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Neural-network-based Path Planning Optimization

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Abstract. In this paper some Unmanned Aerial Vehicles are equipped with a fixed camera to conduct surveillance operations, the route planning method are presented using neural network method. The simulation results are presented to demonstrate the performance and computational efficiency of the method. As neutral network approximation does not require analytic derivatives, speed could be further enhanced, it could be quite useful for real –time optimization control.

General Path Planning Optimization

$$\dot{x} = f(x,u) \tag{1}$$

$$c(x,u) \le 0 \tag{2}$$

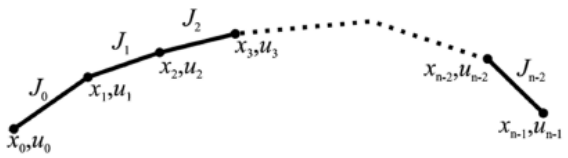


Fig1. sample trajectory

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

$$\int_{to}^{t_f} \gamma(x,u)dt \tag{3}$$

The state at the end of the segment is found by integrating the equations of motion over the segment as shown in Eq.(4)

$$x(t_0+\tau) = \int_{to}^{t_{0+\tau}} f(x(t),u(t))dt \tag{4}$$

Neural-network Method Formulation

The neural network approximation results in

$$x_1 = Y_d(x_0,u_0,u_1) \tag{5}$$

$$x_2 = Y_d(x_1,u_1,u_2) = Y_d[Y_d(x_0,u_0,u_1),u_1,u_2] \tag{6}$$

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

$$x_{\mathbf{i}+1} = Y_d(x_{\mathbf{i}},u_{\mathbf{i}},u_{\mathbf{i}+1}) \quad \mathbf{for\ i} \in [0,1,......n-2] \tag{7}$$

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.

$$J_0 = \int_{to}^{t_{0+t}} g(x,u)dt \tag{8}$$

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

$$J = \sum_{i=0}^{n-2} J_i = \sum_{i=0}^{n-2} Y_J(x_i, u_i, u_{i+1}) \tag{9}$$

Derivative Calculation of Neutral Network

The equation for network output z is

$$z = y_0\{W_0 y_h[W_0 y_i(W_i k + b_i) + b_h] + b_0\} \tag{10}$$

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

$$\nabla z = D_0 W_0 D_h W_h D_i W_i \qquad (11)$$

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

$$\begin{aligned} &\mathbf{J_i} = Y_{\mathbf{J}}(x_{\mathbf{i}}, u_{\mathbf{i}}, u_{\mathbf{i}+1}) \\ &\quad \textbf{for } \mathbf{i} \in [0,1,......n-2] \end{aligned} \tag{12}$$

Where the functions Yd(.) and YJ(.) are now approximated by neural networks. Equation (10) can be applied to calculate the gradient.

UAV Path Planning optimization

Equations of Motion

The state equations used in this path planning problem involve simple two-dimentional kinematics, as shown in Eq.(12). The states include north and east positions of the target(rxtgt and rytgt) and UAV(rx and ry), the true airspeed V, and the aircraft heading Ψ .The controls are longitudinal acceleration command ua and bank angle command $\mathbf{u}_\Phi$:

$$\begin{aligned} &\dot{r}_x = V\cos(\Psi) - V_{wind\,N} \qquad \dot{r}_y = V\sin(\Psi) - V_{wind\,E} \\ &\dot{V} = u_a \qquad \dot{\Psi} = g\tan(u_\Phi)/V_t \\ &\dot{r}_{xtgt} = V_{tgtN} \qquad \dot{r}_{ytgt} = V_{tgtE} \end{aligned} \tag{13}$$

Constraints on the problem include stall airspeed and maximum airspeed ,bank angle limits ,and longitudinal acceleration limits:

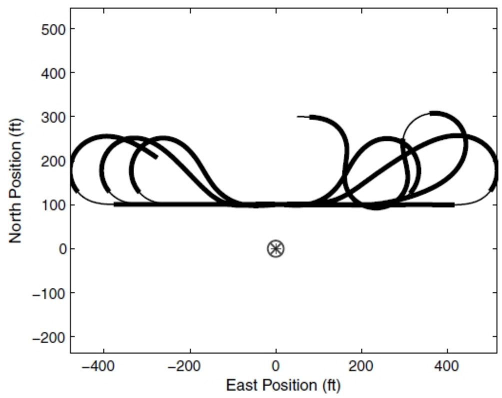
$$\mathbf{V}_{min} < V < V_{max} \qquad \phi_{min} < u_\phi < \phi_{max}$$

$$a_{min} < u_a < a_{max}$$

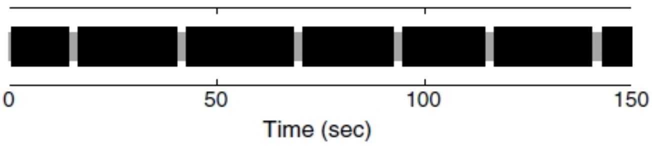
Multiple Unmanned Aerial Vehicles , Fixed camera simulation

(1)Stationary target

Figure2 shows two UAVs observing a stationary target with no-fly zone. The question of collision avoidance is not addressed for this work. As a practical matter, flying the UAVs at different altitudes removes the need for collision avoidance. This would require the target-in-view network to be trained against altitude. For these results, all UAVs are flown at the same altitude. Note in Fig.3a how the black UAV diverts at the start to avoid simultaneous target coverage. The given coverage time is a 30s moving average. Figure 2b shows that the UAVs alternate sensor coverage as desired. The black and blue bars indicate when the sensor onboard UAV 1 or 2 is viewing the target.

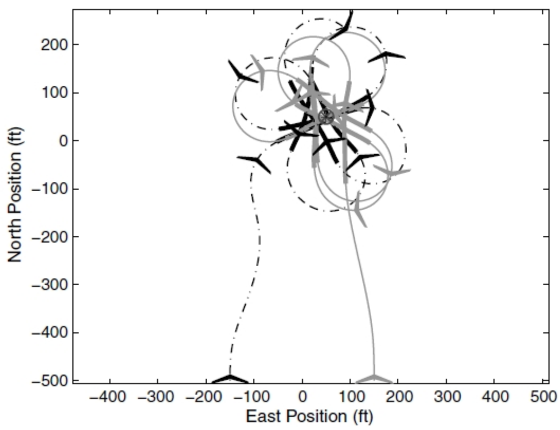


(a)Stationary target with no-fly zone (91.5% coverage,74 sec calculation time)

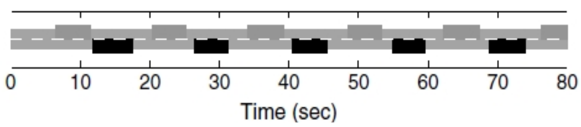


(b) stationary target with non-fly zone observation history

Fig.2 Stationary target with no-fly zone



(a) Ground path(9 nodes,16 sec horizon,71.5% coverage, 0.60 sec average calculation time)

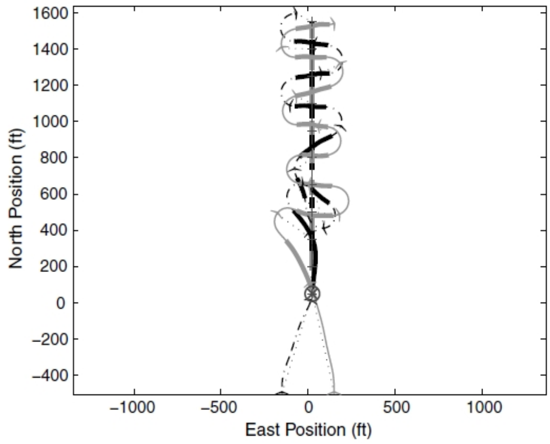


(b)Target coverage time line

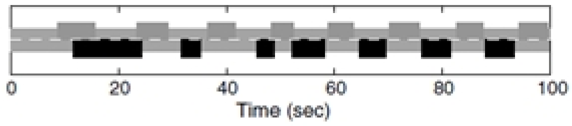
Fig3. Ground track and coverage timeline for two UAVS and stationary target.

(2)Moving Target

A moving target is presented in Fig4.Here,the target is moving north at 15ft/s. After the initial settle time, the UAVs assume a regular pattern of alternating passes over the target.



(a)Ground path(9 nodes,16 sec horizon,91% coverage,0.58 sec average calculation time)



(b) Target coverage timeline

Fig.4 Ground track and coverage timeline for two UAVs and a target at 15 ft/s.

Conclusion

In this paper the neutral network path-planning optimization method is discussed. The results from the multiple UAV with a fixed camera have shown that neutral network approximation generally matches the optimization.

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