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Overview of Optical Flow Technique for Mobile Robot Obstacle Avoidance

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***Abstract*—Visual navigation is a recent trend to navigate robot. This paper presents the utilization of optical flow technique to achieve this with robust results. It helps in detecting the relativistic relation and related movement of the object. An important task for this is, to detect the obstacles and execute navigation without colliding with an obstacle when the robot is moving. Optical flow is calculated from the sequence of images in the video grabbed by the camera raised on the robot. From this, we further calculate the focus of expansion (FOE). This helps to find the time to contact (TTC). This calculation will provide information about an obstacle in the path, depth and the time needed to collide with the obstacle. By this information, the robot can navigate autonomously without the interference of human, since this all is done onboard. For implementing this, we will use coarse to fine warping method. An experiment will be performed under various environment settings, which will show fewer errors than the earlier implementation for mobile robot and increased performance under noise.**

Keywords—Collision avoidance, Optical flow, Focus of expansion, Time to contact, Robot navigation.

I. INTRODUCTION

Nowadays, in the highly automotive world, autonomous robots are preferred in unclean and risky occupancy. Especially in military, industries and urgency places. Some use UAVs (Unmanned Aerial Vehicle) which again needs human intervention. Therefore, an autonomous robot will be the solution for this. Here, autonomous not only means the freedom from any operator, but it also describes that, it does not utilize exterior subsidiary arrangement assemblage viz. radars. The environment where we don't have knowledge of the environment of the robot, we use visual-based navigation. This is performed by an optical flow technique. The assumption about the environment is, it is indoor with flat base due to which robot won't skid. The camera is used for visual sensing to get dimensional and vision knowledge viz. texture, color, etc. Comparing monocular vision to stereo, it claims for less estimate. Due to this, visual sensing is suitable for the low-cost and fast system. Many other methods are also examined. In [1], Santos-victor and Bernardino have implemented collision avoidance. This was done using stereo vision. In [2], the author has performed optical flow on their robot named as robee. This was approached by difference technique of two lateral cameras. In [3], the author has performed a trinocular vision approach for guiding the robot. These approaches follow corridor behavior. Therefore, all approaches require multiple numbers of cameras. With the increase in the number of the camera, processing of image per camera increases. Hence, this becomes more complex and decreases the robustness of the system.

Proposed system focus to implement robust visual navigation. This will result in the fully autonomous robot. Optical flow is computed through a sequence of images from the camera. This gives an idea of the environment of the robot by calculating vital features. All this helps the robot to navigate properly. Therefore obstruction avoidance by the robot will be in real-time. During the motion, left and right flow vectors are been balanced. The concern is to execute everything onboard the robot so that there will be no limitation of the distance of exterior setup. Also with this, there is no chance to break communication.

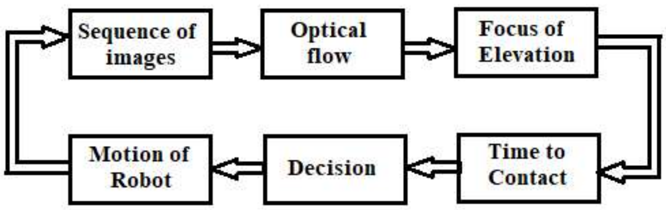

Fig 1: Obstacle avoidance system

After the optical flow vectors are calculated, the FOE calculation is computed for knowing the orientation of the robot. The time to contact and depth calculation is performed, which guides the mobile robot about the presence of the obstacle. If the obstacle is close enough then the robot will stop and change its path giving an alert. Similarly, if an obstacle is far then the robot will keep on moving.

II. RELATED WORK

Navigation of autonomous robots is done using different sensors such as vision, IR, etc. Obstacle avoidance is carried through IR or ultrasonic sensor [4]. Using this, depth can be known easily and hence the obstacle. But the information is founded distinctly. Therefore, other sensor systems are collaborated [5]. Other methods exist which give the knowledge of environment by performing the test from data on landmarks [6] or derive from edge detection exploiting monocular sight [7]. These change with respect to the environment of the mobile robot. One approach of collision is the calculation of left and right optical flow. After this, the robot will move where the less optical flow is present [8]. Movement division of target and background is reported in [9] for optical flow calculation. Many approaches to optical flow navigation technique require multiple numbers of cameras. Stereo vision is one of the used approach [1]. Trinocular vision is another technique [3]. These approaches follow corridor behavior. For this, they require multiple numbers of cameras which increases the calculation cost and execution cost. But approaches based on only one camera are also implemented. This included control laws and activity modalities. This ecological psychology optical flow approach help to keep off the collision [10]. Optical flow through convenient approach encouraging immediate computer sight application was then brought out [11]. Balancing tactics of the left and right flow were introduced [12]. Image segmentation technique using optical flow was put in which guaranteed an instant reaction of the robot to adapt environment immediately [13]. Smoothening restraint was added replacing the quadratic veritable in Horn and Schunck structure resulting in a polished result. Coarse to fine tactics [14, 15] and non-in line structures [16, 17] are used to solve big translation trouble. Labeling immediately from the spatiotemporal slope and expand OF templet ways to absolute cam optics [18] and avoid collision founded on balance strategies is measured [19]. But these all approaches do not give an acceptable result.

Therefore, we aim a new alteration method that will include many formulations named above and which can be lowered using a numerical method. And the coarse to fine tactics through warping approach [14,15], executes optical flow obligation which is non-linearised utilized in [16,17]. This has an important effect: we can incorporate warping method into variance model which was earlier actuated algorithmically. This optimizes the robots movement parameters which increase the systems result rate. The image resolution which we will use is bigger than the earlier used. Also, there will not be any specialized hardware or extraordinary camera used. Thus, this will reduce the experimental cost.

III. Optical Flow Laws

As observance point motion begins, the pattern created by light reflection to the point changes in persistence. This produces optical flow. Optical flow incorporates data about the environment of the robot, the direction of the point of observance, FOE, TOC, and depth.

A. Optical Flow

The optical flow is generated from the relevant motion of obstacle and camera, which is a grouping of apparent velocities of motion of intensity pattern in a picture. Vectors get generated when pixels shift from one frame to other. This vector field is optical flow. While going farther from the middle, pixel change outwards with greater size. If the surrounding is unchanging, there will be still a proportional motion between the obstacles and the cam onboard the robot. In a video camera, we get a sequence of images by the motion of camera or 3-D scene. Using a projection system, this 3D movements of the object is change over to 2D movement on the image plane. Using intensity and color data of video sequence, a 2D movement called optical flow is required to be retrieved [12]. At each time interval, the pixel in 3D motion is converted in 2D vector domain, indicating evident motion. Converting from 3D to 2D, we assume on image the pixel intensity value for the 3D point is identical. We maintain the image intensity by keeping intensity same with respect to time. Therefore, we obtain motion by the difference in images of two different time intervals, say t_0 to t_1. The assumption is made that by the translation, the grey value of pixel remains constant.

$$I(x, y, t) = I(x+u, y+v, t+1) \tag{1}$$

By linearizing, we get popular optical flow restraint.

$$I_x u + I_y v + I_t = 0 \tag{2}$$

Here, $I(x, y, t)$ is luminosity of pixel and, u and v describe the optical flow vectors connected to the certain pixel. Inferior indicates partial differentiation. Our approach is using a differential method which preserves the intensity of point in motion to find the optical flow. This is done based on the theory of warping [20]. This optical flow navigates the mobile robot in a decision which includes maintaining the equilibrium of the left and right side optical flow for collision keep-off.

B. Focus Of Expansion(FOE)

In case of displacement movement of the cam, all the image movement is targeted out from the single point representing the ejection of the displacement vector. This singular point is the focus of expansion (FOE). This works on the rule that the flow vectors point in a particular direction proportional to the focus of expansion. This means, that the flow vector R with horizontal element h_R present at the right of FOE orients right side and the flow vector L with horizontal element h_L present at the left of FOE orients left side as shown in [12, Fig.2].

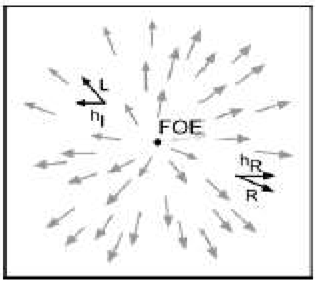

Fig 2: FOE calculation

In the optical field, the horizontal position of FOE equates with the area where a maximum of horizontal elements deviate, is calculated using counting strategy to total the sign of horizontal elements centralized at every image position. Where there is the majority of deviation, the inequality or remainder between the count of h_L elements at the left of FOE and the count of h_R elements at the right of the FOE is reduced. The perpendicular position of the FOE is calculated by discovering the location where maximum perpendicular elements (V_U and V_V) deviate [12].

C. Time To Contact(TTC)

The very important task in the whole process is to calculate the precise time to contact. This will thus result in the proper navigation of robot autonomously. The visualized data helps to decide the distance and velocity of activity in relation to time. Reference of visualized data is obtained from the motion of the robot in direction of object or object in direction of the robot. Accordingly, then, activity is performed based on data of perpetually varying environment. Therefore, for a greater degree of authentication and impressible outcomes from projected algorithm we section the image to the vertical area. The count of areas is dynamically estimated relying upon the resolution. Using optical flow and coordinates of the FOE, TTC respectively the i^{th} area of the image is estimated. An example of a TTC graph is shown below in Fig.3. Given below formula is used where x and y are middle dots of regarded area. FOEx and FOEy represent coordinates of the FOE. u and y are optical flow element of the i^{th} region [21].

$$\tau_i = \sqrt{\frac{(xi-FOEx)^2 + (yi-FOEy)^2}{\sqrt{ui^2 + vi^2}}} \qquad (3)$$

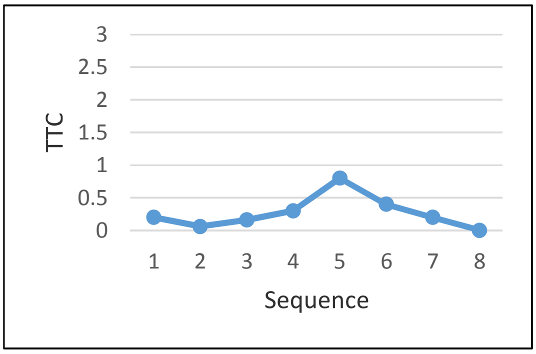

Fig 3: TTC graph

D. Depth Calculation

Depth data for every flow vector is calculated using the optical flow calculated from two sequential images, by compounding time to contact calculation and speed of the robot at a time when the image was captured.

$$X = V \times T \qquad (4)$$

Here, X represents depth, V represents speed and T represent TTC calculation for every optical flow vector [12]. As illustrated in [12, Fig.4], it demonstrates depth image example which will be obtained by time to contact. The blackest area or point is nearest and whitest area or point is farthermost view area. Hence, the whitest area represents the navigation region of the mobile robot.

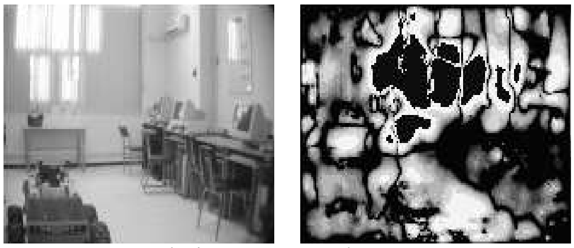

Fig 4: Depth calculation

E. Balance Strategy For Obstacle Avoidance

The strategy used is that when the robot is rendering than the object which is nearer provide quick movement over retina than the farthest object. Nearer object occupies the maximum field. This influence the average near the related flow. The mobile robot moves off from the slope of the maximum field. This is given by:

$$\Delta(F_L\text{-}F_R) = \frac{\Sigma|WL| - \Sigma|WR|}{\Sigma|WL| + \Sigma|WR|} \qquad (5)$$

Where, $\Delta(F_L\text{-}F_R)$ represents the deviation of forces of the robot on either side, and $\Sigma|W|$, is the addition of a mass of optic flow. Based on the above principles, the decision is taken by a robot [12].

IV. Proposed Set-Up

A USB camera is connected to the laptop for capturing the video. The video sequence is captured at the rate of 30 frames per second with a resolution of 640x480 pixels.

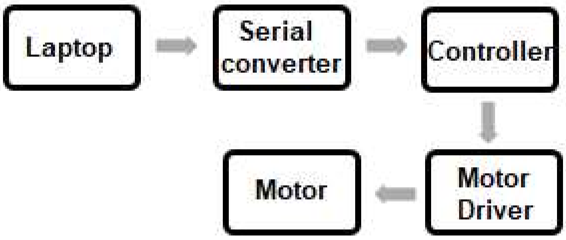

Fig 5: Experimental set-up

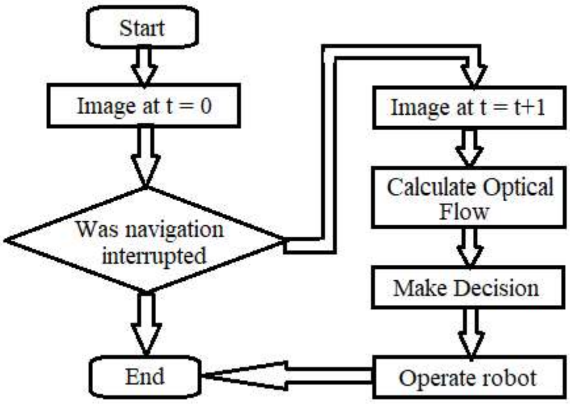

Fig 6: Flowchart of system

But, 320x240 pixels is used to decrease the image-acquirement time. The robot will yield fixed velocity and reduced vibration during the test, so that the inaccuracy from optical flow can be reduced. The robot is having an onboard laptop having Intel i3 processor and 4 GB of RAM memory.

Input contains live image sequences through the camera while the robot is in motion. Through the MATLAB software, the optical flow is computed and the TTC is calculated per frame. Depending on the TTC, the instruction is passed to the robot through controller using USB to serial converter. Arduino micro-controller will receive the instruction through TTL and accordingly, it will transmit a command to sabertooth motor of the robot. Thus, the robot will navigate efficiently.

V. Conclusion

The use of optical flow technique to navigate the mobile robot autonomously onboard without colliding with an obstacle in real-time is described. Using the flow vectors, the presence of the obstacle is detected resulting in close enough or far alert. Difficulty in computing optical flow is, that, it is not known what makes the alteration of gray value. The proposed method will navigate the mobile robot using only one camera as the single sensor through mapless scheme giving increased and reliable results with reduced cost.

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