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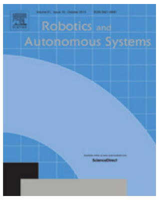

Tangential Gap Flow (TGF) navigation: A new reactive obstacle avoidance approach for highly cluttered environments

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HIGHLIGHTS

- A novel reactive collision avoidance approach, referred to as TGF, is presented.
- The TGF safely drives a mobile robot in very dense and cluttered environments.
- The trajectory is faster, shorter, and smoother compared to the well-known ND method.
- Experimental results demonstrate the power of the TGF approach.
- The performance is evaluated and compared with three different ND variants.

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ABSTRACT

This paper presents a novel reactive collision avoidance method for mobile robots moving in dense and cluttered environments. The proposed method, entitled Tangential Gap flow (TGF), simplifies the navigation problem using a divide and conquer strategy inspired by the well-known Nearness-Diagram Navigation (ND) techniques. At each control cycle, the TGF extracts free openings surrounding the robot and identifies the suitable heading which makes the best progress towards the goal. This heading is then adjusted to avoid the risk of collision with nearby obstacles based on two concepts namely, *tangential* and *gap flow* navigation. The *tangential navigation* steers the robot parallel to the boundary of the closest obstacle while still emphasizing the progress towards the goal. The *gap flow navigation* safely and smoothly drives the robot towards the free area in between obstacles that lead to the target. The resultant trajectory is faster, shorter and less-oscillatory when compared to the ND methods. Furthermore, identifying the avoidance maneuver is extended to consider all nearby obstacle points and generate an avoidance rule applicable for all obstacle configurations. Consequently, a smoother yet much more stable behavior is achieved. The stability of the motion controller, that guides the robot towards the desired goal, is proved in the Lyapunov sense. Experimental results including a performance evaluation in very dense and complex environments demonstrate the power of the proposed approach. Additionally, a discussion and comparison with existing Nearness-Diagram Navigation variants is presented.

1. Introduction

The increasing need for employing robots in high-risk areas hit by natural disasters has attracted the attention of researchers worldwide to develop fully autonomous mobile robots. The main objective of these robots is to carry out the assigned tasks in places where human presence is dangerous, difficult or the tasks to be performed are impossible to be carried out by people [1], such as search and rescue, military and exploration.

Usually, a real world disaster environment is partially or completely unknown and changes over time. Moreover, unpredictable obstacles may block the robot's trajectory while performing tasks. Therefore, traditional motion planning techniques which depend on a predefined map cease to function properly in such environments and the robot is doomed to collide with obstacles. To overcome this limitation the mobile robot should have the capability to explore the unknown area, automatically generate maps, and localize itself within this map. This is achieved by on-board sensing devices detecting instantaneous changes in the environment. In addition, it has to recognize victims and correctly label the map

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with the victims' positions. In all cases, it is necessary to have a reactive obstacle avoidance algorithm to safely reach given goal locations and to deal with dynamic changes such as moving obstacles.

Many existing reactive navigation methods have problems in dealing with dense and cluttered environments, which is usually the case in most robotic applications. This is due to the fact that these methods suffer from several well-known problems [2] such as local trap situations, difficulties of computing motion directions towards obstacles or far away from the goal location, and the failure of driving the robot between closely spaced obstacles. Navigation in these environments whilst avoiding such problems has been addressed by the Nearness Diagram (ND) Navigation method [2]. Over the years, several ND variants have been developed such as the Obstacle-Restriction method [3], the Smooth Nearness-Diagram (SND) [4], and the Closest Gap (CG) Navigation [5].

Nevertheless, all these techniques share the idea of analyzing sensory data to find potential gaps surrounding the robot, and identifying the direction of motion accordingly. The resultant trajectory is then deflected to avoid collisions with nearby obstacles using an idea inspired from the Artificial Potential Field concept [6]. Obstacle avoidance based on potential fields is likely to produce oscillatory robot trajectories. Such oscillations slow down the overall behavior of the mobile robot and may lead to unstable motion in narrow passages [7]. Moreover, the decoupling between the location of the goal/gap and the direction of the avoidance maneuver increases the problem. The Tangential Gap Flow (TGF) navigation method proposed in this paper is especially designed to deal with this limitation. In a nutshell, the TGF method works as follows: the direct path towards the goal is checked for navigability. If it is a collision-free path, the robot is directly driven towards the goal. Otherwise, the goal is located within the navigable gap closest to it. As soon as the distance to an obstacle gets less than a predefined security distance, the TGF method modifies the trajectory based on two concepts: the *tangential* and *gap flow* navigation. Using the *tangential navigation*, the robot navigates parallel to the tangent of the closest obstacle while simultaneously progresses towards the goal. The *gap flow navigation* safely and smoothly drives the robot towards the free area in between obstacles which lead at the end to the target. The trajectory generated by the TGF method is faster, shorter, and less-oscillatory compared to the ND variants. The stability of the motion controller, that drives the robot towards the goal, is proved in the Lyapunov sense.

The *tangential navigation* has appeared in part in [8] and the *gap flow navigation* is inspired from our work in [9]. In this paper, we extend the tangential navigation by integrating the gap flow concept and by considering all obstacle points while computing the avoidance maneuver. Hence, the smoothness of the trajectories has been increased, and therefore a much more stable behavior is achieved. Furthermore, several experiments using our mobile robot, GETbot, in very dense and cluttered environments are provided. We also introduce a performance evaluation to quantitatively estimate the power of the proposed approach, and discuss and compare it with existing ND variants on the basis of the above mentioned limitations.

The remainder of the paper is structured as follows: After discussing the related work in Section 2, we present the reactive navigation method design in Section 3. In Section 4, we show and discuss the experimental results. Finally, Section 5 highlights our conclusions and future work.

2. Related work

In this section, we focus on the local reactive navigation techniques since global motion planning is out of the scope of this paper, and the reader is directed to [10] or [11] for an extended knowledge and taxonomy.

Early work in this topic includes the Artificial Potential Field (APF) approaches, initially proposed by Khatib [6]. The main idea stems from the gravitational force field principle. Within this concept, the robot is repelled from obstacles and attracted towards the goal by assuming that opposite forces are applied to the robot from the goal and surrounding obstacles. The resultant force determines the robot's subsequent direction and motion equations. Researchers have come up with a plethora of proposals to enhance this concept (e.g. [12–14]). Potential field techniques are considered to be fast and computationally efficient. Unfortunately, getting stuck in local minima and failure to find an oscillation-free motion in narrow passages are significant problems of these methods [7]. The Vector Field Histogram (VFH) [15] was then introduced mapping two-dimensional occupancy information into a one-dimensional histogram representation, which is then analyzed to detect potential open areas. Although this method produces smoother behavior and allows robots to travel at faster speeds without getting unstable [16], it, like the APF approach, can get trapped in local minima. Some works address the oscillation problem, such as [17], by using a modified Newton method, or [18], by employing a family of 2D smooth vector fields. Other works address the local minima problem, such as [19] by using a random walk if a local minimum is reached, or [20] by employing a special artificial potential function. While these techniques provide nice solutions to the APF drawbacks, they are either computationally expensive, based on strict assumptions, or not effective in complex environments [21].

The approaches defined in [22] and [23] use a very simple criterion to reach the goal. The appearance of obstacles in the vicinity of the robot pushes it to escape from the closest one by temporarily switching the desired goal location into a virtual one until the risk is passed. The concepts of APF and Tangential Escape (TE) are used for setting the new virtual goal location in [22] and [23], respectively. The latter approach generates smoother robot trajectories than the former one. Although such approaches are very simple to implement and result in faster reactions, they cease to function in slightly complex environments.

Other common techniques take the dynamic constraints of the robot into account and choose a steering command rather than a moving direction. The Curvature Velocity method (CVM) [24,25], and the Dynamic Window (DWA) approach [26,27] are the most popular ones. They work by adding constraints, coming from physical limitations and sensory data, to the velocity space, and choose the speed that satisfies all constraints and maximizes an objective function. While these techniques yield fast and smooth behavior, they may fail to drive the robot between close obstacles. Moreover, the robot can get stuck in local minima.

Several reactive methods are based on the concept of Velocity Obstacles (VO) [28–30] or Inevitable Collision States ICS [31,32]. These approaches consider the velocity of moving obstacles in determining the avoidance maneuver. VO-based approaches perform collision avoidance by identifying the set of robot's velocities that may cause collision at some future time, and select velocities outside of this set. ICS-based methods characterize all vehicle states that lead to collision at a later time in the future, and avoid these states while planning the robot's motion. A VO variant, the reciprocal velocity obstacle RVO [33,34], addresses the problem of cooperative collision avoidance. Although these techniques are applicable for static and dynamic obstacles, they assume known or predictable obstacle velocity. However, in real applications it is hard to predict the future of the scene [35]. Moreover, VO-based approaches require a careful determination of the time horizon. Otherwise, robots find the difficulty of passing through narrow spaces in dense and cluttered environments [36].

We close this section by an overview of the obstacle avoidance algorithms designed for dense and cluttered environments. The