

Mobile Robot-based Antenna System Design Tracking on RPVs or UMs using Intelligent Neural Controller

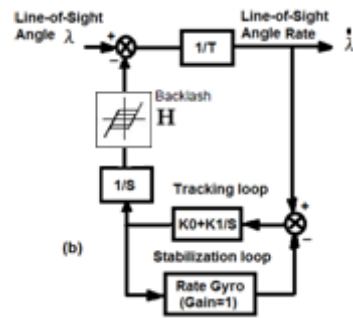


Figure 1: Block diagrams of antenna control systems for stabilization loop with a PI compensator.

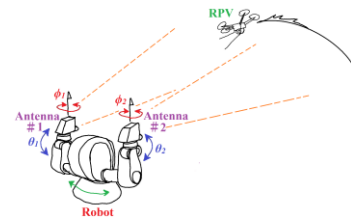


Figure 2: Two antenna tracking systems on the arms of a robot were applied to track a RPV.

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Abstract

This research applied both the traditional PI-based and the neural control methods for a mobile robot-based antenna tracking system on RPV (Remote Piloted Vehicles) or UMV (Unmanned Vehicles). Firstly, the antenna tracking and the stabilization loops were designed according to the bandwidth and phase margin requirements. However, the system

performance would be degraded if either the tracking loop gain parameter was reduced and the motor hysteresis effect existing in the tracking loop. On the other hand a neural controller was also applied for the design. Note that the system performances obtained by the neural controller were better with not only parameter variations but motor hysteresis effect in the tracking loop. Thus the proposed system is more robust.

Keywords

Neural controller; robot; antenna tracking system; RPV.

ACM Classification Keywords

Neural controller; robot; antenna tracking system; RPV.

Introduction

The RPVs or UMV have been applied in many fields, such as geodic image retrieval, agricultural product surveying, and geodetic surveying. If RPVs or UMVs were applied to inspect the battle field, then it is very important to track the RPVs for safety consideration. In order to lock on the RPVs with rapid, agile and small radius of maneuver, thus the simplified antenna tracking systems as shown in Figure 1 can be set on the arms of a robot as shown in Figure 2 to enhance the operational ability for such a near distance

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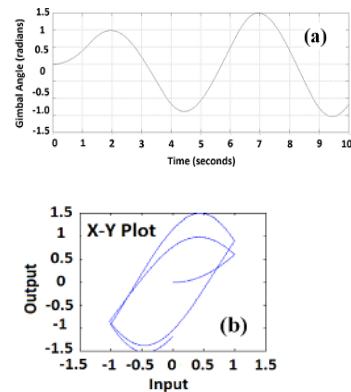


Figure 3: PI-based controller with $T=0.5$ sec and $H=0.5$. (a) Gimbal angle output. (b) X-Y plot (system is unstable).

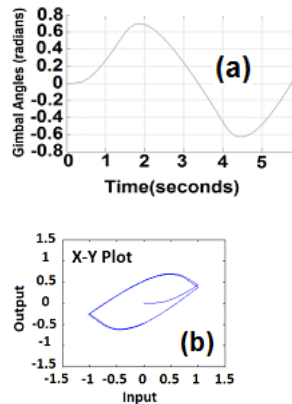


Figure 4: Neural controller with $T=0.5$ sec and $H=0.5$. (a) Gimbal angle output. (b) X-Y plot.

engagement [1-3]. On the other hand, there may be parameter variation of T and motor hysteresis effect of H as in Figure 1. Thus not only the performances of antenna tracking but the stabilization loops should be raised to increase the pointing precision and to decouple the disturbances due to the motion of robot. The traditional PI (Proportion and Integration) compensator was applied for the tracking and stabilization loops design of antennas, the results of gimbal angle and X-Y plot with tracking loop time constant $T=0.5$ sec and hysteresis effect $H=0.5$ are shown in Figures 3a and 3b. Note the system is unstable. Thus this paper integrated both the traditional PI and the neural controllers for a mobile robot-based antenna tracking system design. Firstly, the antenna control system was designed with PI compensator to meet the bandwidth and phase margin requirements of tracking and stabilization loops. Then the neural control method was added in the tracking loop for comparison. Noted the performance with the proposed method was more robust to system parameter variations and the motor hysteresis effects.

Neural Controller Design

Considering both effectiveness and efficient, various neural network training algorithms, namely, conjugate gradient, and LM are applied alternatively in each step of iteration to determine the neural controller [4-5]. The neural controller structure is with three inputs, one hidden layer and one output. The system responses for $T=0.5$ sec and with $H=0.5$ were shown in Figures 4a, and 4b, respectively. Note the antenna performance was still good (and stable) even with system parameter variation and motor hysteresis effect. The proposed system was more robust.

Conclusions

This research applied both the traditional PI and the neural controller for a mobile robot-based antenna tracking system on RPV. Firstly, the antenna tracking and the stabilization loops were designed to meet the traditional bandwidth and phase margin requirements. However, the performances would be degraded if there were parameter variations and hysteresis effects in the system. On the other hand, a neural controller was also applied for tracking loop design. Comparing the results with those of the traditional PI controller, one could see that the system performances obtained by the neural controller were better not only for the degradation of antenna tracking loop gain, but the motor hysteresis effect. Thus the proposed system was more robust. The system decoupling performance considering the robot motion effects would be studied the next in the future.

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