Dynamic path planning based on variable step size rolling window derivation and obstacle prediction

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Abstract. Aiming at the problem of dynamic path planning for UAVs in complex environment, a path planning algorithm combining dynamic obstacle trajectory estimation and variable step rolling window deduction is proposed. When the dynamic obstacle distance is close to the UAV, the Kalman filter is used to estimate the dynamic obstacle trajectory. Then the window deduction is performed to judge the track area of the deduction window, so that the algorithm has certain "forward-looking". In turn, the window step size, the flight speed of the drone and the flight direction are changed, and the avoidance of the dynamic obstacle is completed, and the final goal is reached by the rolling plan. The experimental analysis shows that the algorithm can complete the dynamic path planning of UAVs in complex environment in real time.

1. Introduction

Real-time path planning means that the drone relies on the detected environmental information, autonomously avoids static and dynamic threats, and finds a safe, optimal route from the starting point to the end point according to certain criteria[1]. Since it is difficult to grasp all the information of the flight environment and perform global path planning. It is common to use local sensors such as sensors and cameras mounted on the drone to perceive local environmental information for local path planning. At present, the most successful methods for local path planning are: artificial potential field method[2], rolling window[3], neural network method[4], particle swarm algorithm[5], fuzzy logic algorithm[6] and so on. The artificial potential field method is simple in calculation and has a rapid response to dynamic obstacles, but it is easy to generate local poles. When the obstacle distance is close, the algorithm fails. Intelligent algorithms such as neural network and particle swarm optimization often lead to increased computation time and cannot meet real-time requirements in local planning.

The rolling window planning determines the sub-target points to be moved in the window according to a certain cost function. However, the main research aspect of the rolling window is to design and improve heuristic functions, such as the literature[7], which cannot guarantee that the safety of the drone in an emergency situation and the path to avoid dynamic obstacles are optimal.

Aiming at this problem, this paper proposes a forward stepped variable-step rolling window path planning. The Kalman filter is used to predict the dynamic obstacle trajectory. When it is detected that the drone may meet the dynamic obstacle, the scroll window step is changed based on the drone speed. At the same time push forward the rolling window, select the appropriate sub-target points according to the environmental information and dynamic obstacle information.

2. Kalman filter to estimate the dynamic obstacle trajectory

In this paper, Kalman filter is used to process the sensor data. Assuming that the measurement and system
noise are white noise, the Kalman filter can accurately predict the position of the dynamic obstacle through one-step prediction and correction iterative update, meet the requirements of high precision.

2.1 Dynamic obstacle motion model

Considering that the dynamic obstacle is sudden and maneuverable, the position, velocity and acceleration of the dynamic obstacle are selected as the state quantity, and the position of the dynamic obstacle measured by the sensor is selected as the observation.

Let the position at time $t_k$ be $x_k, y_k$, the speed be $v_{x_k}, v_{y_k}$, the acceleration be $a_{x_k}, a_{y_k}$, the system excitation noise sequence be $W_k = \begin{bmatrix} w_{x_k} \\ w_{y_k} \end{bmatrix}$, the measurement noise sequence be $V_k$, and the measurement sampling period be $T$.

At the same time, $W_k$ and $V_k$ meet the following conditions:

$$
\begin{align*}
E[W_k] &= 0, \text{Cov}[W_k, W_j] = \begin{bmatrix} Q_k & \delta_k \\ \delta_k & \delta_k \end{bmatrix}, \\
E[V_k] &= 0, \text{Cov}[V_k, V_j] = \begin{bmatrix} R_k & \delta_k \\ \delta_k & \delta_k \end{bmatrix}, \\
\text{Cov}[W_k, V_j] &= E[W_k V_j^T] = 0
\end{align*}
$$

(1)

Where $Q_k$ is the variance matrix of the system noise, and $R_k$ is the variance matrix of the measurement noise.

Establish a motion model in the $x$ direction and get the formula (2):

$$
\begin{align*}
x_k &= x_{k-1} + v_{x_{k-1}} T + a_{x_{k-1}} \frac{T^2}{2} + \frac{T^2}{4} w_{x_k} \\
v_{x_k} &= v_{x_{k-1}} + a_{x_{k-1}} T + \frac{T}{2} w_{x_k} \\
a_{x_k} &= a_{x_{k-1}} + \frac{T}{2} w_{x_k}
\end{align*}
$$

(2)

In the same way, establish a motion model in the $y$ direction and get the formula (3):

$$
\begin{align*}
y_k &= y_{k-1} + v_{y_{k-1}} T + a_{y_{k-1}} \frac{T^2}{2} + \frac{T^2}{4} w_{y_k} \\
v_{y_k} &= v_{y_{k-1}} + a_{y_{k-1}} T + \frac{T}{2} w_{y_k} \\
a_{y_k} &= a_{y_{k-1}} + \frac{T}{2} w_{y_k}
\end{align*}
$$

(3)

Take $X_k$ as the state vector and get the formula (4):

$$
X_k = \begin{bmatrix} x_k \\ v_{x_k} \\ y_k \\ v_{y_k} \\ a_{x_k} \\ a_{y_k} \end{bmatrix}
$$

(4)

From the above equations (2), (3), (4), the equation of state of the dynamic obstacle is obtained:

$$
X_k = \Phi X_{k-1} + \Gamma W_{k-1}
$$

(5)

Where $\Phi$ is a one-step transfer matrix and $\Gamma$ is a system noise drive matrix:
Considering the position of the dynamic obstacle as the measured value, the measurement equation is:

\[ Z_k = HX_k + V_k \]  
(7)

In the formula,

\[ H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \]  
(8)

### 2.2 Kalman filter estimation of dynamic obstacle location algorithm steps

If the state \( X_k \) of the dynamic obstacle is estimated to satisfy the equation (5), the quantity measurement \( Z_k \) thereof satisfies the equation (7), the system noise \( W_k \) and the measurement noise \( V_k \) satisfy the equation (1), and the variance matrix of the system noise satisfies the non-negative. The variance matrix of the measured noise satisfies the positive definite. Assuming that the quantity at time \( k \) is measured as \( Z_k \), the estimated value \( \hat{X}_k \) of the state quantity \( X_k \) can be solved as follows.

1) Time update process

According to the system state equation (5), the state of the system is predicted by one step (9):

\[ \hat{X}_{k|k-1} = \Phi \hat{X}_{k-1} \]  
(9)

The one-step prediction of the mean square error equation is given by equation (10):

\[ P_{k|k-1} = \Phi P_{k-1} \Phi^T + \Gamma \Omega \Gamma^T \]  
(10)

2) Measurement update process

The filter gain equation (11) is:

\[ K_k = P_{k|k-1} H^T \left[ H P_{k|k-1} H^T + R \right]^{-1} \]  
(11)

The state estimation equation (12) is:

\[ \hat{X}_k = \hat{X}_{k|k-1} + K_k [Z_k - HX_{k|k-1}] \]  
(12)

The estimated mean square error equation (13) is:

\[ P_k = P_{k|k-1} - K_k H P_{k|k-1} \]  
(13)

### 3. Variable step size scroll window deduction

The rolling window means that the drone uses its own sensor to obtain local environmental information, and realizes the online path planning of the drone by scrolling. The so-called deduction refers to the fact that when the dynamic obstacle is detected to be close to the drone, not only one window \( \text{win}(t) \) at the current moment \( t \), but two windows \( \text{win}(t+1), \text{win}(t+2) \) are further planned to be backward. This strengthens the drone's judgment on the future situation and ensures the drone safety.

#### 3.1 Building a suitable scrolling window

Assume that the effective measurement radius of the UAV-equipped sensor is \( r \), and the measurement angle is \( 0 \sim 180^\circ \). According to the flight principle of the drone and the detection characteristics of the sensor, a semi-circular rolling window as shown in figure 1 is established, and the center of the window symmetry is the flight direction of the previous section.
3.2 Design of heuristic functions

In order to avoid dynamic obstacles and ensure optimal path when the drone is planning the rolling window, the key problem to be solved is how to determine the next sub-target point in the current window. This article guides the search in the most favorable direction by designing a heuristic function.

In heuristic search, we usually define a cost function and use this as a guide to search sub-target points. The general form is $f(x) = g(x) + h(x)$, where $g(x)$ represents the cost from the current position of the drone to the sub-target point of the window, and $h(x)$ represents the cost of the sub-target point to the end point. The cost here refers to the Manhattan distance, and the current window searches for the point at which $f(x)$ takes the minimum value as the sub-target point[8]. However, when the drone may collide with the dynamic obstacle, we must fully guarantee the safety of the drone, that is, we must also consider the influence of the dynamic obstacle on the search strategy. Therefore, this paper improves the general form of the cost function to obtain the new cost function shown in equation (14).

$$f_{new}(x) = g(x) + h(x) + O(x)$$  \hspace{1cm} (14)

Where, $O(x) = m(x) + s(x)$, $m(x)$ is the dynamic obstacle information, $s(x)$ is the static obstacle information, and the distance between the drone and the $i$-th dynamic obstacle in the environment is $L(x, m_i)$, and the distance from the $i$-th static obstacle in the current time window is $L(x, s_i)$, then $m(x)$ and $s(x)$ are the equations (15) and (16), respectively.

$$m(x) = \left( \sum_i L(x, m_i) \right)^{-1}$$  \hspace{1cm} (15)

$$s(x) = \left( \sum_i L(x, s_i) \right)^{-1}$$  \hspace{1cm} (16)

3.3 Rolling window deduction

Based on the idea of window deduction, the UAV can plan the path of the next two windows. However, in the actual flight process, the drone is not to implement all the planned future windows, but only to follow the sub-target points planned in the first window. After the drone reaches the next sub-target point, it makes a judgment on the position of the dynamic obstacle, and then pushes back two windows to obtain a new sequence of deduction windows, thereby completing the path planning.

The idea of the rolling window derivation is further clearly described in figure 2. The shaded semicircle in the figure represents the window of the current moment, and the latter two semicircles represent the window for future deduction.

$$f_{new}(x) = g(x) + h(x) + O(x)$$  \hspace{1cm} (14)

Where, $O(x) = m(x) + s(x)$, $m(x)$ is the dynamic obstacle information, $s(x)$ is the static obstacle information, and the distance between the drone and the $i$-th dynamic obstacle in the environment is $L(x, m_i)$, and the distance from the $i$-th static obstacle in the current time window is $L(x, s_i)$, then $m(x)$ and $s(x)$ are the equations (15) and (16), respectively.

$$m(x) = \left( \sum_i L(x, m_i) \right)^{-1}$$  \hspace{1cm} (15)

$$s(x) = \left( \sum_i L(x, s_i) \right)^{-1}$$  \hspace{1cm} (16)

The advantage of rolling window deduction is that it can respond to unexpected situations in advance. By this method, the drone has a certain ability to think. Improve the intelligence and reliability of drones and ensure the safety of planning paths. Next, the process of rolling window deduction to avoid dynamic obstacles will be described in detail with reference to figure 3.
Figure 3. Rolling window deduction to avoid dynamic obstacle process demonstration.

The solid semicircle represents the current time window, and the dotted semicircle represents the backward two windows; the solid circle represents the position of the current moment dynamic obstacle, and the dashed circle represents the predicted position of the dynamic obstacle in the next two moments. Let the direction of the arrow represent the original flight direction of the drone. In Figure 3, at time $t$, the unmanned aircraft is found to find a feasible path to avoid the dynamic obstacle, and successfully move to the target point of the window planning; $t+1$ moment due to the predicted bias error Influencing the window deducted at time $t$, the drone adjusts the window in time, finds the optimal target point at this moment, and deducts two windows backwards to obtain a new feasible path; $t+2$ moments the drone finally succeeds in avoiding the dynamic obstacle.

When the dynamic obstacle is closer to the drone, the two windows are pushed forward, and the UAV survival rate and the task completion rate are exchanged with less calculation. Of course, the more backwards, the more likely the drone will succeed, but it will increase the amount of calculation, and the real-time path planning will be reduced.

3.4 Variable step size window strategy

In the previous section, we took a fixed-step scrolling window. In order to make the drone more flexible, fast and effective in avoiding obstacles, we design a variable step rolling window related to the flight speed. Combining the variable step size window with the rolling deduction can better accomplish the dynamic path planning task of the drone\cite{9}. The improved variable step size window avoids the dynamic obstacle process as shown in figure 4.

Figure 4. Variable step size window obstacle avoidance process.

When the drone performs path planning, the size of the scroll window is the area surrounded by the window corresponding to the minimum speed $V_{\text{min}}$ and the maximum speed $V_{\text{max}}$. In the moment $t$, the flight direction and position of the drone and the dynamic obstacle are shown in Figure 4. If the drone is flying according to the original speed and direction, it will collide with the obstacle. Therefore, window deduction can be used to determine which flight area the optimal path of the drone belongs to. When $0 \leq \theta < 180^\circ$, if the route deducted by the window belongs to the upper half of the flight area, the drone should gradually reduce its speed to $V_{\text{min}}$, and the window step size will also decrease accordingly; if the window derived by the window belongs to the lower half of the flight area, the drone should gradually reduce its speed to $V_{\text{max}}$, and the window step size will increase accordingly; when
180 ° \leq \theta < 360 ° \), it is the opposite. When the drone successfully avoided the dynamic obstacle, it resumed its original speed flight. Through the variable step design, the impact of window deduction on the maneuverability of the drone is compensated to some extent.

4. Algorithm simulation and analysis

The algorithm proposed in this paper is simulated by matlab, under the knowledge of a priori map, and the effectiveness of the algorithm in the dynamic path planning of UAV is tested. Simulate the generation of dynamic obstacles and static obstacles in the flight environment of the drone, and set the relevant parameters as follows: the departure point of the drone is \([0, 0]\), the end point is \([30, 30]\), the initial flight speed of the drone is \(1 \text{m/s}\), the planning period \(t = 5s\), the rolling window step \(r = 5m\), there are 2 dynamic obstacles in the flight environment of the drone, and 20 static obstacles. The obstacles are all represented by circles.

The two dynamic obstacles set in this paper are S-type maneuver and parabolic maneuver respectively, and the motion model of S-type maneuvering dynamic obstacle is shown in equation (17):

\[
\begin{align*}
x & = 5 + 1.1t \\
y & = 27 - x + 2\sin(0.5x + 0.05t)
\end{align*}
\] (17)

The motion model of the parabolic maneuvering dynamic obstacle is shown in equation (18):

\[
\begin{align*}
x & = -4 + 1.5t \\
y & = 6.5 + (0.05t)^2
\end{align*}
\] (18)

In figure 5, at the beginning of the path planning, the sensor detects that the dynamic threat is far away from the drone, and uses the initial speed flight and the initial window planning path. In figure 6, the parabolic maneuvering dynamic threat is closer to the drone. Kalman filter is used to estimate the dynamic threat trajectory. It is predicted that it may encounter with the drone, deduct the window and change the step size, and determine the dynamic obstacle angle and flight path, reduce the flight speed of the drone, and change the flight direction of the drone. In figure 7, after successfully avoiding the parabolic maneuvering dynamic obstacle, the UAV gradually returns to the initial speed flight. After detecting the S-type maneuvering dynamic obstacle, the processing is similar to before, deduct the window and change the step size, and determine the dynamic obstacle angle and flight path. Increasing the flight speed of the drone, and changing the flight direction of the drone. In figure 8, the drone successfully circumvents the S-type maneuvering dynamic obstacle, gradually returns to the initial speed flight, and reaches the end point.
5. Conclusion

This paper proposes a variable step size rolling window deduction algorithm. When it is predicted that the drone may collide with the dynamic obstacle, the two windows are pushed forward, so that the drone can better cope with the burst. The situation, and overcome the adverse effects brought by the Kalman estimation error, so that the algorithm has a certain forward-looking. At the same time, the variable step size window related to the flight speed is used to change the flight speed of the drone and change the flight direction while avoiding the dynamic obstacle. Through simulation experiments, the algorithm successfully avoids two kinds of dynamic obstacles and reaches the end point, and has certain engineering application value for the dynamic path planning of the drone in the complex environment.

References

[1] LaValle, S.M. (2006) Planning algorithms. Cambridge Univ Pr Publishing, Cambridge.
[2] Ding, J.R., Du, C.P., Ying, D.Y. (2016) Path planning algorithm for unmanned aerial vehicles based on improved artificial potential field. J. Journal of Computer Applications, 36(01):287-290.
[3] Zhang, C.G. (2002) Mobile Robot Path Planning Based on Rolling Windows. J. Systems Engineering and Electronics, (6):63-65.
[4] Wang, N., Gu, X., Chen, J. (2009) A Hybrid Neural Network Method for UAV Attack Route Integrated Planning. J. International Symposium on Advances in Neural Networks-isnn,5553:226-235.
[5] Wang, G., Li, Q., Guo, L. (2010) Multiple UAVs Routes Planning Based on Particle Swarm Optimization Algorithm. International Symposium on Information Engineering & Electronic Commerce. IEEE.
[6] Kurnaz, S., Cetin, O., Kaynak, O. (2010) Adaptive neuro-fuzzy inference system based autonomous flight control of unmanned air vehicles. J. Expert Systems with Applications, 37(2):1229-1234.
[7] Liang, X., Wang, H.L., Cao, M.L., Guo, T.F. (2012) Real-time path planning to track moving target in complex environments for UAV. J. Journal of Beijing University of Aeronautics and Astronautics, 38(09):1129-1133.
[8] Joseph, E. H., Eric, M.S., Brian, R.G. (2012) Neural Network—Based Trajectory Optimization for Unmanned Aerial Vehicles. J. Journal of Guidance, Control, and Dynamics, 2012, 35(2):548-562.
[9] Zeng, J., Shen, G.Z. (2008) An Autonomous Variable Step-length Trajectory Planning Algorithm for UAV. J. Journal of Projectiles, Rockets, Missiles and Guidance, 28(6):21-24.