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A globally converging algorithm for reactive robot navigation among moving and deforming obstacles☆

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ABSTRACT

We present a reactive strategy for the navigation of a mobile robot in dynamic a priori unknown environments densely cluttered with moving and deforming obstacles. Mathematically rigorous analysis of this law with the proof of its global convergence is provided; its performance is confirmed by computer simulations.

1. Introduction

The capability to safely operate in dynamic and a priori unknown environments is a key requirement to mobile robots. Despite extensive research, this issue still represents a real challenge in many cases, often because of uncertainties and deficiencies in available knowledge.

With a focus on the planning horizon, relevant algorithms can be classified into global and local planners (Lapierre, Zapata, & Lepinay, 2007). Global planners (GP) generate a complete trajectory based on a comprehensive model of the scene, which is built from a priori and sensory data (Latombe, 1991). For dynamic scenes, this approach is exemplified by several techniques (surveyed in e.g., Kulić & Vukić, 2006, Large, Lauger, & Shiller, 2005), including state-time space (Erdmann & Lozano-Perez, 1987; Fraichard, 1999; Reif & Sharir, 1994), velocity obstacles (Fiorini & Shiller, 1998; Large et al., 2005), and nonholonomic planners (Qu, Wang, & Plaisted, 2004a). Many GP's are accompanied with guarantees of not only collision avoidance but also achievement of a global objective. However GP's are computationally expensive and hardly suit real-time implementation; NP-hardness, a mathematical seal for intractability, was established for even the simplest problems of dynamic motion planning (Canny, 1988). A partial remedy was offered in the form of randomized architectures (Frazzoli, Dahleh, & Feron, 2002; Hsu, Kindel, Latombe, & Rock, 2002). At the same time, the global planning approach faces significant difficulties when the environmental map is uncertain and unpredictable. The above drawbacks are shared by hybrid approaches that include GP as a core of the navigation algorithm (Belkhouche & Belkhouche, 2005; Belkhous, Azzouz, Saad, Nerguizian, & Nerguizian, 2005; Lamiraux, Bonnafous, & Lefebvre, 2004; Minguez & Montano, 2004b; Qu, Wang, & Plaisted, 2004b; Zhu, Zhang, Song, & Li, 2012).

Local planners (LP) iteratively re-plan a short-horizon portion of the path. This weakens the computational burden towards implementability in real time and reduces the need for information about the environment to data about a nearest fraction of the scene, but makes the ultimate result of the iterations an open issue. Many of the relevant techniques, e.g., the dynamic window (Fox, Burgard, & Thrun, 1997; Seder, Macek, & Petrovic, 2005), curvature velocity (Simmons, 1996), and lane curvature (Nak & Simmons, 1998) approaches, treat the obstacles as static. This is a particular case of predictably moving obstacles, which are assumed, along with access to their full velocities, by methods like velocity obstacles (Fiorini & Shiller, 1998) and the likes (Snape, van den Berg, Guy, & Manocha, 2011), collision cones (Chakravarthy & Ghose, 1998), or

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inevitable collision states (Fraichard & Asama, 2003; Owen & Montano, 2006). However velocity measurement remains a challenging task in practical setting, and predictability of the scene ranges from full to none in the real world (LaValle, 2006). A medium level of predictability is that with uncertainty, where non-conservative estimates of future obstacle positions can be put in place of exact prognosis (Large et al., 2005; Wu & How, 2012). However these and some other approaches (Chakravarthy & Ghose, 1998; Fiorini & Shiller, 1998; Fraichard & Asama, 2003; Owen & Montano, 2006) take excessive precautions against collisions with obstacles. As a result, they may be stuck in cluttered scenes, and tend towards bypassing dense clusters of obstacles as a single whole, even if a better or even the only option is a permeating route. In hardly predictable complex environments, safety typically concerns only a nearest future, and its propagation until the end of the experiment is not guaranteed (Wu & How, 2012).

The basic strong and weak points of LP's attain apotheosis at reactive controllers, which directly convert the current observation into the current control. Some LP's, like Virtual Force Field (Borenstein & Koren, 1989), Potential Field (Khatib, 1986; Rubagotti, Vedova, & Ferrara, 2011), Vector Field Histogram (Borenstein & Koren, 1991), Certainty Grid (Elfes, 1987), Nearness Diagram (Minguez & Montano, 2004a) methods, in fact combine reactive control with elements of global modeling by assuming awareness about the scene above the level given by the snapshot of the sensory data. Purely reactive approaches are exemplified by Chunyu, Qu, Pollak, and Falash (2010), Ferreira, Pereira, Vassallo, Filho, and Filho (2008), Kuc and Barshan (1989), Tang, Ang, Nakhaeinia, Karasfi, and Motlagh (2013), Yagi, Nagai, Yamazawa, and Yachida (2001), Yang and Meng (2001), as well as by biologically inspired methods (Matveev, Hoy, & Savkin, 2013; Matveev, Teimoori, & Savkin, 2011; Matveev, Wang, & Savkin, 2012; Savkin & Wang, 2013; Teimoori & Savkin, 2010).

Because of inevitable failure scenarios, the deficiency of the previous research on LP's is the lack of global convergence results that guarantee achievement of the primary objective in dynamic environments (Nakhaeinia, Tang, Noor, & Motlagh, 2011). At best, rigorous analysis examined an isolated bypass of an obstacle during which the other obstacles were neglected until the bypass ends, with an idea that thereafter, the robot focuses on the main goal. However in cluttered dynamic scenes, bypasses may be systematically intervened by companion obstacles so that no bypass is completed, whereas the robot almost constantly performs obstacle avoidance. The ultimate goal was left, by and large, beyond the scope of theoretical analysis, especially for cluttered unpredictable environments, like a dense crowd of people. However it is in these cases that rigorous quantitative delineation between failure and success scenarios is highly important since by its own right, any experimentation is not convincing enough due to horizonless diversity of feasible scenarios. Another deficiency is that moving obstacles were viewed as rigid bodies undergoing only translational motions, and assumed awareness about the obstacles often meant access to their possibly 'invisible' parts (e.g., to determine the disc center (Chunyu et al., 2010; Rubagotti et al., 2011) or angularly most distant polygon vertex (Masehian & Katebi, 2007) or full velocity (Chunyu et al., 2010; Masehian & Katebi, 2007; Rubagotti et al., 2011)).

The objective of this paper is to show possibility of a purely reactive navigation algorithm with the capacity of being supplied with firm guarantees of achievement of a global objective in planar environments densely cluttered with unpredictably moving and deforming obstacles. This objective is perpetual drift in the desired direction in spite of possibly almost continual obstacle avoidance. Unlike the previous research, the obstacles are not rigid: they have arbitrary time-varying shapes and may rotate, twist, wring, skew, wriggle, etc. This covers scenarios with reconfigurable rigid obstacles, forbidden zones between moving obstacles, flexible obstacles, like a fluttered curtain or fishing net, virtual obstacles, like areas contaminated with hazardous chemicals or on-line estimated areas of operation of a hostile agent.

Our proposed navigation law uses omnidirectional vision of the scene up to the nearest reflection point and, apart from access to the desired azimuth, assumes no further sensing capacity or knowledge of the scene configuration. Like some other algorithms, it starts with finding points where the distance reading abruptly jumps as the angle of measurement continuously varies, which are interpreted as edges of visible facets of obstacles. In the vein of Savkin and Wang (2013), Teimoori and Savkin (2010), these facets are angularly expanded. Finally to determine the motion direction, we propose a certain trade-off between bearings at the edges of the extended facets and the desired azimuth.

The navigation strategy considered in this paper develops some ideas set forth in Savkin and Wang (2013), Teimoori and Savkin (2010). However in Savkin and Wang (2013), Teimoori and Savkin (2010), only rigid and fully visible obstacles were examined, which were static in Teimoori and Savkin (2010) and disk-shaped in Savkin and Wang (2013), and the scene was so sparse that bypasses of obstacles were sufficiently isolated from each other. Now we show that being properly developed, those ideas remain viable for much more general scenarios with dense scenes and deforming obstacles with arbitrary shapes. We first offer a mathematically rigorous justification of the proposed approach. In doing so, we start with conditions necessary for a robot to be capable of obstacle avoidance in scenarios like motion within a dense crowd of people. Then we show that under a slight enhancement of these conditions, obstacle avoidance is ensured by the proposed controller provided that it is properly tuned. Success in following the desired azimuth is proved for convex obstacles undergoing general motions, including translations, rotations, and deformations. By illustrating this result in several particular scenarios, it is better displayed that the algorithm does cope with densely cluttered dynamic scenes. The applicability of the proposed strategy is confirmed via extensive computer simulations. In doing so, its performance has been compared with that of the velocity obstacle approach (Fiorini & Shiller, 1998; Large et al., 2005) and found to be better under certain circumstances.

The body of the paper is organized as follows. Sections 2 and 3 describe the problem setup and the navigation strategy, whereas the main results concerned with collision avoidance and the main control objective are given in Sections 4 and 5, respectively. In Section 6, they are illustrated in special scenarios. Section 7 discusses simulations and Section 8 offers brief conclusions. The proofs are given in Appendices A–C.

The following notations are adopted in the paper:

$\langle\cdot;\cdot\rangle$—the standard Euclidian inner product in $\mathbb{R}^2$;
$|\cdot|$—the standard Euclidian norm in $\mathbb{R}^2$;
$\mathbf{dist}_O[\boldsymbol{r}]$—the distance from point $\boldsymbol{r}$ to the set O;
$O_1(t), \dots, O_N(t)$—moving obstacles;
∂O—the boundary of the set O;
$C_1, \dots, C_K$—disjoint classes of the obstacles;
v_o^i—an upper bound on the speeds of all obstacles from C_i;
$\vec{v}$—the velocity of the robot;
v—an upper bound on its speed;
d—the distance from the robot to the nearest obstacle;
$d(\alpha, t)$—the distance to the nearest obstacle in the direction given by the polar angle α (see Fig. 1);
$\vec{f}$—the unit vector in the desired direction of motion.