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Research article

A probability-based artificial potential field for autonomous vehicles in avoiding uncertain obstacles

Phan Minh Tam[1,2], Ho Pham Huy Anh[1,2,*]

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ABSTRACT

Nowadays unmanned vehicles are compulsorily required to contain a reliable collision avoidance system as to reach closer toward the target of the autonomous vehicle (AV). Up to now lots of obstacle avoidance techniques have been introduced and successfully applied in practice. Unfortunately, in almost of these obstacle avoidance algorithms, the uncertainty of the input that includes obstacle tracking measurements, have not been satisfactorily investigated. This uncertainty happened from measurement approaches along with obstacles' nonlinear locomotion. Several researches have tried to overcome this problem via detecting obstacles directly or indirectly based on global/local communication and/or the third party like the Automatic identification system (AIS). Inspired with these achievements, this paper aims to deal with uncertain information of obstacles resulting in from practical obstacle-avoiding techniques for autonomous vehicles. In fact, this problem is ignored in many researches by assumptions that measurements are perfect or the vehicle can fully observe the state of obstacles. A probability model is proposed to evaluate the possibility of collision quantitatively based on the current position of the vehicle and the probability distribution of obstacles' position. This probability model is then applied to design a new repulsive function. Hence, the resulting artificial potential field can avoid uncertain obstacles by maneuvering the vehicle in the direction of decreasing collision risk. Numerical simulations are carried out to verify the proposed collision avoidance model, and the simulation results show that the proposed method can help autonomous vehicles to efficiently pass obstacles safely with uncertain information. As a consequent, the proposed algorithm can guide the autonomous vehicle (AV) to effectively and safely pass static and dynamic obstacles with respect to uncertain information. Further research can focus on dynamic obstacles which will be investigated via integrating the speed variable into the considered probability model.

Key words: autonomous vehicle (AV), obstacle avoidance, collision avoidance, uncertain obstacle, probability-based artificial potential field method

[1]*Faculty of Electric-Electronics Engineering (FEEE), Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, District 10, Ho Chi Minh City, Viet Nam*

[2]*Vietnam National University Ho Chi Minh City (VNU-HCM), Linh Trung Ward, Thu Duc City, Ho Chi Minh City, Viet Nam*

Correspondence

Ho Pham Huy Anh, Faculty of Electric-Electronics Engineering (FEEE), Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, District 10, Ho Chi Minh City, Viet Nam

Vietnam National University Ho Chi Minh City (VNU-HCM), Linh Trung Ward, Thu Duc City, Ho Chi Minh City, Viet Nam

Email: hphanh@hcmut.edu.vn

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INTRODUCTION

Apart from an intelligent path planner, unmanned vehicles need to have a reliable collision avoidance system to step closer toward the goal of the autonomous vehicle. In recent decades, many obstacle avoidance approaches have been studied, however, can be classified into two major groups: Discretization-based methods (including Regulation-based, Solutions Discretization, Graph Searching methods) and Continuous-based methods (including Virtual field, Trajectory Planning methods). Regulation-based methods create a set of predefined collision situations and a set of respective guidance laws based on the experience of experts and the international regulations as COLREGs. The effectiveness of these methods depends heavily on the generality of situations and the detail of commands. Intelligent algorithms such as Neural networks [1], Fuzzy logic [2] are also utilized in the decision-making systems to enhance the generality of the situation set. Unfortunately, because the situation set is hard to cover all scenarios, there is no collision avoidance command to USVs in the unknown cases. In Discretization Solutions methods, the commands are discretized in a set of commands assumed to be unchanged in a specific time step [3,4]. Then each command is evaluated by collision checking and optimization algorithms to find out the best solutions [5,6]. The most advantages of these methods are low computation cost and ease to put it into use.

Amongst the Continuous-based methods, [7] the potential Artificial Potential Field (APF) algorithm represents virtual force fields coming out from obstacles and virtual force fields converging to a target point. USV can reach the target point and stay away from obstacles due to these virtual force fields. According to [8], the motion of USV and obstacles are considered in the new potential field, and the local minima problem in the previous studies is tackled. The Velocity Obstacle (VO) concept proposed by [9] directly considers the

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collision avoidance trajectory planned in the obstacle's frame where the vehicle moves relatively toward a static obstacle. As a result, all the relative velocity vectors causing collisions are determined by a cone space. Nonetheless, this cone space is only valid with the assumption that the velocity of the vehicle and obstacle is constant. This VO drawback was improved partly by Non-linear VO [10], where the relaxed assumption allows the obstacle's velocity to change but is known in advance. Authors in Kuwata *et al.* (2014) [11] has implicitly treated the nonlinear motion of the obstacle as a source of bounded uncertainty; hence, the VO is expanded to the worst-case VO. Authors in Song *et al.* (2018) [12] has developed a two-level collision avoidance scheme for dynamic obstacles represents a velocity obstacle method for negotiation situations and a compound potential field method for emergencies.

However, the uncertainty of the input (including obstacle tracking measurements) has not been considered in most obstacle avoidance algorithms. This uncertainty might arise from measurement methods and obstacles' nonlinear motion. Some studies tried to overtake this hindrance by observing obstacles directly or indirectly through local communication [13] or the third party like the Automatic identification system (AIS) [14].

Motivated by the results above-mentioned, this study proposes an obstacle avoidance strategy that can deal with the uncertainty of obstacle tracking methods. The main contributions of this paper can be summarized as follow:

- An innovative probability-based model is proposed to calculate the risk of collision between the vehicle and the obstacles where the uncertainty of measurements is necessarily taken into account.
- A new artificial potential field designed based on the probability model is proposed to efficiently plan the collision-free path.

The rest of this study is organized as follows. Section 2 presents the preliminaries. Section 3 presents the problem formulation and discussion of this research. Section 4 introduces the methodology. Section 5 presents the comprehensive numerical simulations and results, and the final section concerns the conclusions.

PRELIMINARIES

Multivariable Normal Distribution

A normally distributed vector $X \in R^N$ (N is an integer) can be expressed by $X \square N(\mu, \Sigma)$, where $\mu \in R^N$ is an expectation, and $\Sigma \in R^{N\times N}$ is a covariance matrix. The probability distribution function $f: R^N \rightarrow R$ is presented as follow:

$$f(X) = \frac{1}{2\pi\sqrt{|\Sigma|}} exp\left(-\frac{1}{2}(X-u)^T \Sigma^{-1}(X-u)\right) \quad (1)$$

Let $S \subseteq R^N$ is a subset of and we have the following probability:

$$p(X \in S) = \int_S fXdX \quad (2)$$

Artificial Potential Field

The Artificial Potential Field (APF) model firstly proposed in [7] contains two main components, including repulsive potential function and attractive potential function. The first component (3) is located at obstacles to encourage the vehicle to move far away from obstacles. The second (4) is located at the goal to encourage the vehicle to move closer toward the goal.

The repulsive potential function:

$$U_{rep} = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 if\ \rho \leq \rho_0 \\ 0\ otherwise \end{cases} \quad (3)$$

where η is a positive scalar, ρ is the Euclidean distance between the vehicle and the obstacle, ρ_0 is the influence range.

The attractive potential function:

$$U_{att} = \varepsilon \rho_g^2 \quad (4)$$

where is a positive scalar, ρ_g is the Euclidean distance between the vehicle and the goal.

PROBLEM FORMULATION AND DISCUSSION

Let $O \in R^{2\times N_0}$ denotes a set of stationary obstacles O_i $(i = 1:N_0)$ in the vehicle's workspace.

Assumption: The position of the obstacle O_i, $o_i = (x_{o,i}, y_{o,i})$ in the Cartesian coordinate, can be obtained by a set of measurements M, and $(x_{o,i}, y_{o,i}) \square N(\mu_{o,i}, \Sigma_{o,i})$.

There are many studies of obstacle tracking approaches providing (x_0, y_0) at the output. For instances, Ushani *et al.* (2015) [15] used SLAM and LiDAR for estimating the trajectory and the shape of the obstacles; Odelga *et al.* (2016) [16] used RGB-D camera and Bin-Occupancy filter to track the obstacles' velocity. Therefore, this assumption is reasonable.

Vehicle model

The holonomic model[17] is utilized for applying the proposed algorithm in this study.

$$\begin{cases} x(k+1) = x(k) + u\cos(\chi)T \\ y(k+1) = y(k) + u\sin(\chi)T \end{cases} \quad (5)$$

where $p\square(x,y)^T$ is the vehicle's position, μ and χ are respectively the vehicle's speed and orientation, T is the sampled time.

Collision avoidance problem

Let $C \subset R^2$ denotes a dangerous zone around the vehicle, and C is defined as follow:

$$C\square\{(x_c,y_c)\,|d(x_c,y_c) \le R_s\} \quad (6)$$

where $d(\cdot)$ indicates the distance from a point to the vehicle, R_s is safety radius.
An obstacle O_i is supposed to collide with the vehicle when $o_i \in C$. The main objective of this paper is to determine the orientation command for the vehicle such that the possibility of collision is minimal or to find the solution for the following problem:

$$\chi^* = \underset{\chi}{argmin}\,p\left(\bigcup_{i=1}^{N_0} o_i \in C\right) \quad (7)$$

where χ^* is the desired orientation the vehicle should follow for obstacle avoidance.

METHODOLOGY

Probability of Collision

Let define a randomly vector as follow:

$$\delta_i\square\left(\delta_{x,i},\delta_{y,i}\right)^T = o_i - p \quad (8)$$

Thus:

$$\delta_i\square N\left(\mu_{\delta_i},\Sigma_{\delta_i}\right) \quad (9)$$

where $\mu_{\delta_i} = \mu_{o,i} - p$, $\Sigma_{\delta_i} = \Sigma_{o_i}$
We have:

$$\begin{aligned} & p(o_i \in C) = \int_C \frac{1}{2\pi\sqrt{|\Sigma_{o,i}|}} exp\times \\ & \left(-\tfrac{1}{2}\left(o_i-\mu_{o,i}\right)^T \Sigma_{o,i}^{-1}\left(o_i-\mu_{o,i}\right)\right) dx_{o,i}y_{o,i} \\ & = \int_C \frac{1}{2\pi\sqrt{|\Sigma_{o,i}|}} exp\times(-\tfrac{1}{2}\left(o_i-p-(\mu_{o,i}-p)\right)^T \\ & \times\Sigma_{o,i}^{-1}\left(o_i-p-(\mu_{o,i}-p)\right))dx_{o,i}y_{o,i} \\ & = \int_C \frac{1}{2\pi\sqrt{|\Sigma_{o,i}|}} exp\times \\ & \left(-\tfrac{1}{2}\left(\delta_i-\mu_{\delta_i}\right)^T \Sigma_{o,i}^{-1}\left(\delta_i-\mu_{\delta_i}\right)\right) dx_{o,i}y_{o,i} \end{aligned} \quad (10)$$

From (6) and (8), it yields:

$$\begin{aligned} & C_\delta = \{(\delta_x,\delta_y)\,|\delta_x = r\cos\theta, \\ & \delta_y = r\sin\theta,\ r\in[0,R_s],\ \theta\in[0,2\pi]\} \end{aligned} \quad (11)$$

Substitute (11) into (10), we obtain:

$$\begin{aligned} & p_i\square p(o_i \in C) = \int_0^{R_s}\int_0^{2\pi} \frac{1}{2\pi\sqrt{|\Sigma_{\delta_i}|}} \\ & \times exp\left(-\frac{1}{2}\left(\delta_i-\mu_{\delta_i}\right)^T \Sigma_{\delta_i}^{-1}\left(\delta_i-\mu_{\delta_i}\right)\right) rdrd\theta \end{aligned} \quad (12)$$

Proposed Probability-based Artificial Potential Field

Once the probability of collision, p_i, is determined as in (12), a new repulsive potential function can be developed by exploiting this value as follow:

$$U_{p_i} = -\eta_p \ln(1-p_i) \quad (13)$$

The repulsive potential field illustration is fully presented in Figure 1.

Remark:

It is necessary to note that the vehicle velocity will affect the performance when implementing on the dynamic models and/or on the real vehicles. The fact is that the vehicle's manoeuvrability will be restricted when the velocity increases, i.e. the maximum turning angle will be decrease. Up to a certain threshold of velocity, the vehicle is unable to track the obstacle avoidance trajectory, because the trajectory is too sharp in comparison with the vehicle's manoeuvrability. The solution here is to make the vehicle react earlier by enlarging detection range of sensor as well as increasing the scalar coefficient η_p used in equation (13). Here, the vehicle velocity does not affect the simulation result since it is implemented based on vehicle's kinematic model. The velocity was by 1 m/s in the simulation tests.

It can be from (13) that when there is no risk of collision (i.e. $p_i = 0$), U_{p_i} is equal to zero, i.e. the repulsive field has no influence on the vehicle's movement. Otherwise, the repulsion force derived from (13) can be obtained as below:

$$F_{rep,i} = -\nabla U_{p_i} = \eta_p \frac{1}{1-p_i}(-\nabla p_i) \quad (14)$$

From (12), we have:

$$\begin{aligned} & \nabla p_i = p_i \nabla\left(-\frac{1}{2}\left(\delta_i-\mu_{\delta_i}\right)^T \Sigma_{\delta_i}^{-1}\left(\delta_i-\mu_{\delta_i}\right)\right) \\ & = -\frac{1}{2}p_i(\left(\nabla\left(\delta_i-\mu_{\delta_i}\right)^T\right)\Sigma_{\delta_i}^{-1}\left(\delta_i-\mu_{\delta_i}\right) \\ & +\Sigma_{\delta_i}^{-1}\left(\delta_i-\mu_{\delta_i}\right)^T\Sigma_{\delta_i}^{-1}\left(\nabla\left(\delta_i-\mu_{\delta_i}\right)\right)) \\ & = -p_i\Sigma_{\delta_i}^{-1}\left(\delta_i-\mu_{\delta_i}\right). \end{aligned} \quad (15)$$

Substitute (15) in (14), it yields:

$$F_{rep,i} = \eta_p \frac{p_i}{1-p_i}\Sigma_{\delta_i}^{-1}\left(\delta_i-\mu_{\delta_i}\right) \quad (16)$$

Besides, we also have the attraction force derived from (4):

$$F_{att} = \varepsilon\rho_g \overrightarrow{n}_{vg} \quad (17)$$

where $\overrightarrow{n}_{vg}$ represents a unit vector pointing from the vehicle to the goal.

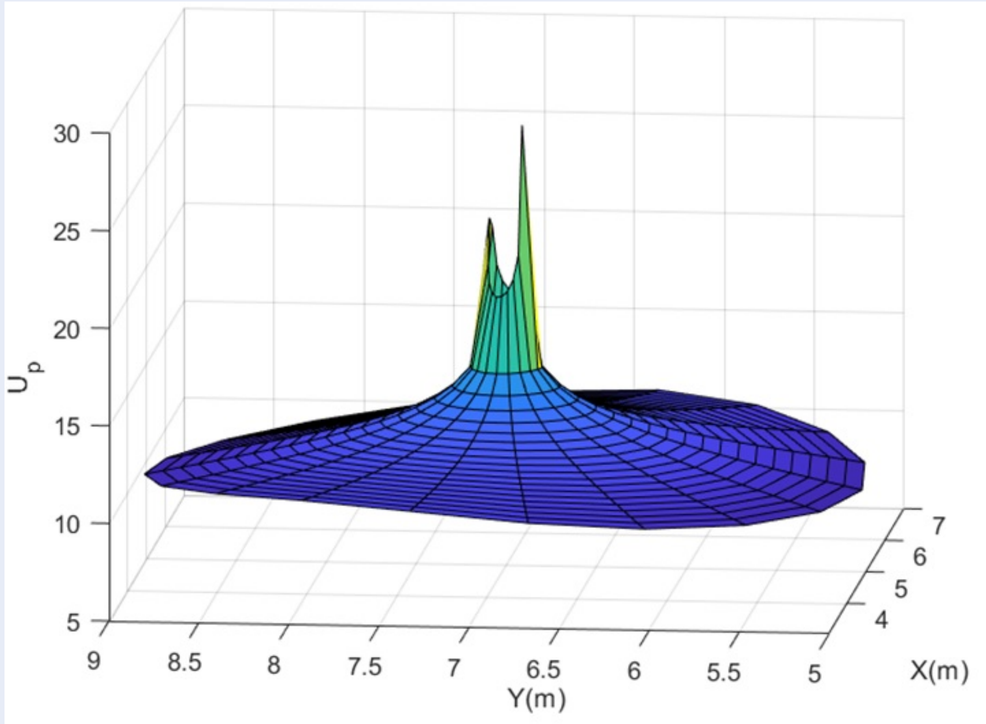

Figure 1: Repulsive potential field with $\mu_0 = (5,7)^T$, $\Sigma_0 = [2\ 1; 1\ 4]$, $R_s = 10m$.

Finally, the resultant force of the potential field model is presented as follow:

$$F_{total} = \sum_{i=1}^{N_0} F_{rep,i} + F_{att} \tag{18}$$

The course command for manoeuvring the vehicle to avoid obstacles can be determined from F_{total} as the following equation:

$$\chi_{cmd} = a\tan 2\left(F_{total,y},\ F_{total,x}\right) \tag{19}$$

NUMERICAL SIMULATION AND RESULTS

In this section, numerical simulations are carried out to verify the capability of avoiding uncertain obstacles of the proposed algorithm. As an above presentation, the proposed obstacle avoidance algorithm makes the decision based on the probability distribution. To clarify the influence of this approach for handling uncertain obstacles, APF, a sample-based approach, is also simulated for comparison. Parameters of the proposed algorithm and APF are chosen as follows: ε=0.2, ηp=20, Rs= 5 m, T=0.1s, η=600, ρ0=15 m. The inputs are the estimations of the position and the covariance matrix of the static obstacles given as follows:

$O_1 = (\mu_1 = 12, 9)^T$, $\Sigma_{o,1} = [3.6\ 1.2;\ 1.2\ 2.4]$
$O_2 = (\mu_1 = 12, 15)^T$, $\Sigma_{o,2} = [3.6\ -1.2;\ -1.2\ 2.4]$
$O_3 = (\mu_3 = 20, 28)^T$, $\Sigma_{o,3} = [3.6\ -1.2;\ -2\ 2.4]$

Two benchmark tests will be investigated which includes the case-1 regarding to single obstacle and the case-2 for multiple obstacles.

Case 1: Single obstacle

It can be seen from Figure 2 and Figure 3 that the proposed method smoothly avoided an uncertain obstacle O_1 and safely approached the goal. Meanwhile, the trajectory of APF was very sensitive to uncertainty, fluctuated and could not converge to the goal. Furthermore, APF put the vehicle at a high risk of collision that was higher than 0.25 and even got the peak of 0.4.

Case 2: Multiple obstacles

In Case 2, two additional obstacles were O_2 and O_3 interrupting the direction of approaching the goal. Therefore, the proposed method performed evasive actions to avoid these two obstacles that can be observed from Figure 4b and Figure 4c at the timestamp t=12s and t=20s, respectively. However, the existence of multiple uncertain obstacles made the performance of APF worse when Figure 5 witnessed the higher

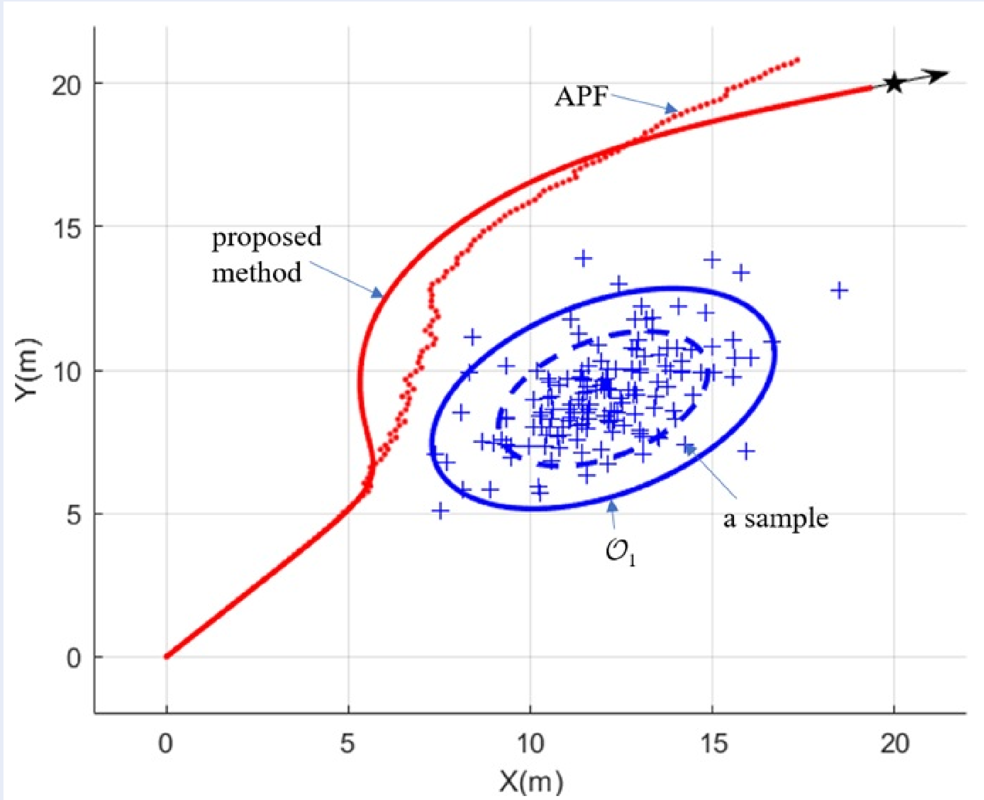

Figure 2: Performance of the probability-based artificial potential field for a single obstacle. The dashed blue ellipse and the solid blue ellipse represent the distribution of O_1 with α=0.95 and α=0.683, respectively. The black arrow depicts the velocity command.

peak (0.55) of the probability of collision. In summary, the proposed method convincingly improves the performance of APF in avoiding uncertain obstacles.

CONCLUSIONS

In this paper, a probability model was proposed to calculate the possibility of collision between the autonomous vehicles with uncertain obstacles. Then a new probability-based artificial potential field was introduced to exploit this probability model to help the vehicle navigating safely in environments of uncertain obstacles. Numerical simulations are carried out to verify the proposed collision avoidance model, and the results show that the proposed method can keep the autonomous vehicles to efficiently and safely pass obstacles regarding to uncertain information.

For further work, this study can be extended for the dynamic model by modifying the repulsive function such that the velocity command is admissible for the dynamic constraints. Dynamic obstacles are also considered by integrating the velocity into the probability model.

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CONFLICT OF INTEREST

The authors confirm that there is not any conflict of interest related to the content reported in this paper.

AUTHORS' CONTRIBUTION

Phan Minh Tam: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – review & editing.

Ho Pham Huy Anh: Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing.

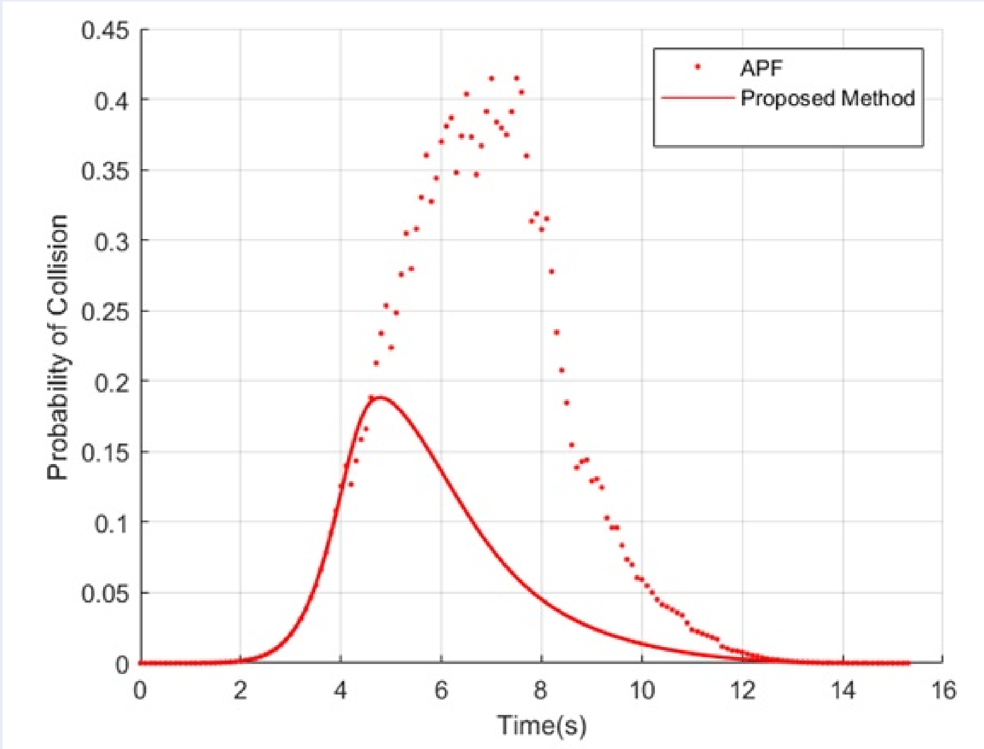

Figure 3: Probability of collision of the proposed method and APF in Case 1

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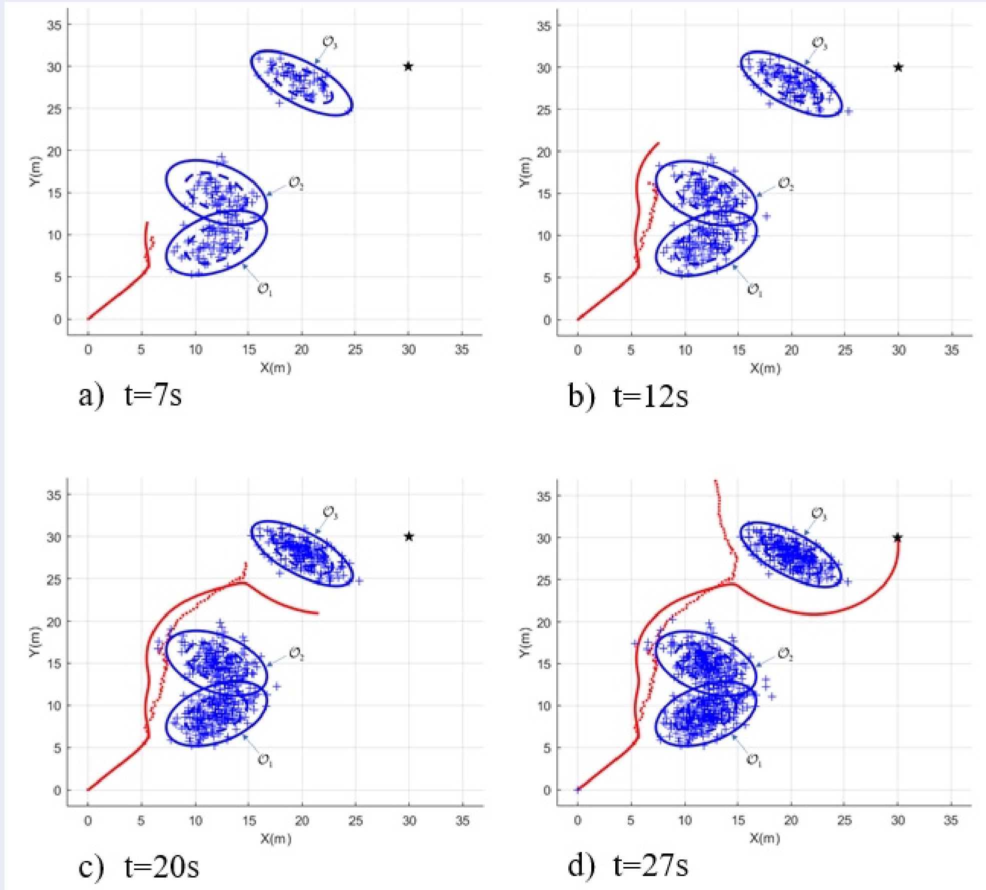

Figure 4: Performance of the probability-based artificial potential field for a single obstacle. The dashed blue ellipse and the solid blue ellipse represent the distribution of O_1 with α=0.95 and α=0.683, respectively. The solid red line and dotted red line respectively depict the paths generated by the proposed method and APF.

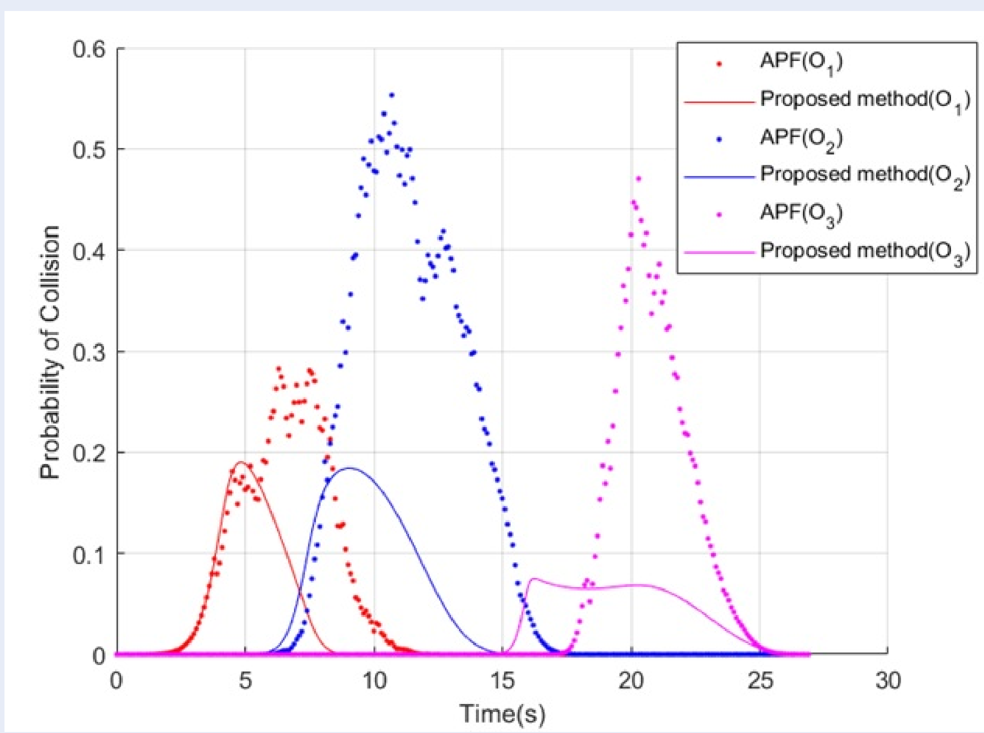

Figure 5: Probability of collision of the proposed method and APF in Case 2

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Bài nghiên cứu

Thuật toán trường thế nhân tạo (APF) tựa xác xuất dành cho xe tự hành giúp tránh vật cản không xác định

Phan Minh Tâm[1,2], **Hồ Phạm Huy Ánh**[1,2,*]

TÓM TẮT

Hiện nay các xe không người lái đều bắt buộc yêu cầu phải trang bị hệ thống tránh vật cản tin cậy nhằm tiến gần hơn đến tiêu chuẩn xe tự hành (*autonomous vehicle* - AV). Cho đến nay đã có nhiều thuật toán tránh vật cản đã được giới thiệu và ứng dụng thành công trong thực tiễn. Đáng tiếc là, trong hầu hết các thuật toán tránh vật cản này, tính bất định của số liệu đo đạc khoảng cách giữa xe đến vật cản, vẫn chưa được quan tâm khảo sát đầy đủ. Yếu tố bất định phát sinh từ bản chất các phương pháp đo cùng với tính phi tuyến của thông số vị trí vật cản. Một số nghiên cứu đã cố gắng giải quyết phần nào đó bài toán trên, bao gồm hướng trực tiếp hoặc gián tiếp phát hiện vật cản dựa trên nền tảng truyền thông toàn cục / cục bộ hoặc nhờ vào đối tác thứ ba là các hệ thống nhận dạng tự động (AIS). Được thúc đẩy từ các kết quả vừa nêu, bài báo đề xuất hướng xử lý dựa vào thông tin bất định vị trí vật cản có được từ các kỹ thuật tránh vật cản thực tế dành cho xe tự hành. Cụ thể, bài toán này thường được ước lược bỏ qua trong nhiều nghiên cứu bằng cách giả thiết rằng số liệu đo được xem như hoàn hảo hoặc xe tự hành bảo đảm quan sát đầy đủ trạng thái của vật cản. Ở đây ta sẽ xây dựng một mô hình xác xuất giúp đánh giá định lượng khả năng va chạm vật cản dựa theo vị trí hiện thời của xe phối hợp với xác xuất phân bố của vị trí vật cản. Từ đó mô hình xác xuất này sẽ được dung để thiết kế một hàm đáp ứng mới. Nhờ đó, trường thế nhân tạo (*artificial potential field* – APF) sẽ được dung hiệu quả giúp tránh các vật cản bất định bằng cách vận hành xe về hướng giảm nhẹ rũi ro va chạm. Các thử nghiệm mô phỏng số được tiến hành giúp kiểm tra mô hình tránh vật cản được đề xuất. Kết quả mô phỏng cho thấy phương pháp đề xuất giúp các xe tự hành vượt qua các vật cản hiệu quả và an toàn dù chỉ dựa vào các thông tin đo đạc bất định. Hệ quả là, thuật toán đề xuất cho phép hướng dẫn các xe tự hành (AV) vượt qua các vật cản tĩnh và động một cách hiệu quả và an toàn dù chỉ dựa vào các kết quả đo lường bất định. Hướng nghiên cứu tiếp theo sẽ tập trung vào các đối tượng vật cản động thông qua khả năng tích hợp các dữ liệu tốc độ vào mô hình xác xuất được thiết kế.

Từ khoá: xe tự hành (AV), giải thuật tránh vật cản, giải thuật tránh va chạm, vật cản bất định, phương pháp trường thế nhân tạo tựa xác xuất

[1]*Khoa KT Điện-Điện Tử (FEEE), Trường ĐH Bách Khoa TP Hồ Chí Minh (HCMUT), 268 Lý Thường Kiệt, Quận 10, TP Hồ Chí Minh, Việt Nam*

[2]*Đại học Quốc Gia TP Hồ Chí Minh (VNU-HCM), P. Linh Trung, TP. Thủ Đức, TP Hồ Chí Minh, Việt Nam*

Liên hệ

Hồ Phạm Huy Ánh, Khoa KT Điện-Điện Tử (FEEE), Trường ĐH Bách Khoa TP Hồ Chí Minh (HCMUT), 268 Lý Thường Kiệt, Quận 10, TP Hồ Chí Minh, Việt Nam

Đại học Quốc Gia TP Hồ Chí Minh (VNU-HCM), P. Linh Trung, TP. Thủ Đức, TP Hồ Chí Minh, Việt Nam

Email: hphanh@hcmut.edu.vn

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