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Neuro-Controller Design with Learning Rate Modification for the Line of Sight Stabilization System

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Abstract

This paper presents an application of back propagation neural network to the tracking control of line of sight stabilization system. We design a neuro-control system having two neural networks one for learning system dynamics and the other for control. We use a learning method which adjusts learning rate and momentem as a function of plant output error and error change.

1. Introduction

Common control objective of most industrial plants is that the outputs of the plants track given reference trajectories in order to obtain satisfactory performance. The dynamics of controlled systems are usually simple (e.g. linear) and explicitly known so that modern control theory can be applied successfully. Even if it is possible to development an accurate model, the resulting control algorithm is so computationally intensive that it becomes infeasible to implement in a real time control environment. Investigating the performance exhibited by an experienced human operator, it is believed that the controller should be designed to have experience and knowledge gained during the training process. Recently, neural networks are of interest to the control community because they have potential to treat many problems that cannot be handled by traditional approaches. The application of artifical neural network promises a high computation rate provided by massive parallelism, and a great degree of robustness, or fault tolerance due to the distributed representation, and the ability of adaptation, learning, and generalization to improve performance. Back propagation neural network are most prevalent neural nework architecture for control applications because they have the capability to learn system characteristics through the nonlinear mapping.

The application of neural networks for controlling physical systems has been explored[1-3]. The back propagation algorithm[4] is widely used for learning multilayered neural networks, but it converges very slowly. In order to improve its convergence and performance, several accelerated learning algorithms have been proposed, for example Jacob's delta-bar-delta algorithm[5], a parallel kalman algorithm[6] and new accelerated learning algorithm[7]. These algorithms take the heuristic approach where some local information of the error function is utilized. However, these algorithm still have some room for improvement because they fail to sufficiently reduce the oscillation of weights.

In this paper, we proposed to a learning method which adjusts learning rate and momentem as a function of plant output error and error change in order to reduce oscillation of weights and obtain good performance. Also, we will design a neuro-controller instead of conventional lead lag controller for the Line Of Sight (LOS) stabilization system. The neuro-controller controls/stabilizes angular position and angular velocity of LOS stabilization system. Since the conventional design approach is first to develop a stabilization subsystem to minimize inertial jitter and then to design a tracking subsystem to control overall orientation[8-10]. The primary purpose of this paper is to examine and discuss design considerations and tradeoffs which arise under the proposition that neuro-controller substitute the lead lag controller of the LOS stabilization system.

Section 2 of this paper reviews typical LOS stabilization and tracking system with emphasis on how the characteristics of the stabilization and tracking sensor play into overall pointing and tracking performances. In order to accelerate learning speed and to improve convergence, we implement a new variable learning algorithm and overall neural control scheme in section 3. Simulation results in Section 4 provide comparision of the neuro-controller with learning rate modification and the conventional neural controller.

2. Line of sight stabilization and tracking system

Design and developmemt of the line of sight stabilization/tracking system seeks to configure an electro-mechanical assembly that is capable of rejecting and responding to the effects of environments, target maneuver and host vechicle maneuvers and distburances so that payload LOS is maintained on the target with sufficient accuracy and without jitter. Typically, two subsystems compromise the LOS stabilization and tracking system and each addresses specific functions and requirements.

The stabilization subsystem is an electro-mechanical assembly designed to isolate the payload from host vechicle. Passive, active and combined approaches may be used to obtain required perfomance. The performance of active systems, also commonly refered to as stabilization servo systems, is inherently tied to the performance of the inertial sensor. Currently the majority of LOS stabilization subsystems are implemented using gyroscope to sense inertial angular motions of the payload, and in some cases, also the disturbance environment. The sensor noise and frequency response characteristics of the gyroscope are important parameters which constrain and govern stabilization subsystem performance.

The tracking subsystem, on the oter hand, is a process which serves the function of controlling the stabilization subsystem so that payload is accurately pointed at the target. Its implementation typically uses analog and digtal electronic, optical, electro-optical, electro-mechanical and computer software. The relative geometry and dynamics of the target and tracking system host vechicle drive the function and performance requirement of tracking subsystem. The LOS tracking subsystem and gyroscope model are shown in more detail in Fig.1. Tracking error is defined as the angular velocity error, ω_e :

$$\omega_e = \omega_{cmd} - \omega_{los} \tag{1}$$

where ω_{cmd} is the commanded angular velocity by gunner's handle and ω_{los} is the angular velocity of LOS.

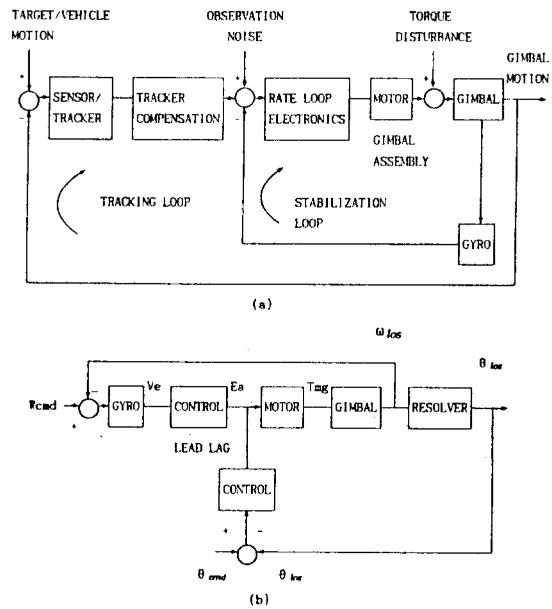

Fig.1. (a) Functional block diagrom of LOS stabilization and tracking system.
(b) Tracking subsystem of LOS.

2.1 Gyroscope

Most tracking systems use gyroscopes to help stabilize and control the LOS for tracking sensor. Typically, the gyroscope may be a significant part of the cost of the tracking system and, also require significant power which is often limited, espeoially for tactical applications. The gyro senses any rotation of the gimbal. The gyro output signal is conditioned and amplified by servo electronics and fed to the motor. A simple rate integrating gyroscope is modeled in Fig.2.

This type of gyroscope wil be mounted directly on the structure that supports the payload which is to be stabilized. Transfer function of gyroscope is given as follows

$$\frac{v_e}{\omega_{cmd} - \omega_{los}} = \frac{k_g}{s(1+\tau_g s)} \tag{2}$$

where k_g = 8 V rms/RAD, τ_g = 0.00087. The gyroscope input is velocity error between commanded angular velocity by gunner's handle and angular velocity from LOS. v_e is the voltage from gyro pick

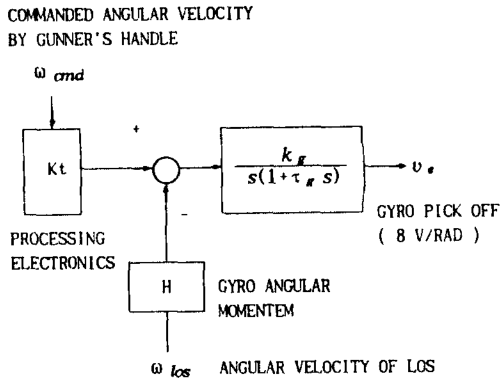

Fig.2. Block diagram of rate integrating gyro.

off, which transforms angular velocity error to rms voltage by 8 v per radian.

2.2 Motor and actuator

The types of motor/actuator include dc, ac or brushless dc, hydraulic, and many others, each of which can be directly coupled or geared to the load. Dc motors are used in most stabilized gimbals because they have an ideal mechanical form factor and because they eliminate gear train backlash, ripple, and low frequency resonances often inherent in gear trains. However, each type of actuator has its applications. The geared drive, for example, is often used for low-performance gimbals that are exposed to high torque distburances such as unbalanced payloads and aerodynamic loads. Piezoelecric actuators and voice coils are also candidates for servomechanisms, particularly for small loads. Regardless of the type of motor/actuator selected, it must provide the combined torque and rate required for all operating scenarios. The main tradeoffs and specifications that must be considered in motor/actuator are peak torque, power, slew rate, smoothness, form factor/size and mechanical coupling.

Block diagram of torque motor of LOS stabilization system is in Fig.3. This figure shows that the torque motor is driven by current signal through the current amplifier and current limit. Transfer function of the torque motor is $T_{mg}(s) = K_{vc} \cdot K_m \cdot E_a(s)$ where K_{vc} is transfer coefficient of voltage to ampere and K_m is a torque constant and T_{mg} is motor torque. The perimissible maximum input voltage of torque motor is restricted by 10 volts.

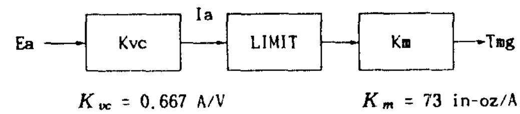

Fig.3. Block diagram of a torque motor.

2.3 Gimbal dynamics

Gimbal assembly provides the interface between the base of the system and line of sight. System performance cannot be realistically asserted without complete evaluation of the various mechanism through which base motion is coupled into line of sight angular motion. Angular velocity coupling is due to gimbal geometry, and torque coupling is due to the kinematic relationships between the gimbal assembly parameter and base motions. In a given system, the significance of many of the terms depend on the severity of the base motion environment, the modes of system operation and the implemention of gimbaling mechanism. However, we will use the linearized transfer function which is written as

$$\frac{\Omega_{los}(s)}{T_{mg}(s)} = \frac{s}{J_a s^2 + C_g s + K} \tag{3}$$

where J_a=28, C_g=8, K=0.244 and J_a is the inertial moment and C_g is the coefficient of viscous friction and K is the equivalent spring force.

3. Neural network learning method and control scheme.

The proposed neural network control architecture for LOS stabilization system is depicted in Fig.4. This architecture consist of two neural networks, which is one for identification and the other for control. In order to train neural network for identification, We define the cost function as follows.

$$E = \frac{1}{2} \sum_k (Y_k - OUT_k)^2 \tag{4}$$

where Y_k is the plant output and OUT_k is the neural network output for identification. The structure of neural networks is shown in Fig 5. State of each neuron unit is given as the weighted inputs from the previous layer and each neuron's bias. State of each neuron is transformed nonlinearly by a nonlinear sigmoid function f(x) to obtain input except one of the input layer which is transformed linearly. The input-output relationship of neuron unit is described as follows.

$$net_i = \sum_{j=1}^{n} (W_{ij}\ OUT_j)$$

$$OUT_j = f\ (net_j)$$

$$f\ (x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{5}$$

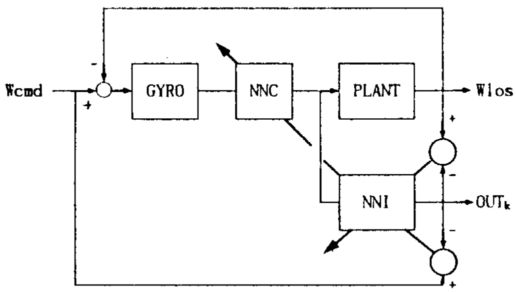

Fig.4. Architecture of neural network control system to LOS stabilization system.

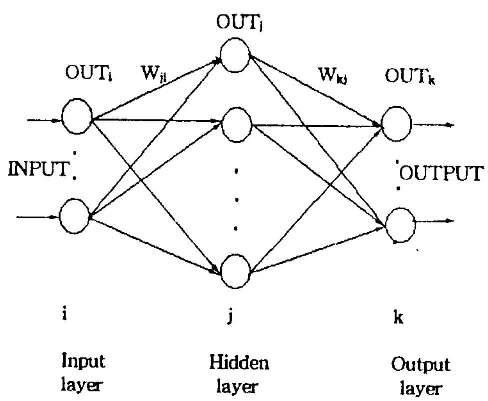

Fig.5 Multilayer neural network structure.

We use the back propagation algorithm to minimize cost function E. Let ΔW_{kj} be the increment of output weight and W_{kj} be the updated weight values. Then, the steepest descent method gives the following weight updating algorithm.

$$W_{kj}(k+1) = W_{kj}(k) + \Delta W_{kj} + \alpha(\ W_{kj}(k) - W_{kj}(k-1))$$

$$\Delta W_{kj} = -\eta \frac{\partial E}{\partial W_{kj}} = \eta\ \delta_k\ OUT_j \tag{6}$$

where η is the learning rate and α is the monentem. Similarly, the weight of hidden layer W_{ji} can be updated by the following steepest descent algorithm.

$$W_{ji}(k+1) = W_{ji}(k) + \Delta W_{ji} + \alpha(\ W_{ji}(k) - W_{ji}(k-1))$$

$$\Delta W_{ji} = -\eta \frac{\partial E}{\partial W_{ji}} = \eta\ f'(net_j) \sum_k (\delta_k W_{kj}) OUT_i \tag{7}$$

We use the activation function multiplied by a constant since output of activation function is restricted by one. In order to train neuro-controller, we define the cost function for control as follows.

$$E_c = \frac{1}{2} \sum_k (d_k - OUT_k)^2 \tag{8}$$

where d_k is a reference signal. In indirect control of nonlinear plants using neural network, the weights of the neural controller are adjusted by backpropagating the control error between desired value and plant output through the neural network for identification.

In our learning algorithm, the momentem is also used in updating of weights to further improve the converging speed. Generally, the following heuristic learning rates and monentem is used. 1) Learning rate and momentem should be kept positive less than one. 2) If error increases, then both learning rate and momentem should increase to speed up the learning. 3) If error decreases, then both learning and momentem should decrease. 4) If parameters are overadjusted and the error increases, then parameters set to a constant value. This heuristic algorithm can be written as following equations.

$$\eta = \begin{cases} \eta 1, & error(E) > e1 \\ \eta 2 + |E|, & error(E) < e1 \end{cases}$$

$$\alpha = \begin{cases} \alpha 1, & error\ \ change(\Delta E) > e2 \\ \alpha 2 + |\Delta E|, & error\ \ change(\Delta E) < e2 \end{cases} \tag{9}$$

where E is the difference between reference input and plant output and $\eta 1, \eta 2, e1, e2, \alpha 1\ \alpha 2$ are constants.

4. Simulation and results

We simulated the line of sight stabilization system to see how angular position and angular velocity behave. The gimbal and gyro dynamics transformed to discrete time system with sampling time (Δt) 0.01 second can be described as follows:

$$
\begin{aligned}
x_1(k+1) &= x_1(k)+\Delta t\ x_2(k) \\
x_2(k+1) &= \frac{-0.244\ \Delta t\ x_1(k)\ -\ 8\ sgn(x_2(k))}{28} \\
&\quad + \frac{73\ 0.667\ \Delta t\ E_a}{28} + x_2(k) \\
x_3(k+1) &= x_3(k)+\Delta t\ x_4(k) \qquad (10) \\
x_4(k+1) &= x_4(k) - \frac{\Delta t\ x_4(k)\ -\ 8\ \Delta t\ (\omega_{cmd}-\omega_{los})}{0.00087}
\end{aligned}
$$

where $x_1(k)$ is the angular position of LOS, $x_2(k)$, the angular velocity of LOS, $x_3(k)$, the gyro pick off voltage and $x_4(k)$, the voltage rate of gyro pick off.

Design specification of LOS stabilization system is that angular velocity in azimuth is greater than 10/sec and in elevation greater than 40/sec. Plant output of unit step response using lead lag controller is plotted in Fig.6. Fig.7 shows reference signal and angular velocity of LOS using neural controller. The neural controller is composed of an input layer, a hidden layer and an output layer. The number of nodes are 3-10-1. The learning rate is initially chosen to be 0.5 and momentem 0.2. The neural controller learned the contol action and adapted plant dynamics gradually after long time. From the comparison of Fig 7. and Fig 8., the neural controller with learning rate modification is superior to neural controller with constant learning rate in settling time and oscillation. Therfore, it is important to select learning rate and momentem in order to obtain satisfactory performance. The adjusting plan of learning rate and momentum is presented in Fig.9. Fig.10 shows plant output using the neural controller and the proportional controller in parallel.

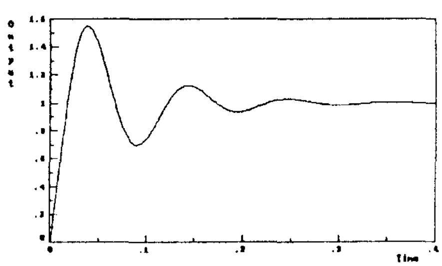

Fig.6. Angular velocity of LOS using lead lag controller.

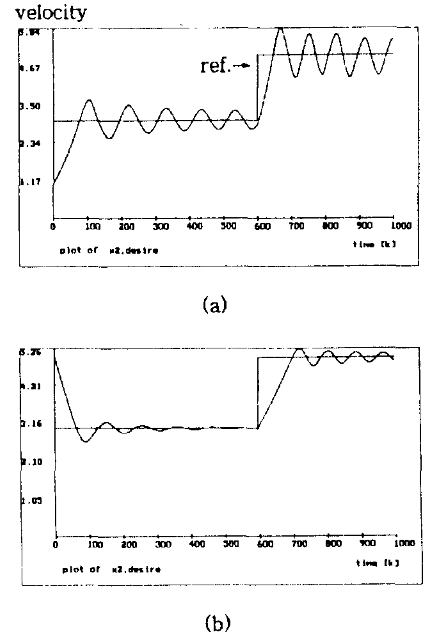

Fig.7. Angular velocity of LOS using neural controller. (a) from the begining (b) after 20 seconds.

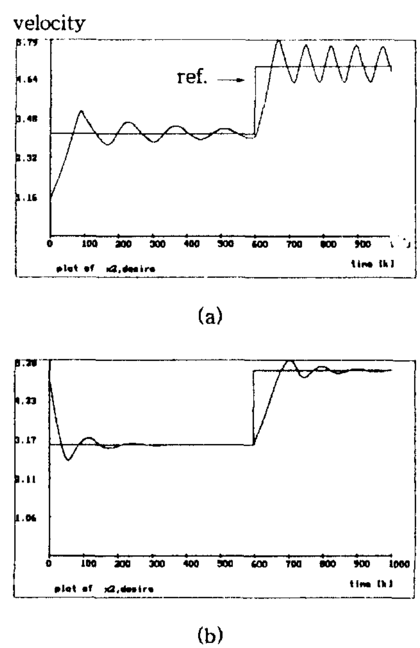

Fig.8. Angular velocity of LOS using neural controller with learning rate modification. (a) from the begining (b) after 20 seconds.

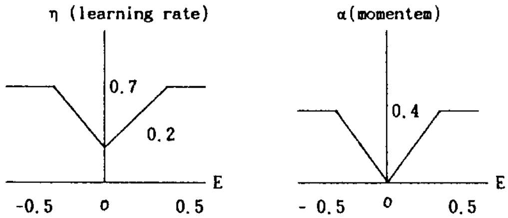

Fig.9. Plot of adjusting plan of learning rate and momentem.

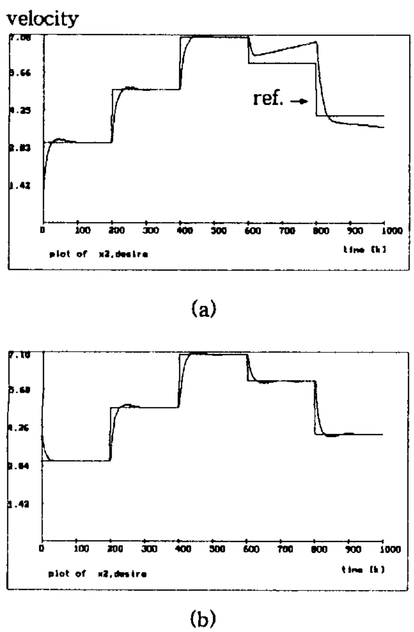

Fig.10. Angular velocity of LOS using neural controller and proportional controller.
(a) from the begining (b) after 20 seconds.

5. Conclusion

This paper describes a neural network controller implemented in the LOS stabilization system. As demonstrated in the simulation results, we know that the neuro-controller can be a substitute to the conventional lead lag controller in LOS stabilization system. we realize that it is important to select learning parameters by investigating the control peformance such as rising time, oscillation and settling time in the proposed neural control scheme.

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