanced cross correlation so as to obtain even better disparity maps.

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