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The Lane-Curvature Method for Local Obstacle Avoidance

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Abstract

The Lane-Curvature Method(LCM) presented in this paper is a new local obstacle avoidance method for indoor mobile robots. The method combines Curvature-Velocity Method(CVM) with a new directional method called the Lane Method. The Lane Method divides the environment into lanes, and then chooses the best lane to follow to optimize travel along a desired heading. A local heading is then calculated for entering and following the best lane, and CVM uses this heading to determine the optimal translational and rotational velocities, considering the heading direction, physical limitations, and environmental constraints. By combining both the directional and velocity space methods, LCM yields safe collision-free motion as well as smooth motion taking the dynamics of the robot into account.

1 Introduction

A local obstacle avoidance method for indoor mobile robots in unknown or partially known environment is investigated. The method should guide a robot through a collision free space to a given goal heading, or to a goal location, as fast as possible. For fast and smooth robot movement, it should be efficient for real-time implementation, and take the dynamics and physical limitations of the robot into account. Though many approaches efficiently yield commands guiding the robot through a collision free path, they often do not address the dynamics of the robot, and results in slow or jerky movement.

The directional approaches compute a direction for robot to head in, in Cartesian space or configuration space. The V-graph search methods [1], potential field methods [2], [3], and Vector Field Histogram method [4] belong in this category. Though they are simple and efficient in producing a directional command for collision free movement, they are not adequate for taking the robot dynamics into account. The Vector Field Histogram [4] method is able to achieve smoother navigation and is more successful in traveling through narrow openings. However, it is still not adequate to deal with vehicle dynamics, which can cause problems in cluttered environments.

Velocity space approaches, on the other hand, choose rotational velocity along with translational velocity, and can incorporate vehicle dynamics [5], [6], [7], [8], [9]. They typically presume that the robot travels along arcs of circles. The Curvature-Velocity Method(CVM) chooses a point in translational-rotational velocity space which satisfies some constraints and maximizes an objective function [5]. The constraints represent both the presence of obstacles and physical limitations on robot's velocities and accelerations. Though it produces reliable, smooth, and speedy navigation in office environments, it has some shortcomings. Often, at an intersection of corridors, it fails to guide the robot into an open corridor toward the goal direction. It often passes over some paths which are at right angles to the current robot orientation. Also, it sometimes lets a robot head towards an obstacle until the robot gets near the obstacle, even if there is a clear space around the obstacle. These problems all stem from the fact that CVM chooses commands based on the collision-free length of the arcs assumed to be robot's trajectories. It does not consider that the robot may be on that arc for just a short distance, and will soon be turning again. In short, CVM pays less attention to collision free *directions* than do the directional approaches.

The Lane-Curvature Method(LCM), described in this paper, improves the velocity space approach by considering collision free direction as well as the collision free arc length. It uses a two-step approach to navigation. First, given a desired goal heading, a directional approach, called the Lane Method, chooses a "lane" for the robot to be in, taking into consideration obstacle avoidance, motion efficiency, and goal directedness. Then, the Lane Method calculates a local heading that will guide the robot either into, or along, that lane. Since, the Lane Method alone can-not account for the physical constraints of the robot motion, the local heading is supplied to CVM. Based on this heading, CVM produces translational and rotational velocity commands, taking into consideration the physical constraints of the robot.

The Lane Method chooses the direction to a wide and collision free opening since it decides heading direction based on the collision free distance and width of lanes. On the other hand, the VFH method chooses a direction to the opening with wide collision free *angular* range rather than an opening with wide width. So, it may force a robot into a narrow opening near the robot because even a narrow opening can offer wide collision free angular range to a robot if the opening is close to the robot. In this respect, the Lane Method can provide safer heading commands to CVM than the VFH.

2 The Curvature-Velocity Method

The CVM formulates local obstacle avoidance problem as one of constrained optimization in the velocity space of the robot. It determines translational velocity tv and rotational velocity rv, maximizing the objective function $f(tv, rv)$:

$$
\begin{aligned}
& f(tv, rv) = \alpha_1 \cdot dist(tv, rv) + \alpha_2 \cdot head(rv) \\
& + \alpha_3 \cdot speed(tv) \\
& dist(tv, rv) = d(tv, rv, OBS)/L \\
& head(rv) = 1 - |\theta_c - rv \cdot T_c|/\pi \\
& speed(tv) = tv/tv_{max}
\end{aligned}
\tag{1}
$$

$d(tv, rv, OBS)$ is the arc distance that the robot can go with the curvature $c = rv/tv$ before hitting a set of obstacles OBS. The arc distance $d(tv, rv, OBS)$ is normalized to $dist(tv, rv)$ by some limiting distance L(three meters, in our implementation). The $head(rv)$ is the normalized error in goal heading. It is defined to be the difference between the commanded heading θ_c(in the robot's local reference frame) and the heading the robot will achieve if it turns at rv for some time constant T_c. In other words, the objective function tries to have the robot achieve high speed movement close to the command heading direction, while traveling longer before hitting the obstacles.

The constraints maintaining the robot motion within its physical limitations are the followings:

$$
\begin{aligned}
& 0 \leq tv \leq tv_{max}, -rv_{max} \leq rv \leq rv_{max} \\
& rv \geq rv_{cur} - (ra_{max} \cdot T_{accel}) \\
& rv \leq rv_{cur} + (ra_{max} \cdot T_{accel}) \\
& tv \geq tv_{cur} + (ta_{max} \cdot T_{accel})
\end{aligned}
\tag{2}
$$

These constraints limit the robot's translational velocity, rotational velocity, translational acceleration, and rotational acceleration within the maximum values tv_{max}, rv_{max}, ta_{max}, and ra_{max}, respectively. The constraint $0 \leq tv$ prohibits the robot from moving backward. Here, T_{accel} is the time interval with which commands are issued.

As a whole, CVM finds a point in translational-rotational velocity space satisfying the constraints (2), and maximizing the objective function (1). This produces rotational and translational commands that move the robot through a safe and goal directed path as fast as possible, within the robot's physical driving ability.

3 The Lane Method

To find a heading direction for collision free movement, the Lane Method divides the environment into lanes oriented in the direction of the desired goal heading. Then it selects the best lane for collision free and efficient motion. Finally, it calculates a heading direction to enter, or continue along, the selected lane.

3.1 Lanes

All the lanes are constructed by determining the maximum collision-free distance to obstacles along the desired goal heading. Adjacent lanes with similar collision-free distances are merged. To facilitate the lane determination, and to match the implementation of CVM, the obstacles are approximated as circles, represented by their locations and radii. The radii of the obstacles are increased by the radius of the robot to convert from Cartesian space to configuration space obstacles, since our robot is also circular. The parameters describing the k-th lane are lane width $w(k)$, collision free distance $d(k)$, and viewing direction $va(k)$, which is the angle at which a line from the robot to the lane passes through only collision-free areas. These parameters are depicted graphically in Figure 1.

In Figure 1, the number of lanes N_L is six. The working area is divided into lanes within the range of

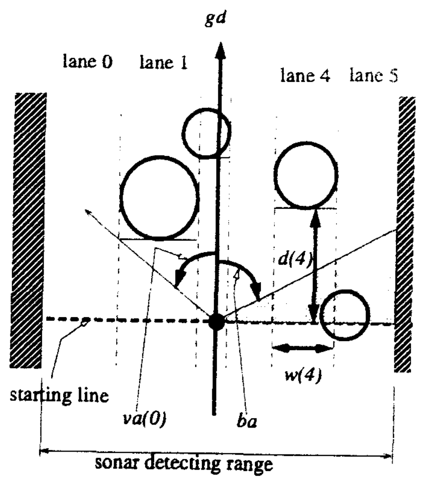


Figure 1: Lanes and their describing parameters

the maximum obstacle sensing distance(set to 4 meters in our experiments). In determining lanes, we ignore the obstacles that are "behind" the robot. Since the robot is continually moving forward, we actually determine what obstacles are "behind" the robot as those whose angular distance from the desred goal heading is beyond some predefined angle limit. The angular limits for the clockwise and counter clockwise direction are determined individually. The blocking angle limit, ba for each direction is defined as:

$$|ba| = \begin{cases} 90^\circ, & \text{if there are no obstacles} \\ & \text{on the starting line} \\ 55^\circ, & \text{If there is some obstacle} \\ & \text{on the starting line} \end{cases} \quad (3)$$

The collision-free distance of the k-th lane, $d(k)$ is defined as the distance the robot can go through the k-th lane before hitting obstacles, from the starting line. The view angle for the k-th lane, $va(k)$ is the minimum angle from the desired goal heading gd to the collision-free direction to the k-th lane. In determining $va(k)$, it is assumed that the k-th lane is blocked at the distance $d(k)$ from the starting line.

A lane with very narrow lane width is merged to a neighboring lane by the following rule: If $w(h) \leq w_{min}$ and $d(h) > Min\{d(h-1), d(h+1)\}$ for some $1 \leq h \leq N_L - 2$, then merge the h-th lane into the neighboring lane with the smaller collision-free distance. In the experiment w_{min} is set to be $2.0cm$. Also, two lanes with similar collision-free distances are merged together using the following rule: If $|d(h) - d(h+1)| \leq \Delta d_{min}$, $0 \leq h \leq N_L - 2$, then merge the lane with larger collision-free distance into the other lane. We set $\Delta d_{min} = 2.5cm$ in the experiment.

3.2 Lane Selection

Once lanes are constructed, the Lane Method chooses the best lane to be in for efficient and collision-free movement. For safe, collision-free movement, it is desired to go through a lane with longer collision-free distance and wider lane width. For efficient steering, smaller change of heading command is desired. Also, abrupt change of heading command due to noisy sonar reading can be prevented by keeping the change of heading command as small as possible. For fast and efficient robot motion, heading command closer to the current robot orientation o_r is preferred. To address the above discussions, we choose the following linear function $f_s(k)$ as a lane selection function.

$$\begin{aligned} & f_s(k) = \beta_1 \cdot \overline{d}(k) + \beta_2 \cdot \overline{w}(k) - \beta_3 \cdot \overline{ad}_{va,c}(k) \\ & \quad - \beta_4 \cdot \overline{ad}_{va,o}(k) \\ & \overline{d}(k) = Min\{d(k), D_{limit}\}/D_{limit} \\ & \overline{w}(k) = Min\{w(k), W_{limit}\}/W_{limit} \\ & \overline{ad}_{va,c}(k) = Min\{va(k) - c_p, C_{limit}\}/C_{limit} \\ & \overline{ad}_{va,o}(k) = Min\{va(k) - o_r, O_{limit}\}/O_{limit} \\ & c_p : \text{previous heading command} \\ & o_r : \text{current orientation of the robot} \end{aligned} \quad (4)$$

Since the viewing angle $va(k)$ is the minimum collision-free angular deviation from the goal direction gd, we use it as a guiding direction to the k-th lane in the selection function (4). Here, each term in $f_s(k)$ is limited and normalized by the corresponding maximum values, D_{limit}, W_{limit}, C_{limit}, and O_{limit}. The term $\overline{ad}_{va,c}(k)$ indicates a preference for smaller change of heading command. Similarly, the term $\overline{ad}_{va,o}(k)$ indicates a preference for a heading command closer to the current robot orientation.

The β values are the weights to be given to each term of the selection function and they are all positive. In our experiment, they are set to be $\beta_1 : \beta_2 : \beta_3 : \beta_4 = 6 : 1 : 6 : 1$. Maximizing the $f_s(k)$ selects a wide, collision-free, and motion-efficient lane.

3.3 Local Heading

If the robot is already in the best lane, CVM is sent the original desired goal heading, and uses this to command the robot. Otherwise, a local heading is calculated that will cause CVM to transfer lanes. Assume the n_s-th lane is selected as the best. Since the view angle $va(n_s)$ is the minimum collision-free angle to the n_s-th lane, the local heading hc should be $|va(n_s)| \leq |hc|$. Also, we confine the local heading to be within the blocking angle ba, that is $|hc| \leq |ba|$. So, the local heading hc becomes:

$$hc = \begin{cases} gd, & \text{if } n_r = n_s \\ va(n_s) + \delta * (ba - va(n_s)), & \text{if } n_r \neq n_s \end{cases} \tag{5}$$

where,

n_r : the number of the lane where the robot is in

$0 \leq \delta \leq 1.0$

The value δ determines how far the local heading is from the viewing angle of the selected lane. If $\delta = 0$, then the local heading is just the viewing angle, and there is no clearance for safe motion. If $\delta = 1.0$, local heading always directs to the extreme left hand side or right hand side. In our experiments, δ is set to 0.5. The relationship between the local heading, viewing angle, and blocking angle is shown in the Figure 2.

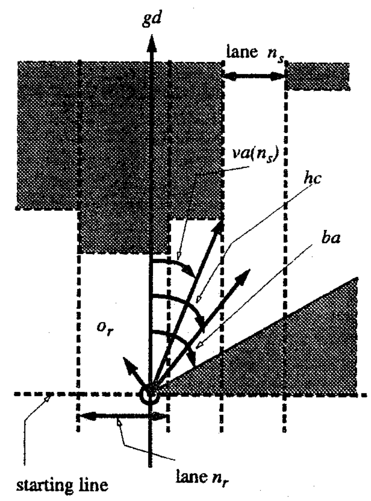


Figure 2: Determination of local heading

4 Experiments and Results

The LCM algorithm has been implemented and extensively tested on the Xavier mobile robot(Figure 3) [10]. Xavier is built on a four-wheel synchro-drive base, produced by RWI, and has independent control over translational and rotational velocities. For obstacle detection, it uses a ring of 24 sonars(data rate 2 Hz) and a 30 degree field of view front-pointing Nomadics laser range sensor. The base provides Xavier with dead-reckoning information at 8 Hz, which is the rate at which the LCM algorithm runs. The LCM algorithm runs on an on-board 200 MHz Pentium-Pro computer.

The α values of the CVM objective function (1) were determined through a number of empirical trials as the values resulting in best safe, smooth, and efficient robot movement. The values used in the combined LCM approach differ from those used when CVM is the only obstacle avoidance mechanism. In LCM, they are set to be $\alpha_1 = 0.1$, $\alpha_2 = 0.6$, $\alpha_3 = 0.3$, while they are set to be $\alpha_1 = 0.6$, $\alpha_2 = 0.1$, $\alpha_3 = 0.3$, if CVM alone is used for obstacle avoidance [5]. While α_1, which dictates the importance of long, collision-free arcs, is set high for obstacle avoidance in the CVM-only case, it is lowered in LCM because obstacle avoidance is fully addressed by the Lane Method. On the other hand, the α_2, which dictates the importance of staying close to the goal heading, is set higher in LCM, to force the robot to adhere more closely to the local heading that is issued by the Lane Method.

For comparison, the results of the CVM and LCM are shown for four environments: (1) turning a corner with three obstacles, (2) going through a corridor with an obstacle, (3) entering to a narrower corridor, and (4) turning right through a narrow entrance. The maximum translational and rotational velocities are set to be $tv_{max} = 50cm/sec$, $rv_{max} = 60°/sec$.

The results for the first environment are shown in the Figure 4(note that in all the environments, the robot has no initial knowledge of the environment-it is just provided with the desired heading gd). In this experiment, the goal heading gd is $-90°$. That is, the robot is commanded to find and go through a collision-free path in the direction -90 ° from its initial orientation(that is, to the right in the figure). There are two possible collision-free paths: One is over the second obstacle, and the other is below the second

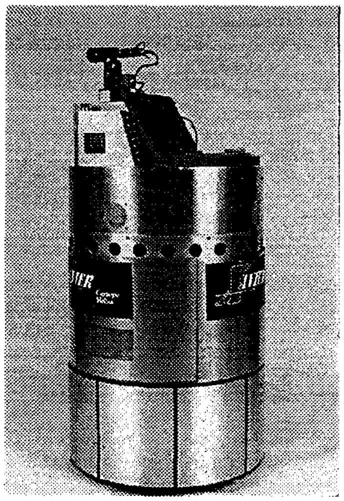
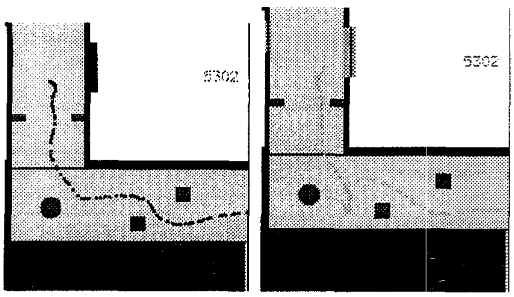


Figure 3: The Xavier mobile robot

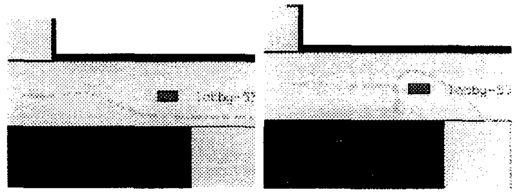


(a) LCM (b) CVM

Figure 4: Turning at a corner avoiding obstacles

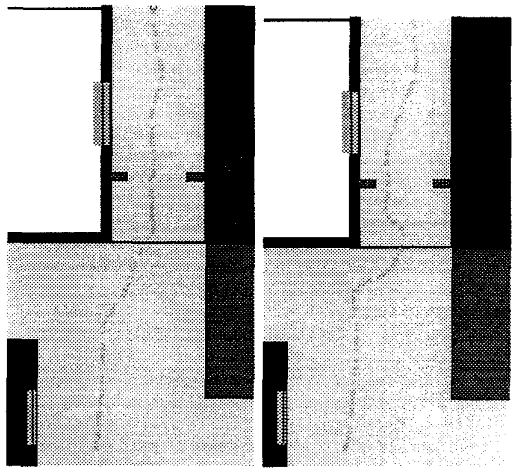
obstacle which is narrower than the other. The LCM finds the wider collision-free path successfully, but the CVM first tries to find a collision-free path below the second obstacle. As the robot gets closer, it discovers that the collision-free path below the second obstacle is too narrow, and so CVM directs it back, and eventually finds the collision-free space. In this case, at first the CVM misses the wider collision-free path.

Figure 5 shows the results for the second environment. The goal direction is $gd = 0°$(that is, to the right in the figure). The LCM forces the robot to steer away from the obstacle sooner than does CVM. CVM lets the robot head towards the obstacle until it gets too close to turn smoothly. This is because the CVM prefers longer collision-free distance of arc, rather than collision-free space itself. On the other hand, LCM can detect wide collision-free lane from earlier stage, and the avoidance motion begins earlier(in fairness to CVM, it usually handles such situations much more



(a) LCM (b) CVM

Figure 5: Avoiding an obstacle in a corridor



(a) LCM (b) CVM

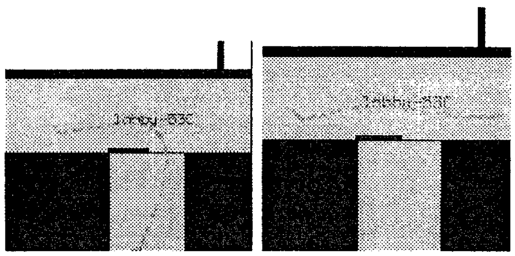
Figure 6: Entering into a narrower corridor

smoothly-this is just an extreme case).

Figure 6 shows results for the third environment. The goal direction is $gd = 0°$(that is, heading up in the figure). Though there is a corridor in the direction gd, CVM guides the robot straight towards the wall, turning late to avoid it. With LCM, the robot notices the long open corridor, and enters that lane fairly early.

In Figure 7, results in the fourth environment are shown. The goal direction here is $gd = 90°$(that is heading down in the figure). LCM smoothly guides the robot into the correct corridor, while CVM fails to find the perpendicular corridor 90°, and continues straight(later turning down the next corridor). This result is similar to the result for environment 1, where the CVM passes over an opening and fails to find collision-free path. In this environment, the width of the entrance to the perpendicular corridor is $120cm$. If the width of the entrance increases by 20cm, CVM can also find the perpendicular corridor.

The failure of CVM for these experiments can be explained using figure 8. Since the CVM prefers longer



(a) LCM (b) CVM

Figure 7: Turning right through a narrow entrance

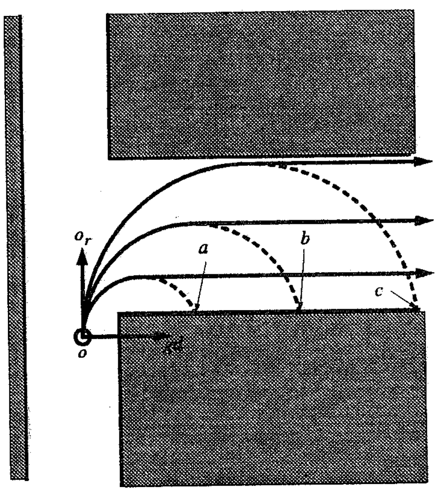


Figure 8: Problems of CVM

collision-free arc lengths, and α_1 is much greater than α_2, it prefers the path through the arc *oc* rather than the path through the arc *oa* or *ob*. However, the path through *oc* is not better than the other paths, regarding the obstacle avoidance and motion efficiency. In the CVM-only case, it does not help to make α_1 less than α_2, however, since then CVM will be reluctant to turn the robot to avoid obstacles, preferring to keep heading in the goal direction. This is not a problem in the combined LCM approach, since the Lane Method supplies CVM with a local heading that will avoid obstacles(under the assumption of straight-line motion).

As shown in these results, LCM overcomes some of the CVM's shortcomings. Through experiments, we found that proper selection of α values is critical to have the LCM to overcome the shortcomings of CVM. As the α_2 decreases below 0.6 and α_1 increases above 0.1, the LCM produces similar paths as the CVM does. If LCM uses the same α values as the CVM-only case, no noticeable difference is found between the results of the both methods.

LCM is a two-step approach: the first step is Lane Method, and the second step is CVM. The Lane Method concerns primarily about obstacle avoidance. The CVM step works to produce commands taking account of the robot dynamics, as well as obstacle avoidance. Though obstacle avoidance is considered in both steps, they consider obstacle avoidance in different aspects. While the CVM counts on collision free *arc* length for obstacle avoidance, Lane Method uses collision-free *straight-line* distance and collision free *lane width.* Combining these two steps, LCM considers more aspects for obstacle avoidance than does either CVM-only or Lane Method. Notice that since the α values in LCM differ from those for CVM-only case, the CVM stage in LCM pays less attention to obstacle avoidance than does in CVM-only case.

Since the LCM uses CVM to yield final commands, it maintains the advantages that CVM has over potential field approaches [2], [3], and Vector Field Histogram method [4]. Potential field approaches use vector sum of repulsive and attractive features to compute a desired robot heading. Speed control is sometimes handles by choosing velocity proportional to the magnitude of the potential vector, or proportional to the distance to obstacles ahead. So, the potential field method yields less smooth path than the CVM, as shown in [5].

Though there are some other methods studied in the context of off-line path planning, taking vehicle dynamics and non-holonomic constraints into account [11], [12], they generally require more computations than the LCM.

5 Conclusions

We have presented the Lane-Curvature Method (LCM) for local obstacle avoidance which incorporates a velocity space method(CVM) with a directional method(Lane Method). The Lane Method determines a local heading which directs robot to a wide and collision-free lane. So, it resolves some problems of using the CVM-only for collision avoidance, such as passing over a collision-free corridor in the goal direction. By using CVM to actually choose commands, LCM simultaneously controls the speed and heading of the robot and incorporates constraints from the robot dynamics.

The method has been implemented and tested on Xavier, a synchro-drive robot. Our extensive experiments show that, in many cases, LCM produces safer and smoother robot motion than does CVM(in many other cases, not shown here, their behavior is essentially identical). In particular, LCM can often guide the robot along collision-free paths that CVM misses.

This work shows that by combining the directional and curvature-based velocity-space methods, we can obtain an efficient and reactive local navigation algorithm which produces smooth and speedy, as well as safe, collision-free movement.

Further work on the LCM includes finding more systematic procedure to choose optimal values of various parameters in applying CVM and Lane Method. Also, a method will be investigated to change and adjust the parameters in accordance with the environment change caused by robot motion.

Acknowledgments

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