

## NEURAL NETWORK BASED THREE AXIS SATELLITE ATTITUDE CONTROL USING ONLY MAGNETIC TORQUERS

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### Abstract

*Magnetic actuation utilizes the mechanic torque that is the result of interaction of the current in a coil with an external magnetic field. A main obstacle is, however, that torques can only be produced perpendicular to the magnetic field. In addition, there is uncertainty in the Earth magnetic field models due to the complicated dynamic nature of the field. Also, the magnetic hardware and the spacecraft can interact, causing both to behave in undesirable ways. This actuation principle has been a topic of research since earliest satellites were launched. Earlier magnetic control has been applied for nutation damping for gravity gradient stabilized satellites, and for velocity decrease for satellites without appendages. The three axes of a micro-satellite can be stabilized by using an electromagnetic actuator, which is rigidly mounted on the structure of the satellite. The actuator consists of three mutually orthogonal air-cored coils on the skin of the satellite. The coils are excited so that the orbital frame magnetic field and body frame magnetic field coincides i.e. to make the Euler angles to zero. This can be done using a Neural Network controller trained by PD controller data and driven by the difference between the orbital and body frame magnetic fields.*

**Keywords:** Neural control, Three axis attitude control, magnetic control, PD controller, attitude stabilization, attitude control, micro-satellites.

### Introduction

The main sub-system in Satellite development is Attitude control system. The attitude control system requirements are decided by the payload of the satellite as given in [11]. Also there exists so many disturbance torques in space which may deviate the satellite from the desired attitude. To overcome the effects of the disturbance torques some stabilization has to be provided to the satellite [10]. Satellite stabilization takes three possible forms: (1) spin stabilization, whereby the satellite is spun at 10-30 rpm; (2) gravity gradient stabilization using a large weight attached to the satellite by a length of line; (3) inertial stabilization using heavy wheels rotating at high speed - typically three wheels, one for each axis, providing three-axis stabilization.

Three-axis stabilization and control: A type of stabilization in which a spacecraft maintains a fixed attitude relative to its orbital track. This is achieved by nudging the spacecraft back and forth within a dead-band of allowed attitude error, using small thrusters or reaction wheels. In this paper this is achieved using

Magnetic-torquers by Neural Network based controller. [1] – [9] describes the same three axis control using different methods. With a three-axis stabilized spacecraft, solar panels can be kept facing the Sun and a directional antenna can be kept pointed at Earth without having to be de-spun. On the other hand, rotation maneuvers may be needed to best utilize fields and particle instruments. The problem in three axes magnetic control is shown in Fig. 1.

### Previous Works

In 1975, Schmidt described using magnetic attitude control on three-axis stabilized, momentum-biased satellites. Here, a momentum wheel was mounted along the pitch axis to provide bias, or nominal angular momentum that is not zero. Schmidt showed that this system required minimum switching of the closed loop controller, and thus was reliable for long duration missions. This work was used towards the RCA Satcom geosynchronous satellite, which was a three-axis stabilized using air core coil.

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Manuscript received on 26 Jun 2005, Paper reviewed, revised and accepted on 03 Jan 2006

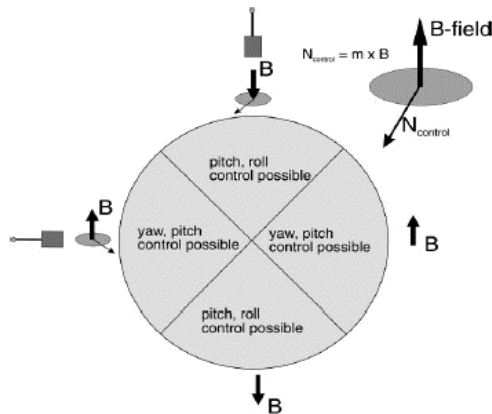


Fig. 1 Three-axis magnetic control problem

Stickler and Alfriend further examined using magnetic control with momentum bias. They developed a three-axis closed-loop attitude control system, which was fully autonomous. Analytical expressions of system response were compared with numerical solutions of the governing equations. The two solutions of equations were in agreement, suggesting a feasible three-axis control system [6].

Goel and Rajaram developed a closed-loop control law, which performed both attitude corrections and nutation damping for three-axis stabilized spacecraft with momentum bias. In this system, a magnetic torquer was placed along the roll axis of the spacecraft, and yaw control was obtained by the roll/yaw coupling from the momentum wheel. Simulation results matched with analytical results, and indicated that there was adequate damping of the system [1].

Martel, Pal, and Psiaki examined using magnetic control for gravity-gradient stabilized spacecraft in 1988. Whereas previous spacecraft used momentum wheels to augment the magnetic control, Martel, Pal, and Psiaki claimed that the proper ratio of moments of inertia, causing gravity-gradient stabilization, along with magnetic control could provide three-axis stabilization. Simulations showed that the algorithms performed well over a large range of orbital inclinations and attitude angles [3].

In 1989, Musser and Ebert were among the first to attempt to use a fully magnetic attitude control system for three-axis stability. They claim that this became possible due to the increase in computer computational power onboard spacecraft. Musser and Ebert developed linear feedback control laws, which use a linear

quadratic regulator to obtain the value of the magnetic control torque [4].

Wisniewski further developed the ideas of Musser and Ebert. He used a combination of linear and nonlinear system theory to develop control laws for three-axis stabilization of the spacecraft. Linear theory was used to obtain both time varying and constant gain controllers for a satellite with a gravity gradient boom. His analysis used the fact that the geomagnetic field varies nearly periodically at high inclination orbits. In addition, he developed a nonlinear controller for a satellite without appendages based on sliding mode control theory. He showed that three-axis control can be achieved with magnetic torquers only, and implemented this idea on the Danish Ørsted satellite [8] – [9].

Grassi developed a three-axis, fully autonomous, magnetic control system for use on a small remote sensing satellite. This control could be carried out solely with magnetometer measurements and orbital location information. Control laws were numerically tested to show that the magnetic control system works within resolution limits [2].

## Neural Network Controller

### Conventional Controller

A simple PD attitude controller is designed with the configuration ( $I_x$ ,  $I_y$  and  $I_z$  are 1.3, 1.3 and 1.4  $\text{kgm}^2$  respectively) and the controller gains are tuned manually to stabilize the satellite in three axes. Coils in the X, Y and Z-axes will produce a dipole moment vector  $\mathbf{M}$ . This vector then reacts with the local geomagnetic field  $\mathbf{B}$  to produce a torque vector [5],

$$\mathbf{T} = \mathbf{M} \times \mathbf{B} \quad (1)$$

From the above equation it is clear that the torque is limited by the direction of the  $\mathbf{B}$  vector [10]. For a polar orbit, the pitch and yaw attitude angles can be controlled over the equatorial region and pitch and roll attitude angles over the polar region.

$$\mathbf{M} = -\mathbf{K}_p (\mathbf{B}_{\text{exp}} - \mathbf{B}_{\text{mes}}) - \mathbf{K}_d (d\mathbf{B}_{\text{exp}}/dt - d\mathbf{B}_{\text{mes}}/dt) \quad (2)$$

where  $\mathbf{B}_{\text{exp}}$  is Expected Magnetic field,  $\mathbf{B}_{\text{mes}}$  is Measured Magnetic field,  $\mathbf{K}_p$  is Proportional gain,  $\mathbf{K}_d$  is Derivative gain. The main problem in PD controller is the selection of gains for different spacecraft configurations.

### Back Propagation

The algorithm used here is the Back propagation algorithm. Back propagation adjusts the weights and biases of the network so as to minimize the sum squared error of the neural network at the output layer. The value of weights and biases are changed in the direction of the steepest descent with respect to the error between the neural network output and actual output corresponding to the input until a specified error tolerance is satisfied. It is the basis for training a supervised neural network. Back propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly i.e. the negative of the gradient.

$$\mathbf{X}_{k+1} = \mathbf{X}_k - \alpha_k \mathbf{g}_k \quad (3)$$

Where

$\mathbf{X}_k$  - Vector of current weights & biases

$\mathbf{g}_k$  - Current gradient

$\alpha_k$  - Learning rate

Output layer:

$$\begin{aligned} \mathbf{Y}_p &= \mathbf{f}(\mathbf{Y}_p), & \mathbf{p} &= 1, 2, \dots, n_y \\ &= \sum \gamma_{pi} \mathbf{V}_i & \mathbf{i} &= 1, 2, \dots, n_2 \end{aligned} \quad (4)$$

Hidden layer:

$$\begin{aligned} \mathbf{V}_p &= \mathbf{f}(\mathbf{V}_i), \\ &= \sum \alpha_{ij} \mathbf{Z}_j & \mathbf{j} &= 1, 2, \dots, n_1 \end{aligned} \quad (5)$$

Output layer:

$$\begin{aligned} \mathbf{Z}_p &= \mathbf{f}(\mathbf{Z}_j), \\ &= \sum \beta_{il} \mathbf{U}_l & \mathbf{l} &= 1, 2, \dots, n_u \end{aligned} \quad (6)$$

where  $n_y$  is the number of outputs,  $n_u$  is the number of inputs,  $n_1$  is the number of neurons in the output layer,  $n_2$  is the number of neurons in the hidden layer and  $\gamma_{pi}$ ,  $\alpha_{ij}$ ,  $\beta_{il}$  are interconnected weights. The activation function used is tangent sigmoid activation function for hidden and output layer and linear activation function for input layer.

### Neural Network Training

There are generally four steps in the training process:

1. Assemble the training data
2. Create the network object
3. Train the network
4. Simulate the network response to new inputs.

Training of feed forward network is considered as an unconstrained optimization problem in which the network weights are updated to reduce the cost function over the interval  $[1 \dots L]$ . Here the training data is generated from the PD controller simulated for various spacecraft configurations. The neural network used here is developed with the following specifications.

#### Neural Network Architecture:

Number of Inputs	: 3
Number of Layers	: 3
Bias Connect	: [1; 1; 1]
Input Connect	: [1; 1; 1]
Layer Connect	: [0 0 0; 1 0 0; 0 1 0]
Output Connect	: [1 1 1]
Target Connect	: [1 1 1]
Number of Outputs	: 3 (read-only)
Number of Targets	: 3 (read-only)
Number of Input Delays	: 0 (read-only)
Number of Layer Delays	: 0 (read-only)

#### Network Functions:

Adapt Function	: 'trains'
	Sequential order incremental training
Initialization Function	: 'initlay'
	Layer-by-layer network Initialization
Performance Function	: 'mse'
	Mean squared error performance
Training Function	: 'trainlm'
	Levenberg-Marquardt Backpropagation

#### Training parameters:

Data length	: 5000
Epochs	: 10000

### Neural Network Based Attitude Controller

Although a conventional PD controller has been widely applied because of its various advantages, it is dependent seriously upon the system parameter perturbations or the external disturbances [7]. Therefore, the frequent trivial manipulations for PD gains are required. These problems were not solved even if the complicate gain scheduling algorithms were adopted. Therefore, it is necessary to adjust the gain on-line. However, if the parameter perturbations or different

initial conditions were given, the rapid readjustment approach of the controller's gains is absolute. Furthermore, it is difficult to design the non-linear controller, which can be matched at various operating points. However, these problems can be solved by the neural network controller with learning ability and nonlinear adaptability. Its main defects are the tedious learning procedures and are to make on-line tuning impossible in fast response systems. Therefore, in this paper, the neural network based controller with simple structure to make a learning time reduce shall be proposed. A spacecraft mathematical model under several assumptions is developed and tries to control to a desired position using the magnetic torque obtained from torquers. Furthermore, this proposed controller should be effective even for a strong nonlinear and mutual coupling dynamic system such as a real spacecraft. There are many unknowns that are not accounted for when designing conventional control algorithms such as non-rigidity, accurate atmospheric effects, and changes in the system like a malfunctioning torque coil. The Neural network controller used here is trained by the method of back propagation from the data obtained from various constant gain PD controller simulated with different initial conditions and different spacecraft inertia tensor. The neural controller outputs the value of current necessary to be given to the torquers to produce the required torque.

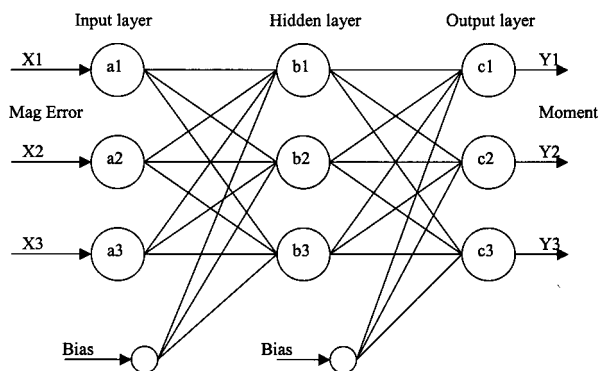


Fig. 2 Neural network structure

The neural network used for attitude control has the structure as shown in Fig. 2. In Fig. 2  $X_1$ ,  $X_2$ ,  $X_3$  are the inputs to the neural controller which is the error between the desired magnetic field and the actual magnetic field measured in X, Y and Z axes of the spacecraft respectively.  $Y_1$ ,  $Y_2$ ,  $Y_3$  are the outputs from the neural controller which is the moment to be generated by the torquers in X, Y and Z-axes respectively. The weights of the neurons in the first layer or input layer are  $a_1$ ,  $a_2$  and  $a_3$ , in the second layer

or hidden layer are  $b_1$ ,  $b_2$  and  $b_3$ , in the third layer or output layer are  $c_1$ ,  $c_2$  and  $c_3$  respectively for the three neurons in the layers. This moment generated by the torquers interact with the earth's magnetic field and produces the desired torque in all the three axes.

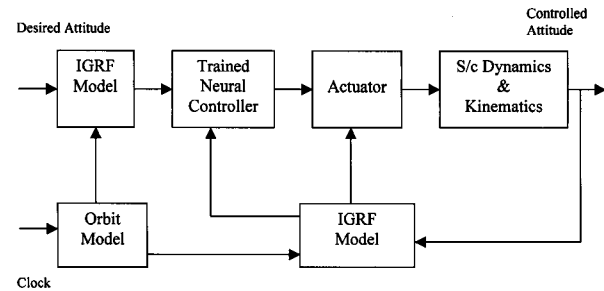


Fig. 3 Block diagram of neural attitude controller

### Execution of the Model

The general block diagram of Neural Network based magnetic attitude controller is as shown in Fig. 3. The Magnetic field model used here is the International Geomagnetic Reference Field (IGRF), which is used for finding both the desired magnetic field and the actual magnetic field. The orbit model is used to give the position of the spacecraft at the particular clock time. From this position the orbital frame magnetic field is measured and this is used as a reference for the controller. The IGRF model in the feedback loop gives the actual magnetic field in spacecraft body coordinates. The aim of the control system is to make the body frame magnetic field to coincide with the orbital frame magnetic field. Since the orbital frame magnetic field also varies with time, the orbital frame at a particular time has to be feed to the controller for reference. This difference in magnetic field is given to the trained neural controller, which will find the moment required to nullify the difference in magnetic field. The required moment generated by the torquer interacts with the earth's magnetic field and produces the torque in all the three axes. This torque is fed to the dynamics and kinematics model to find the change in the spacecraft parameters and the whole process gets repeated until the body frame magnetic field coincides with the orbital frame magnetic field i.e. the Euler angles become zero. The main blocks involved in the model are listed below.

1. Orbit model
2. Spacecraft Dynamics model
3. Earth's magnetic field model
4. Actuator model
5. Controller

The inputs to and the outputs from the blocks are shown here for better understanding of the model.

Orbit model

Input : Orbital parameters and time  
 Output : Position of spacecraft in orbit at the given time

Spacecraft dynamics model

Input : Torque  
 Output : Rates

Spacecraft kinematics model

Input : Rates  
 Output : Euler angles

Earth's magnetic field model

Input : Position of satellite in orbit and Euler angles  
 Output : Magnetic field in X, Y and Z axes

Actuator model

Input : Current to be applied to torquer, Earth's field  
 Output : Torque generated

Controller

Input : Orbital frame and spacecraft body frame magnetic fields  
 Outputs : Current to be given to torquer

**Simulation Procedure**

The steps involved in neural network based three-axis satellite attitude control system are shown below

1. Interconnect the models as shown in Fig. 3.
2. Set the spacecraft configuration in the spacecraft dynamics model and initialize the value of Euler angles.
3. Simulate the attitude control system with PD controller designed using the procedure given above.
4. Repeat Step 2 and 3 with different spacecraft configurations.
5. Tabulate the data collected from above simulations.
6. Create a feed forward neural network with the architecture given in previous section.
7. Train the network with the data collected until the requirements are satisfied.
8. Introduce the neural controller in the model simulated, replacing the PD controller,

9. Now simulate the attitude control system for any spacecraft configuration and different initial Euler angles.
10. Check the results, the Euler angles settle down to zero at 3 to 4 orbits.

By following the above procedure one can able to design a neural network based three-axis satellite attitude control system for a satellite equipped with only magnetic torquers as the sole actuators.

**Simulation Results**

**Results**

The Neural controller is simulated with different spacecraft configurations and tested for various initial conditions. This spacecraft configuration is referred to as gravity-gradient stabilized satellite.

Satellite Configuration:

$I_x = 100 \text{ kg.m}^2$   
 $I_y = 100 \text{ kg.m}^2$   
 $I_z = 10 \text{ kg.m}^2$

Initial conditions:

Euler Angles [Phi Theta Psi] = [85 85 85] Degrees

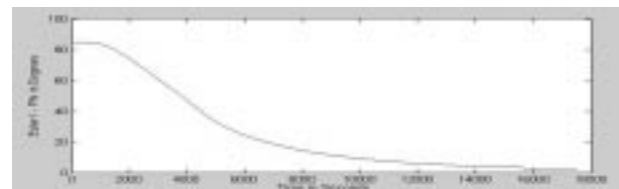


Fig. 4 Sat I – Time versus Euler I

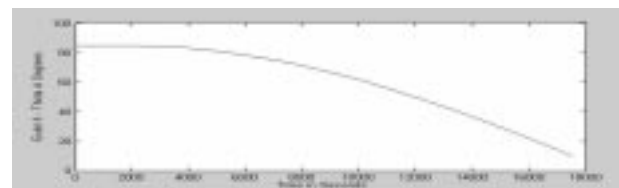


Fig. 5 Sat I – Time versus Euler II

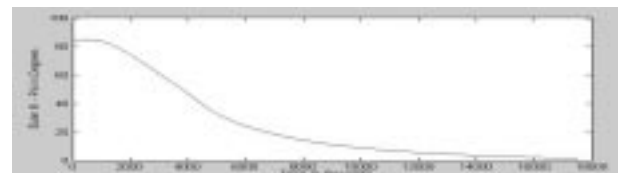


Fig. 6 Sat I – Time versus Euler III

From the results shown above as Figs. 4 – 6, it is observed that Euler angles stabilize to zero around 18,000 seconds. This shows that the neural controller is able to stabilize the attitude of a gravity-gradient stabilized satellite for all range of initial Euler angles. Here a sample output is shown from the set of simulations with different Euler angles. The outputs from the neural controller are shown below as Figs. 7 – 9, which are the current to be given to the torquers, placed along X, Y and Z axes of the spacecraft respectively. From the time versus torquer current plots it is observed that the X and Z torquer currents decreases to zero as the attitude settles to zero indicating that they contribute more for stabilization and the torquer current Y is varying between the limits +60 and -60  $\mu\text{A}$  to maintain the attitude by applying a torque which balances the external disturbances in that axis.

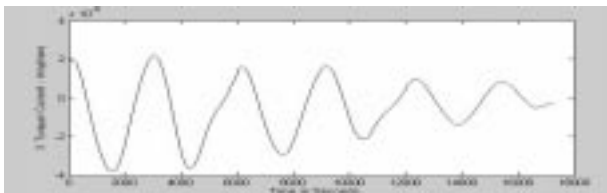


Fig.7 Sat I - Time versus X Torquer current

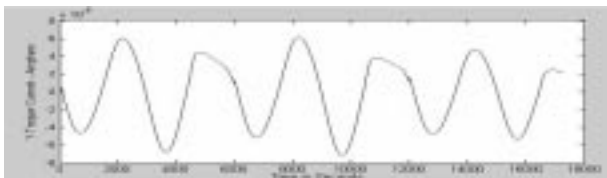


Fig.8 Sat I - Time versus Y Torquer current

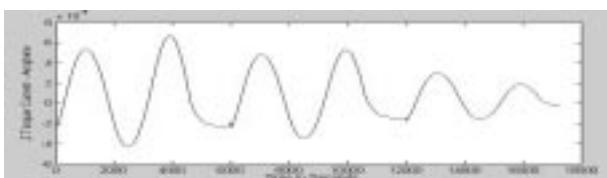


Fig.9 Sat I - Time versus Z Torquer current

## Conclusion

### Summary

Magnetic control laws are developed to bring a spacecraft to the desired equilibrium. This is accomplished by using a well-trained Neural Network controller. Simulations are performed with different spacecraft configurations and initial conditions. From the results obtained it is observed that the controller is good for all spacecraft configurations.

### Future Work

Further research on magnetic control would be beneficial in training the neural network controller with the real time data, so that the controller can adapt any uncertainties in the space during its mission.

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### **TEJAS COMPLETES 500 TEST FLIGHTS**

The Tejas Light Combat (LCA) was developed by ADA/HAL for the Indian Air Force and Navy. The first Technology Demonstrator flew on 04 Jan 01 and four ac completed 500 sorties as on 09 Mar 06. The first 200 sorties were flown to demonstrate the four core technologies that were developed viz. composite structure, digital quadruplex fly-by-wire flight control system, microprocessor controlled utility systems management and glass cockpit. This phase was called the Full Scale Engineering Development (FSED) Phase-1. Subsequent tests encompassed system performance and reliability, envelope expansion and ac performance leading to Initial Operational Clearance (IOC) for induction into services.

During the development phase, tests were carried out across several facilities such as the Iron Bird, Real-Time Simulator, in-flight simulation on the T-33, Learjet, F-16 ac, extensive system rigs and cockpit evaluation facilities. Flight tests were made in a phased manner with regard to envelopes defined by the FCS Control Law. Initially, ac handling qualities were cleared in a ‘first flight ‘ fixed gain envelope and then expanded to scheduled gains and increasing nz, CAS, altitude and M No limits. The envelope tested was 15 km, 1.4 m, 1113 km/h CAS, 4.5 ‘g’ and 20° AoA. The test points covered envelope expansion, handling qualities, air data calibration, loads, flutter, parametric identification, performance and systems assessment, within the envelope covered.

The systems tested include limited tests carried out of state-of-the-art. open architecture based avionics of the prototype vehicle (PV-2). Eleven test pilots (10 from the IAF and 1 from IN) were introduced into the flight test programme, who expressed that the ac was very pleasant to fly throughout the flight envelope with flying and handling qualities in most tasks meeting Level-1 criteria.

The flight control system will be further upgraded by bringing in Control Law (CLAW) versions, which will provide larger flight envelopes, envelope limiting features as well as autopilot modes. Future control law versions will also have provisions for stores configuration corresponding to the standard of preparation of the aircraft for induction into the service.

The major tasks to be covered towards IOC are sensor and weapon system integration and envelope expansions. The current phase of flight test is progressing smoothly towards meeting these objectives set out for initial operational clearance of the aircraft.