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Path-Planning of a Certain UAV Using Neural-Network Method

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***Abstract*—Unmanned Aerial Vehicles(UAVs) are widely used for civilian and military purposes, such as surveillance, reconnaissance, search and rescue, border patrol etc. In this paper a single UAV is equipped with a gimballed camera to conduct surveillance operations, the route planning method that uses neural network method is presented. The Neutral network method reduces computational requirements by removing the need for collocation and providing fast computation of gradients and thus the computation costs reduces significantly. The simulation results show the flexibility of the neutral network.**

Keywords-Unmanned Aerial Vehicle(UAV), path planning optimization, neural-network

I. INTRODUCTION

Unmanned Aerial Vehicles(UAVs) are widely used for civilian and military purposes, such as surveillance, reconnaissance, search and rescue, border patrol etc. UAV has the characteristic of wide flight envelope curve, super maneuverability and good agility. But its mathematical model has high error, flight control law only applied with neural-network method can fully satisfy UAV path planning optimization. this paper introduces neural-network theory to analyze system design by removing the need for collocation and providing fast computation of gradients and thus the computation costs reduces significantly.

II. NEURAL-NETWORK THEORY

A. Neural-network Method Formulation

The neural network approximation results in, as in [1]

$$x_1 = Y_d(x_0, u_0, u_1) \tag{1}$$

$$\begin{aligned} x_2 &= Y_d(x_1, u_1, u_2) \\ &= Y_d[Y_d(x_0, u_0, u_1), u_1, u_2] \end{aligned} \tag{2}$$

The states at each node are recursively computed from x_0 and u[0,1…n-1]:

$$\begin{aligned} x_{i+1} &= Y_d(x_i, u_i, u_{i+1}) \\ \text{for} \quad & i \in [0,1,\ldots\ldots n-2] \end{aligned} \tag{3}$$

Similarly, to approach the objective function, the neural network is trained to approximate the value of the objective along a segment. Again the value of the objective function along such a segment depends only on the initial state and the control history.

$$J_0 = \int_{to}^{t_{0+\tau}} \gamma(x, u)dt \tag{4}$$

Thus the objective function value depends only on the initial state at the first node and the controls at each node:

$$J = \sum_{i=0}^{n-2} J_i = \sum_{i=0}^{n-2} Y_J(x_i, u_i, u_{i+1}) \tag{5}$$

B. Derivative Calculation of Neural Network

The equation for network output z is

$$z = y_0\{W_0 y_h[W_0 y_i(W_i k + b_i) + b_h] + b_0\} \tag{6}$$

Using the chain rule, the gradient of the entire network with respect to the inputs is easily computed. For a three-layer network, the gradient is

$$\nabla z = D_0 W_0 D_h W_h D_i W_i \tag{7}$$

where $D_{[i,h,o]}$ denote diagonal matrices

$$\begin{aligned} J_i &= Y_J(x_i, u_i, u_{i+1}) \\ \text{for} \quad & i \in [0,1,\ldots\ldots n-2] \end{aligned} \tag{8}$$

where the functions $Y_d(x_i, u_i, u_{i+1})$ and $Y_J(x_i, u_i, u_{i+1})$ are now approximated by neural networks. Equation (6) can be applied to calculate the gradient.

III. General Path Planning Optimization

$$\dot{x} = f(x, u) \tag{9}$$

$$c(x, u) \leq 0 \tag{10}$$

where x and u are the state and control input vectors respectively. One seeks the control input u(t) that minimizes a scalar objective function J of the form, as in [3]

$$\int_{to}^{t_f} \gamma(x,u)dt \tag{11}$$

The state at the end of the segment is found by integrating the equations of motion over the segment as shown in (12)

$$x(t_0+\tau) = \int_{to}^{t_{0+\tau}} f(x(t),u(t))dt \tag{12}$$

IV. UAV Path Planning optimization

A. Model of UAV

Its mathematical model can be described by below state equations, as in [4].

$$\dot{V} = \frac{1}{M}[-D + (Y + Y_T)\sin\beta - Mg\sin\chi] + \frac{1}{M}(T_x \cos\beta\cos\alpha + T_z\cos\beta\sin\alpha) \tag{13}$$

$$\dot{\chi} = \frac{1}{MV}(L\cos\Phi - Mg\cos\chi) - \frac{1}{MV}(Y + T_y)\cos\beta\sin\Phi) + \frac{T_x}{MV}(\sin\Phi\cos\beta\cos\alpha + \cos\Phi\sin\alpha) + \frac{T_z}{MV}(\sin\Phi\sin\beta\sin\alpha - \cos\Phi\cos\alpha) \tag{14}$$

$$\dot{\psi} = \frac{1}{MV\cos\chi}L\sin\Phi + \frac{1}{MV\cos\chi}(Y + T_y)\cos\Phi\cos\beta + \frac{T_x}{MV\cos\chi}(\sin\Phi\sin\alpha - \cos\Phi\cos\beta\cos\alpha) - \frac{T_z}{MV\cos\Phi}(\cos\Phi\sin\beta\sin\alpha + \sin\Phi\cos\alpha) \tag{15}$$

$$\dot{\alpha} = q - \tan\beta(p\cos\alpha + \gamma\sin\alpha) + \frac{1}{MV\cos\alpha}(-L + Mg\cos\chi\cos\Phi) + \frac{1}{MV\cos\beta}(-T_x\sin\alpha + T_z\cos\alpha) \tag{16}$$

$$\dot{\beta} = (-\gamma\cos\alpha + p\sin\alpha) + \frac{1}{MV}[(Y + T_y)\cos\beta + Mg\cos\chi\sin\Phi)] + \frac{1}{MV}(-T_x\sin\beta\cos\alpha - T_z\sin\beta\sin\alpha) \tag{17}$$

$$\dot{\Phi} = \sec\beta(p\cos\alpha + \gamma\sin\alpha) + \frac{1}{MV}(\tan\beta + \tan\chi\sin\Phi) + \frac{Y + T_y}{MV}\tan\chi\cos\Phi\cos\beta - \frac{Mg}{MV}\cos\chi\cos\Phi\tan\beta + \frac{T_x\sin\alpha - T_z\cos\alpha}{MV}(\tan\chi\sin\Phi + \tan\beta) - \frac{T_x\cos\alpha + T_z\sin\alpha}{MV}(\tan\chi\cos\Phi\sin\beta) \tag{18}$$

here, p: rolling angle rate, q : pitch angle rate, γ :is yaw angle rate , α:attack angle, β:sideslip angle, ϕ:rolling angle, V :velocity, χ: flight path angle,andψ: climb angle

B. Fixed Camera, Single Unmanned Aerial Vehicle

The desired behavior for the UAV is to maximize sensor coverage of the target. The objective function that derives this behavior is a weighted sum of four separate objectives, as in [5].

$$J = \int_{to}^{t_f}(\omega_1 u^2{}_I + \omega_2 u^2{}_\phi)dt + \int_{t_0}^{t_f}\left\{\omega_3[(r_x - r_{xtgt})^2 + (r_y - r_{ytgx})^2] + \omega_4 J_{tiv}\right\}dt \tag{19}$$

C. Neural Network Implementation

Neural networks were also used to produce the final output for both the camera range of motion and camera effort objectives, the camera range of motion and camera effort objectives are more complicated and require preprocessing of the data to enable accurate training using available hardware. First, the dynamics network is used to find the states at the next node, then the states and controls at each node are passed to a function that outputs a unit vector[d_i , e_i , f_i] in the direction of the target originating at the camera in the camera's coordinate frame. The value of this unit vector at each node is then passed to the neural networks for processing, as in [6].

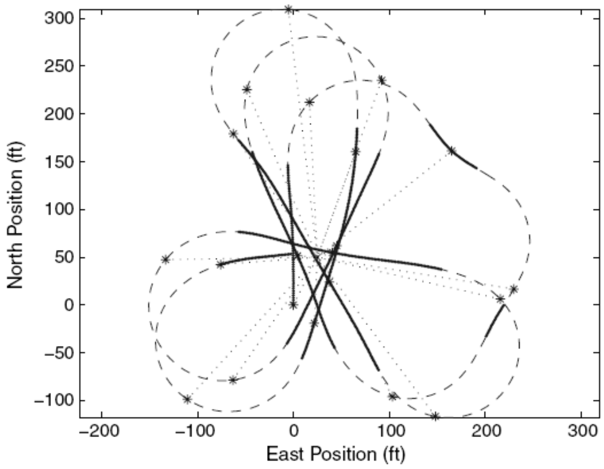

FIGURE I. NEURAL NETWORK PATH PLANNING WITH 40% COVERAGE TIME, 0.8S MEAN PATH GENERATION TIME.

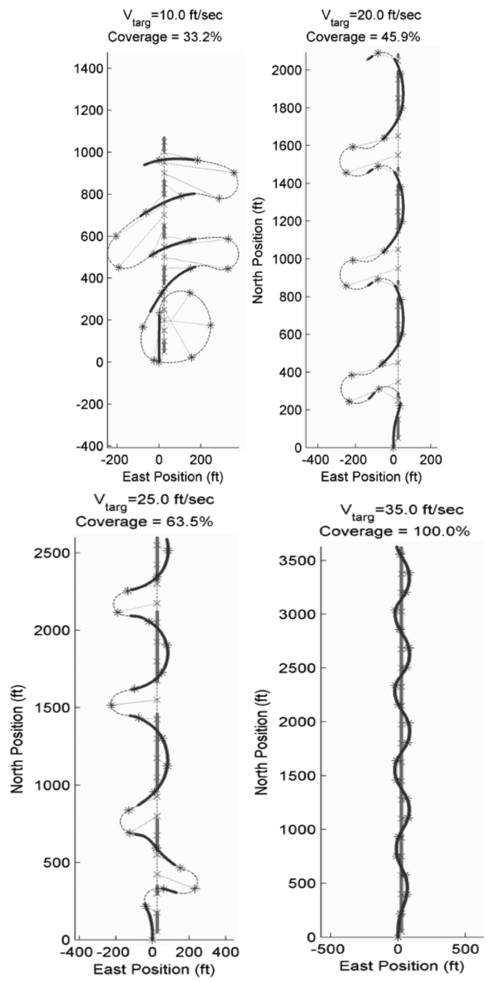

FIGURE II. MOVING TARGETS, NEUTRAL NETWORK (NN) RESULTS

Figure I show the full training set for each network. The network outputs are plotted against the true output, thus it is desired that the plots follow the line y=x. The synamics and distance-to-target plots are centered on this line, indicating that networks approximate their functions very accurately. The camera range of motion network outputs a binary decision based on whether the target is viewable, thus all target points are centered at the two extreme values. Using this trained network all test points match closely with the desired values, as shown in the figure .The simulation results are presented in Figure II. The results show that the neural network results are functional. The states include north and east positions of the target(r_{xtgt} and r_{ytgt}) and UAV(r_x and r_y), the true airspeed *V*, and the aircraft heading ψ in Figure II.

V. CONCLUSION

In this paper the neutral network path-planning optimization method is discussed. The results from the single UAV with a fixed camera have shown that neutral network approximation generally matches the optimization performance of the direct collocation and pseudo spectral methods but requires 2-5 less computation time than using analytical derivatives and 5 times less than the automatic derivative methods. As neutral network approximation does not require analytic derivatives, speed could be further enhanced, it could be quite useful for real –time optimization control. Next, the neutral network approximation could be extended to solving a multiple –UAV survellancd problem. The work further demonstrated the flexibility of the network path planning method to cases involving a single UAV with a gimbaled camera.

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