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Visual Robot Navigation based on Improved Optical Flow Algorithm and Optimized Bessel Curves

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Abstract: This study first describes the problems which occurred when using optical flow algorithm in robot navigation. Then, an improved optical flow algorithm was proposed and a navigation algorithm for visual obstacle avoidance of autonomous mobile robot was developed. By improving the optical flow algorithm, a path optimization algorithm based on the Bessel curve by bat algorithm for path planning was developed. In the first part of this study, we will describe the methods to obstacle avoidance when using optical flow algorithm. Then we will focus on the improvement measures to optical flow algorithm. Finally, the improved optical algorithm was used on P3-DX mobile robots platform to test the effectiveness of the proposed algorithm. The experimental results indicate that the proposed method is effective and feasible.

Key words: Optical flow, bat algorithm, obstacle avoidance, bessel curve, navigation

INTRODUCTION

In robot navigation, obstacle avoidance is the most basic function. The approach for vision based robot navigation in the case of an unstructured environment, where no prior knowledge of the robot environment can be acquired, is generally based on optical flow calculation (Widrow and Steams, 1995; Loren and Benson, 1999; Karp, 1972; Lorentz and Benson, 1983; Park and Lee, 2011; He *et al*., 2012; Guzel and Bicker, 2010; Boroujeni *et al*., 2012; Liyanage and Perera, 2012; Mammarella *et al*., 2012; Kumar *et al*., 2013). Though, some stereo based and pattern matching based techniques are also tested. But the main disadvantage of these systems is that they require two or more cameras. This makes the system computationally more intensive than a single camera system. Our study is to develop algorithms for visual robot navigation. The input consists of a sequence of images that are continuously demanded by the navigation system while the robot is moving. This image sequence is provided by a monocular vision system for a moving robot.

The basic algorithm of this mobile robot navigation system is optical flow algorithm. And optical flow algorithm consists of a series of assumptions, such as motion discontinuities, illumination changes and camera image with the robot relative motion between velocity and other factors but in the real image sequences, these assumptions are simplified. Most single-camera systems estimate Time-To-Contact (TTC) by using the optical flow vectors. TTC shows the time to contact predicted. Combining TTC with the position of optical flow vector convergence center (in some studies called FOE), obstacle avoidance can be achieved. But the drawback of optical flow approach is the large computation cost. In this study, a fast optical flow estimation algorithm was developed. The mobile robot obstacle avoidance get lower successful rate in the experiment because of the interference of the external light-environment and high motion speed compared with large calculating amount. So, we use the bat algorithm to optimize robot motion parameters so as to improve the robot obstacle avoidance success rate.

FAST OPTICAL FLOW ESTIMATION ALGORITHM

Lucas-Kanade method is one of the most commonly used technologies of optical flow estimation; this method has high speed and simple (Zhao *et al*., 2012). Suppose the image intensity of a pixel is denoted by I(u, v, n), (u, v) is one pixel location in the image, n is the capture frame.

If the sequence image acquisition time interval between frames is very short, the scene and illumination condition changes slowly while the two adjacent frame image to meet the constant gray constraint. This pixel moves a distance ξ in the x direction and η in the y direction respectively. We use the following formula to represent this relationship:

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$$I(u, v, n) = I(u+\xi, y+\eta, n+1) \quad (1)$$

So, we get an optical flow vector $d = (\xi, \eta)^T$ which contains the motion information of corresponding pixels between the frames. The LK method assumes that the image local small windows of all the pixels with the same optical flow, then the residuals are minimized to obtain the estimated value of d.

Let, (x) = I(u, v, n), I(x+d) = I(u+ξ, y+η, n+1). So, the objectives function:

$$E = \Sigma_w[I(x+d)-J(x)]^2 \quad (2)$$

In this function, W represents a rectangular window. By using Taylor series expansion and the linear approximation, we can get:

$$I(x+d) \approx I(x)+I'(x)d \quad (3)$$

By minimizing the E to get the estimated value of d, E on the D derivative is zero:

$$0 = \frac{\partial}{\partial d} E \approx \frac{\partial}{\partial d} \sum_w [I(x)+I'(x)d-J(x)]^2 = \sum_w 2I'(x)[I(x)+I'(x)d-J(x)]\ d \approx \frac{\sum_w I'(x)^T[J(x)-I(x)]}{\sum_w I'(x)^T I'(x)} \quad (4)$$

By using the Newton's method we can get more accurate estimation of the value, the iterative equation is:

$$\begin{cases} d_0 = 0 \\ d_{k+1} = d_k + \dfrac{\sum I'(x+d_k)^T[J(x)-I(x+d_k)]}{\sum I'(x+d_k)^T I'(x+d_k)} \end{cases} \quad (5)$$

According to Eq. 5, the optical flow and optical flow field can be calculated.

For translational motion of the camera, pixel motion of the image is directed away from a singular point corresponding to the projection of the translation vector on the image plane. This point is called the Focus Of Expansion (FOE), as shown in Fig. 1. It is computed based on the principle that flow vectors are oriented in specific directions relative to the FOE.

The Time-To-Contact (TTC) is the time when a robot collides with a surface moving at a constant velocity. Using TTC, the relative distance between an object and robot can be calculated and thus can be used for obstacle avoidance navigation. There are several ways to compute TTC. One way is to calculate the Focus Of Expansion (FOE) and the translational optical flow (d):

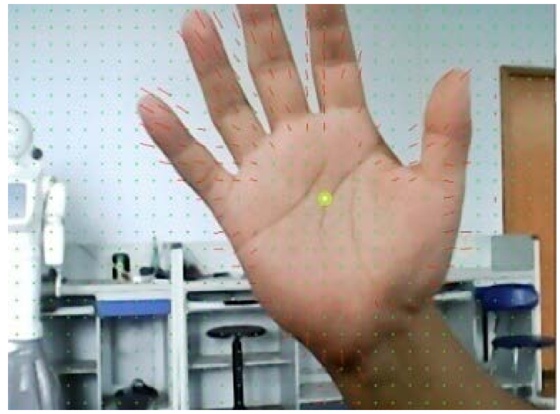

Fig. 1: Result of the FOE calculation, the FOE is shown by the yellow scar in the image

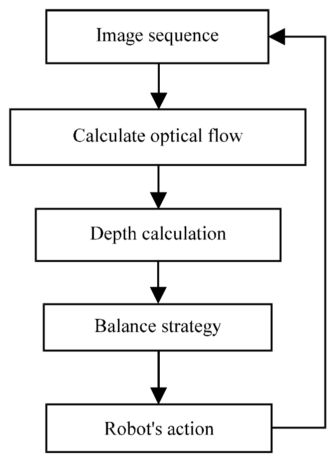

Fig. 2: Block diagram of the navigation algorithm when use optical flow

$$TTC = \frac{\Delta_i}{|\vec{d}_i|} \quad (6)$$

In this equation Δ_i is the distance of a pixel (u, v, n) from the FOE. The FOE is a point in the image plane from which all pixels motion originate. Once the TTC is known, the speed (V) of the robot is set constant, thus, depth (Z) can be computed by:

$$Z = TTC \times v \quad (7)$$

When the depth is gained, we can use this data for a balance strategy. The algorithm depicted as Fig. 2.

The robot can determine the magnitude and direction of rotation by trying to eliminate the magnitude of the sum of the left and right difference of the optical flow vectors.

In such a case, the sum of the magnitudes of the optical flow vectors on the right side is greater than the left side sum. Therefore, the robot should turn left to avoid the obstacle. According to this method, we need use a fixed low speed and robot need to constantly adjust the direction of motion to keep the residual balance. In this case, the computer on robot spends more time in calculating. As a result, the robot get lower success rate in obstacle avoidance.

OPTIMIZATION OF PATH BASED ON BAT ALGORITHM AND BESSEL CURVE

In order to solve the problem mentioned previously, we use the Bessel curve (Zhu, 2012) and the bat algorithm (Yang, 2010; Bora *et al*., 2012) for local path planning. The bat algorithm is a new metaheuristic method which based on the echolocation behavior of bats. This algorithm combines the major advantages of particle swarm optimization and genetic algorithms.

With the help of Bessel curve, the local path planning problem was converted into the optimization problem of point position selection of the Bessel curve. In this study, the collision time and the real-time speed are all considered to dynamically optimize the location of these points to get an optimal motion path.

Determination of Bessel curve depends on the number of control points, the curve parameter equation for each point can be calculated as:

$$p(t) = \Sigma^{N}{}_{i}p_iB_{i,N}(t),\ t\epsilon[0, 1] \tag{8}$$

where, Pi is the i coordinates of vertices. The basis function is listed as:

$$B_{i,N}(t) = C^{i}_{N}t^{K}(1-t)^{N-i}\ i = 0, 1,\ldots, n \tag{9}$$

The secondary Bessel curve is represented by three points:

$$\overline{B}(t) = (1-t)^2\overline{P}_0 + 2t(1-t)\overline{P}_1 + t^2\overline{P}_2 t \in [0, 1] \tag{10}$$

According to Eq. 8, combined with optical flow algorithm, a Bessel curve worked as path section in navigation can be obtained. But this path was sub-optimal in most cases. Therefore, the bat algorithm was chosen to find the optimal path.

This study uses secondary Bessel curve to perform path planning of robot, secondary Bessel curve has three control points, P_0, P_1 and P_2 as shown in Fig. 3.

Robot visual camera is represented by the P_0 point. P_1 point is the intermediate point and P_2 is the end point of mobile robot task. Thus, the Bessel curve is determined by the three control point. The parameters TTC and FOE combined with the robot moving speed are all used to calculate the obstacle distance L_1 and L_2. In order to use secondary Bessel curve to construct path section, we need to develop an evaluation function, evaluation for individual bat algorithm benefits. There are two main aspects of the object function.

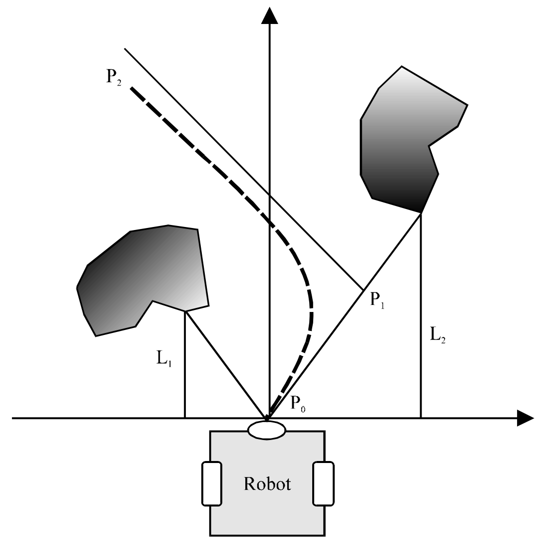

Fig. 3: Secondary Bezier curve in path planning

Shortest path: During path planning, so many factors should be taken into account such as gloss property, feasible for robot to follow and as short as possible, so that the robot can quickly go bypass the barriers.

For calculating length of the Bessel curve, the derivative of the quadratic Bezier curve should be obtained:

$$\frac{\partial\overline{B}(t)}{\partial t} = 2t\left(\overline{P_0} - 2\overline{P_1} + \overline{P_2}\right) + 2\overline{P_1} - 2\overline{P_0} \tag{11}$$

In case of secondary Bessel curve, using its derivatives, this integral can be written as:

$$L_B = \int_0^t \sqrt{B'_x(t)^2 + B'_y(t)^2 dt} \tag{12}$$

For simplicity, some substitutions can be made:

$$\overline{a} = \overline{P}_0 - 2\overline{P}_1 + \overline{P}_2,\ \overline{b} = 2\overline{P}_1 - 2\overline{P}_0 \tag{13}$$

In order to make this integral easier, making some algebra and grouping elements in order to parameter we will do another substitution. A, B, C is a constant that calculated according to P_0, P_1 and P_2:

$$A = 4(a^2_x+a^2_y),\ B = 4(a_x b_x+a_y b_y),\ C = b^2_x+b^2_y \quad (14)$$

Finally we get simplified integral, it can be written as having the following magnitude:

$$L_B = \int_0^1 \sqrt{At^2+Bt+C}dt \quad (15)$$

To make the motion path as short as possible, define the following function to evaluate the path:

$$f_{len} = \left(1-\frac{L_{min}}{L_B}\right)^2 \quad (16)$$

L_{min} is robot to reach the target point of the straight line distance.

Obstacle avoidance safety: The Bessel curve path length provides an index to optimize the robot path but to complete the obstacle avoidance, the security evaluation criteria to evaluate the path should be set. Base on the experimental experience, when the minimum collision time calculation is less than safety turn time, the robot cannot avoid the obstacle avoidance effectively. Combining the path length calculating, the security evaluation function can be calculated as:

$$f_{safe} = \begin{cases} 0 & d_{min}>D_{safe} \\ \left(1-\frac{d_{min}}{D_{safe}}\right)^2 & 0\le d_{min}\le D_{safe} \end{cases} \quad (17)$$

Avoidance objective function f_{safe} has been combined with path length fitness function f_{len} to form over all fitness function f, as shown below:

$$f = a_1 f_{safe}+a_2 f_{len} \quad (18)$$

In Eq. 18, a_1, a_2 are the weighting coefficients, the smaller the evaluation value, the better the path quality. According to the fitness function, the block diagram of the bat algorithm shows in Fig. 4.

RESULTS AND DISCUSSION

In order to validate the feasible of our proposed method, practical experiment was performed on a real mobile robot-Pioneer DX. The Pioneer robot equipped with a sonar ring, encoders, a camera and an inertial measurement unit. During the experiment, we only use camera as the vision sensor unit.

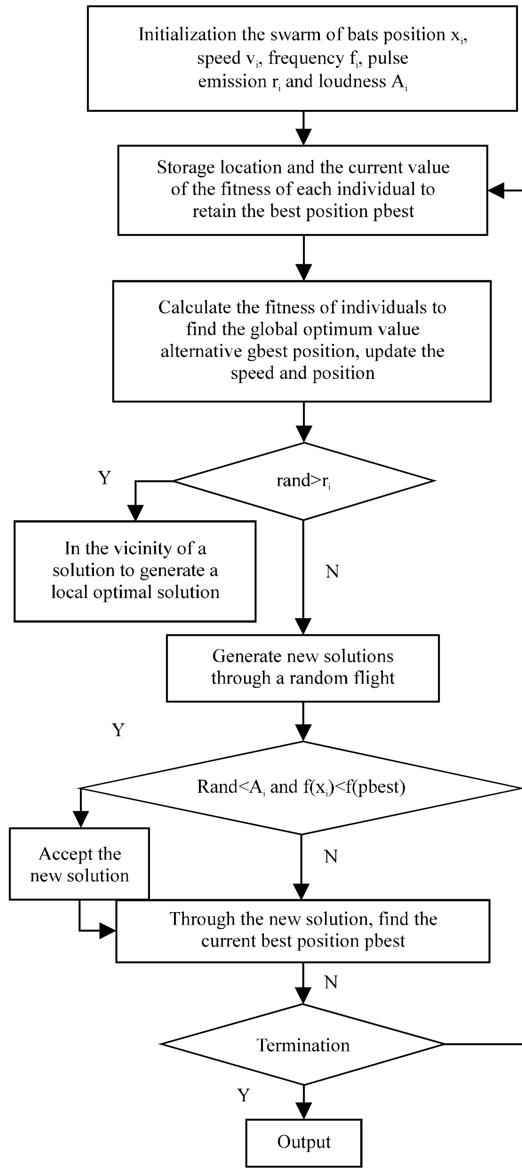

Fig. 4: Block diagram of the bat algorithm

The speed of the robot in the experiments ranged from 0-350 mm sec^{-1}. Ground environment is wooden floor, no tire slip. The inertial measurement unit can record the path during robot task. Two experiments were conducted just for comparison. In the first experiment, only optical flow algorithm was used to do the path planning. In the second one, optical flow algorithm based on Bessel curve path design was used to perform path planning and optimized by bat algorithm.

In experiments, the safe distance between robot and obstacle area is set about 1 m, the distance between two barriers is about 0.6 m. In order to eliminating the

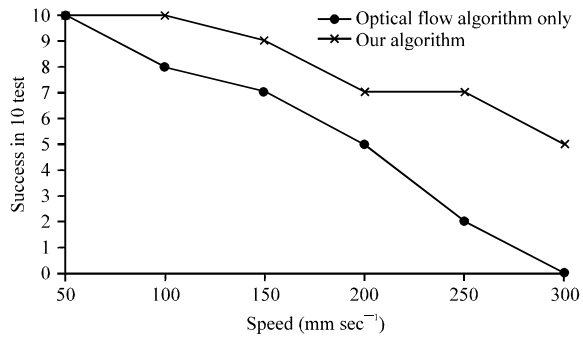

Fig. 5: Results in every ten times of experiments

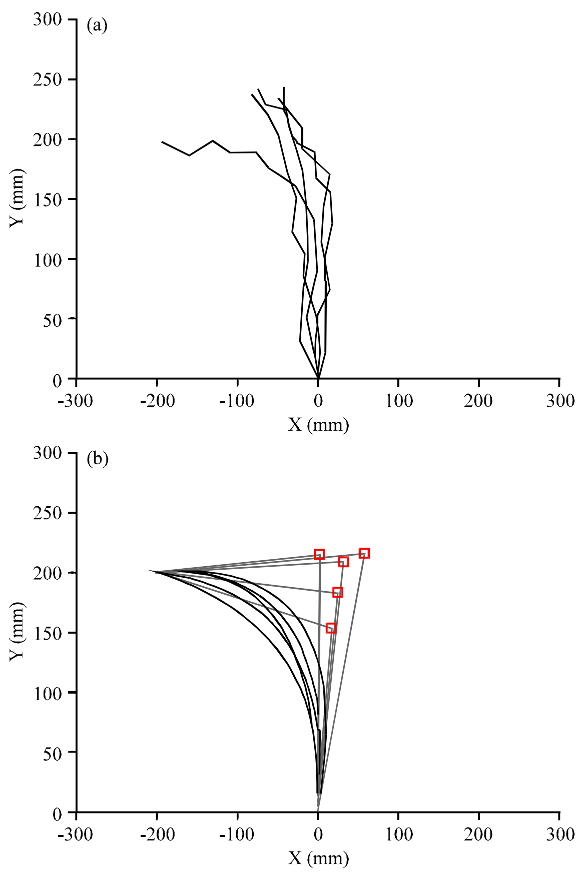

Fig. 6(a-b): Experimental results under the two different methods as motion path generated with (a) Optical flow algorithm and (b) Proposed method

disturbance from the surrounding environment, a threshold for optical flow computation value was set as well. If the optical flow computation value is less than the threshold, then the optical flow vector will be ignored. Thus, the interference from camera captured images and light interference can be eliminated to some extent.

In the two different experiments, the robot should go through a region with three obstacles by using two different algorithms, the speed of the robot was not set constant any more but it can only be vary in a specified scope.

For each algorithm, the experiment was repeated 10 times under the same velocity and the number of successful rate was recorded, as shown in Fig. 5.

During the experiments, the robot motion paths were recorded by the inertial measurement unit. In Fig. 6a, experiments were executed with optical flow algorithm only and the robot speed was set 300 mm sec^{-1}. In Fig. 6b, our proposed algorithm was tested under the same conditions.

As can be seen from the experimental results, when only using the optical flow algorithm, the robot needs to adjust the angle constantly to keep balance so that the motion path is not smooth. At the same time, because of the quick speed, the robot only successfully avoids obstacles once. When using our proposed method, the robot path is smooth and short. Thus, the robot spends less time on following the path and has more chance to by pass the obstacles.

CONCLUSION

In this study, the problems emerging during obstacle avoidance by using optical flow were discussed. A modified schedule was proposed. By combining the Bessel curve design method and bat algorithm optimization technology, an optimal path was generated which guarantee the robot complete its task with high successful rate. The experimental results showed the proposed algorithm is feasible and effective to solve the problems of optical flow algorithm for navigation. Of course, our proposed algorithm is not perfect, for example, the derived path is short and localized which will be the emphasis of our future research. Motion speed is another key content of robot navigation system. What we have done here in visual navigation will cast light for practical robot usage.

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