Motion Detection and Velocity Estimation for Obstacle Avoidance using 3D Point Clouds

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Abstract: This paper proposes a novel three dimensional ($3D$) velocity estimation method by using differential flow techniques for the dynamic path planning of Autonomous Ground Vehicles (AGV) in a cluttered environment. We provide a frame work for the computation of dense and non rigid $3D$ flow vectors from the range data, obtained from the time-of-flight camera. Combined Lucas/Kanade and Horn/schunck approach is used to estimate the velocity of the dynamic obstacles. The trajectory of the dynamic obstacle is predicted from the direction of the $3D$ flow field and the estimated velocity. By experiments, the utility of the approach is demonstrated with the results.

1 INTRODUCTION

Velocity estimation is an important research area in autonomous mobile systems, which have been used in dynamic path planning. The basic requirement for the path planning is to plan the best possible path in such a way that the AGV traverses the path and can replan its path whenever it senses the obstacles in its way, and can repeat the process until it reaches its goal. In dynamic path planning, the vehicle has to modify its path as per the dynamic characteristics of the surroundings and plan to complete its ultimate task. In dynamic environments, the obstacles will move randomly causing the possibility of collision in the vehicle's path. In order to avoid the collision, the AGV has to monitor the behaviour such as the position and the orientation of the obstacles. So, it needs an opt sensor that can sense the dynamic behaviour of the obstacles.

Most of the researchers have been working on various image processing approaches in order to detect, track and estimate the moving objects. The motion estimation has been studied extensively over the past two decades in the field of computer vision (B D Lucas, 1981) (Horn and Schunck, 1981). Most of the traditional methods are virtually based on analysing the 2D data, ie images (Holte et al., 2010). These 2D images are only the projection of the actual 3D data on the camera image plane. So the processing of these images will depend upon the view point (not on the actual information about the object). In order to overcome this drawback the use of 3D information has emerged.

The intensity based image processing techniques are mainly based on grey scale or color in the images which is obtained from the conventional cameras. The main disadvantages of these techniques are that the image processing becomes inadequate in low illumination conditions and when the objects and the background look similar to each other (Yin, 2011).

As a result, three dimensional range data (x,y,z) has been introduced. Usually there are three basic optical distance measurement principles (Ahlskog, 2007) such as Interferometry, Stereo/Triangulation and Time-of-Flight $[TOF]$ which can construct these data (x,y,z). These range data can be used in flow vector techniques to improve the quality of 3D object segmentation, calculate object trajectories and time-to-collision (Schmidt et al., 2008).

The objective of this paper is to detect the dynamic obstacles and estimate the velocities in X,Y,Z directions based on the $3D$ point cloud from the Photonic Mixer Device (PMD) camera. The paper uses the combined Lucas/Kanade and Horn/Schunck differential flow techniques (Bauer et al., 2006), (Bruhn et al., 2005) to estimate the velocities in 3D coordinates.

The paper is organised as follows: Section II describes about the PMD camera. Section III provides the velocity estimation using the modified differential flow technique. In Section IV, the experimental results are discussed. Section V summarises the work.

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2 PMD CAMERA

We are using Photonic Mixer Device (PMD) camera, a TOF camera in this work, in figure 1. A time of flight camera is a system that works with the TOF principles (Weingarten et al., 2004), and resembles a LIDAR scanner. In the TOF unit (Lange, 2000), a modulated light pulse is transmitted by the illumination source and the target distance is measured from the time taken by the pulse to reflect from the target and back to the receiving unit. PMD cameras can generate the range information, which is almost independent of lighting conditions and visual appearance, and a gray scale intensity image, similar to conventional cameras. The coordinates of the obstacle with respect to the PMD camera are obtained as a 200 by 200 matrix, each element corresponding to a pixel. It provides fast acquisition of high resolution range data. As the PMD range camera provides sufficient information about the obstacles, it is proposed to estimate the trajectory of the moving obstacles.

These TOF camera provide a 3D point cloud, which is set of surface points in a three-dimensional coordinate system (X,Y,Z), for all objects in the field of view of the camera.

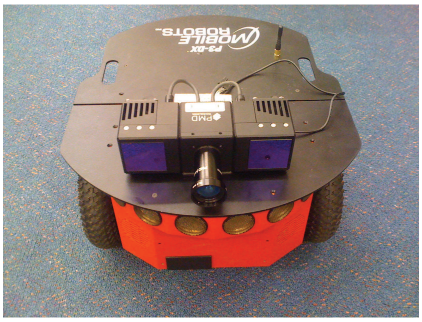

Figure 1: PMD Camera.

3 SCENE FLOW

Optical Flow (Barron et al., 1992) is an approximation of the local image motion based upon local derivatives in a given sequence of images. That is, in 2D it specifies how much each image pixel moves between adjacent images while in 3D, it specifies how much each volume voxel moves between adjacent volumes. The moving patterns cause temporal varieties of the image brightness. In general, the process of determining optical flow is using a brightness constancy constraint equation(BCCE). The spatiotemporal derivatives of image intensity are used in differential techniques to get the optical flow.

Differential techniques can be classified as local and global. Local techniques involve the optimization of a local energy, as in the Lucas and Kanade method. The global techniques determine the flow vector through minimization of a global energy, as in Horn and Schunck. Local methods offer robustness to noise, but lack the ability to produce dense optical flow fields. Global techniques produce 100 percent dense flow fields, but have a much larger sensitivity to noise. The paper (Bauer et al., 2006) involves combining local and global methods of Lucas-Kanade and Horn-Schunck, to obtain a method which generates dense optical flow under noisy image conditions.

Scene Flow (Vedula et al., 2005) is the three-dimensional motion fields of points in the world; just as optical flow is the 2D motion field of points in an image. Any optical flow is simply the projection of the scene flow onto the image plane of a camera. If the world is completely non-rigid, the motions of the points in the scene may all be independent of each other. One representation of the scene motion is therefore a dense three-dimensional vector field defined for every point on every surface in the scene.

These 2D images are only the projection of the actual 3D data on the camera image plane, which is illustrated in figure 2. Figure 2 shows a point M=(X,Y,Z) from world coordinates which is projected and imaged on a point $m = x,y$ in the camera's image plane. These coordinates are with respect to a coordinate system whose origin is at the intersection of the optical axis and the image plane, and whose x and y axes are parallel to the X and Y axes (Iwadate, 2010). The three dimensional coordinates are based on the optical projection centre C. Here, (u,v) are the

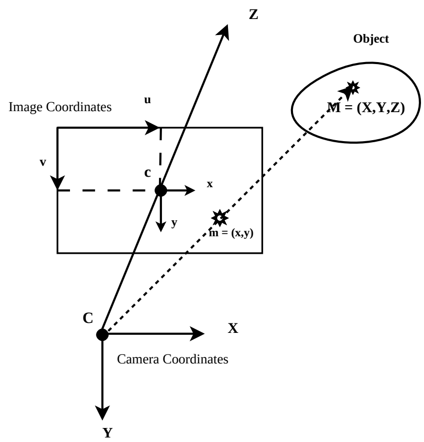

Figure 2: Camera Coordinates and Image coordinates.

camera pixel coordinates or image coordinates. The point M on an object with coordinates (X,Y,Z) will be imaged at some point $m = (x,y)$ in the image plane.
In order to compute the $3D$ motion constraint equation (Barron and Thacker, 2005), the derivatives of the

depth function with respect to the other world coordinates have to be computed. For instance, the dynamic object at (x,y,z) at time t is moved by $(\delta x, \delta y, \delta z)$ to $(x+\delta x,\ y+\delta y,\ z+\delta z)$ over time δt. The $3D$ Motion Constraint Equation (1) is obtained after performing 1^{st} order Taylor series expansion (Barron and Thacker, 2005).

$$R_x V_x + R_y V_y + R_z V_z + R_t = 0 \tag{1}$$

where, $\vec{V} = (V_x, V_y, V_z) = (\delta x/\delta t, \delta y/\delta t, \delta z/\delta t)$ is the $3D$ volume velocity, $\nabla R = (R_x, R_y, R_z)$ are the $3D$ spatial derivatives and R_t is the $3D$ temporal derivative. It is the analogue of the brightness change constraint equation (Spies et al., 2002) used in optical flow calculation.

3.1 Lucas and Kanade

In practice, the Lucas/Kanade algorithm (B D Lucas, 1981) is an intensity-based differential technique, which assumes that the flow vector is constant within a neighborhood region of pixels. The flow vectors are calculated by applying a weighted least-squares fit of local first-order constraints to a constant model for $\vec{V}$ in each spatial neighbourhood (Bauer et al., 2006). The velocity estimate is given by minimizing the equation as follows.

where $W(x,y,z)$ denotes a Guassian Windowing function. The velocity estimates is given by (2).

$$\vec{V} = [A^T W^2 A]^{-1} A^T W B \tag{2}$$

where,

$$A = [\nabla R(x_1,y_1,z_1), ..., \nabla R(x_n,y_n,z_n)] \tag{3}$$

$$W = diag[W(x_1,y_1,z_1), ..., W(x_n,y_n,z_n)] \tag{4}$$

$$B = -(R_t(x_1,y_1,z_1), ..., R_t(x_n,y_n,z_n)) \tag{5}$$

3.2 Horn and Schunck

Horn Schunck (Horn and Schunck, 1981) combines the gradient constraints with a global smoothness term. The flow velocity can be determined by minimizing the squared error quantity of constraint equation and smoothness constraint. The global smoothness constraint is given by $\|\nabla V_x\|^2, \|\nabla V_y\|^2, \|\nabla V_z\|^2$ and also expressed as (6).

$$\left(\frac{\partial V_x}{\partial x}\right)^2 + \left(\frac{\partial V_x}{\partial y}\right)^2 + \left(\frac{\partial V_x}{\partial x}\right)^2 + \left(\frac{\partial V_y}{\partial x}\right)^2 + \left(\frac{\partial V_y}{\partial y}\right)^2 + \left(\frac{\partial V_y}{\partial z}\right)^2 + \left(\frac{\partial V_z}{\partial x}\right)^2 + \left(\frac{\partial V_z}{\partial y}\right)^2 + \left(\frac{\partial V_z}{\partial z}\right)^2, \tag{6}$$

The error to be minimised is defined in equation (7).

$$\begin{aligned} E^2 &= \int_D (\nabla R.\vec{V} + R_t)^2 \\ &+ \alpha^2 \left(\|\nabla V_x\|^2 \|\nabla V_y\|^2 \|\nabla V_z\|^2\right) dxdydz \end{aligned} \tag{7}$$

where α is a weighting term that identifies the influence of smoothness constraint.

3.3 Combined Lucas/Kanade and Horn/Schunck

The combined differential approach involves applying a locally implemented, weighted least squares fit of local constraints to a constant model for flow velocity, which is combined with the global smoothness constraint. The velocity estimates can be minimised by equation (8).

$$\begin{aligned} E^2 &= \int_D (W_N^2 (\nabla R.\vec{V} + R_t)^2) \\ &+ \alpha^2 \left(\|\nabla V_x\|^2 \|\nabla V_y\|^2 \|\nabla V_z\|^2\right) dxdydz \end{aligned} \tag{8}$$

$A^T W^2 A$ is calculated as (9)

$$A^T W^2 A = \begin{pmatrix} \sum W^2 R_x^2 & \sum W^2 R_x R_y & \sum W^2 R_x R_z \\ \sum W^2 R_x R_y & \sum W^2 R_y^2 & \sum W^2 R_y R_z \\ \sum W^2 R_x R_z & \sum W^2 R_y R_z & \sum W^2 R_z^2 \end{pmatrix} \tag{9}$$

The velocity estimates can be solved through an iterative process.

$$V_x^{n+1} = V_x^n - \frac{W_N^2 R_x (R_x V_x + R_y V_y + R_z V_z + R_t)}{\alpha^2 + W_N^2 (R_x^2 + R_y^2 + R_z^2)} \tag{10}$$

$$V_y^{n+1} = V_y^n - \frac{W_N^2 R_y (R_x V_x + R_y V_y + R_z V_z + R_t)}{\alpha^2 + W_N^2 (R_x^2 + R_y^2 + R_z^2)} \tag{11}$$

$$V_z^{n+1} = V_z^n - \frac{W_N^2 R_z (R_x V_x + R_y V_y + R_z V_z + R_t)}{\alpha^2 + W_N^2 (R_x^2 + R_y^2 + R_z^2)} \tag{12}$$

where, the average of previous velocity estimates (V_x^n, V_y^n, V_z^n) are used along with the derivates estimates to obtain the new velocity estimates (V_x^{n+1}, V_y^{n+1}, V_z^{n+1}).

3.4 Experiment

The experiment is conducted by mounting the *PMD* camera over the Pioneer $3DX$ mobile robot, AGV. In our work, this PMD camera has been used as the vision sensor for efficient dynamic path planning. The scenario has been developed such that a person is walking towards the AGV from the far end. The task is to detect and estimate the movement of the person. So the relative distance between the vehicle and the moving person is calculated using the camera. As the camera senses the three dimensional coordinates of the person at different frame sequences, this 3D information is utilised to estimate the resultant velocity by using the combined Lucas/Kanade and Horn/Schunck differential techniques.

Two frames of 3D point clouds ($R_1(x,y,z,t)$, $R_2(x,y,z,t)$) are stored, as shown in figure 3 and 4. Figure 5, figure 6 and figure 7 show the velocity vectors along X,Y,Z direction. The resultant of these three vectors (V_x, V_y, V_z) are shown in 3D scale, figure 9. The vector flow which is also generated using the range data, $r(x,y,t)$,with r being the distance and x,y being camera pixel coordinates, is shown in figure 10.

Figure 3: Frame 1.

Figure 4: Frame 2.

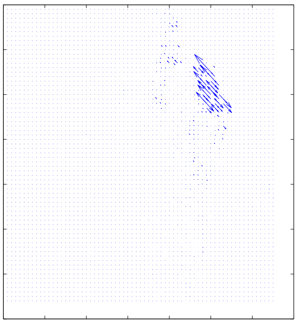

Figure 5: Flow vector along X direction.

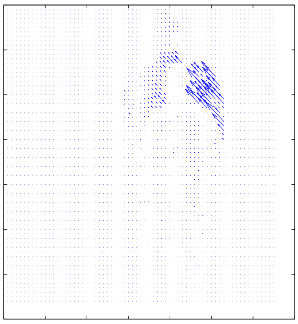

Figure 6: Flow vector along Y direction.

Figure 7: Flow vector along Z direction.

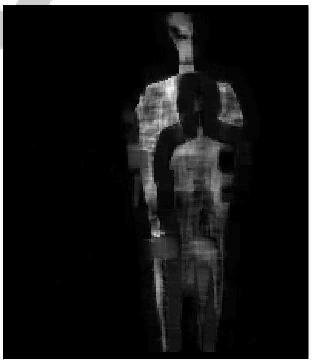

Figure 8: Edge Detection.

4 CONCLUSIONS

The paper shows the novel approach for velocity estimation using combined Lucas/Kanade and Horn/Schunck range-based differential technique. As the PMD camera gives suffient information about the obstacles, it is integrated with a Pioneer mobile robot to develop an efficient dynamic path planning in a cluttered environment. Our future work will focus on prediction of the dynamic obstacle's trajectory using the estimated velocity.

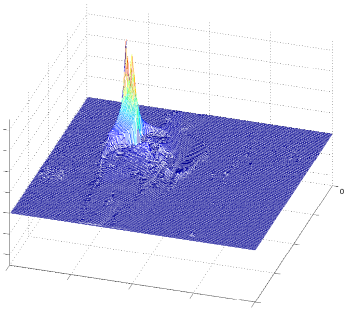

Figure 9: Resultant Vectors in 3D Scale.

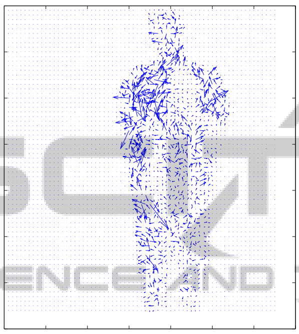

Figure 10: Flow Vectors using PMD Range data.

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