NEURAL PREDICTIVE SATELLITE ATTITUDE CONTROL BASED ON KALMAN FILTERING ALGORITHMS

Jaime Augusto DA SILVA[1]
Atair RIOS NETO[2]

[1]*Instituto Nacional de Pesquisas Espaciais – INPE*
[2]*Universidade do Vale do Paraíba – UNIVAP / IP&D*
São José dos Campos, SP, Brazil

ABSTRACT *– An artificial neural network predictive control scheme is considered for satellite attitude control. Kalman filtering algorithms are used not only to train the associated feedforward neural network modeling the dynamics of the plant but to also estimate the control actions. It is shown that the optimization of a predictive quadratic performance functional, used to determine the discrete control actions, can be viewed and treated, in a typical iteration, as a stochastic optimal linear parameter estimation problem. The algorithms obtained are shown to be the result of application of Newton's method to appropriate control optimization functionals that provide solutions that converge to smooth and reference tracking controls. The proposed scheme is then applied to a three-axes satellite attitude control with a double-gimbaled momentum wheel. Results of simulations and tests for the situation of fine pointing torques and errors in the initial satellite attitude show excellent performance of the proposed scheme.*

1 - INTRODUCTION

Although practical processes involve nonlinear behavior, most predictive control algorithms are based on a linear model of the process. As a result, they do not give satisfactory control performance when the controlled process is highly nonlinear. Recently, it has been proved that multilayer feedforward neural networks can model and approximate nonlinear functions arbitrarily well (Cybenko, 1989, Hornik, Stinchcombe and White, 1989, Funahashi, 1989). Based on this fact, a large number of identification and control structures that use neural networks have been proposed (Narendra and Parthasarathy, 1990, Sanner and Slotine, 1992, Chen and Billings, 1992, Soloway and Harley, 1997, Liu, Kadirkamanathan and Billings, 1998). For neural network training, many authors have explored recursive least squares (Chen and Billings, 1992) and Kalman filtering theory (Singhal and Wu, 1989, Watanabe, Fukuda and Tzafestas, 1991, Iiguni, Sakai and Tokumaru, 1992, Chen and Ögmen, 1994, Lange, 1995, Rios Neto, 1997) to develop both off line and on line neural network supervised training algorithms. It has been observed that, generally, these algorithms furnish better performance than the usual backpropagation algorithm (e.g., Silva and Rios Neto, 1999).

When a predictive control scheme is considered, besides training the neural network that will model the plant dynamics, one needs to solve an optimization problem to get the control actions (Su and McAvoy, 1993, Mills, Zomaya and Tadé, 1994, Liu, Kadirkamanathan and Billings, 1998, Soloway and Harley, 1997, Zhu, Qin and Chai, 1999). In this case, control performance indexes are generally minimized using nonlinear programming techniques.

A different approach is used here in the sense that, stochastic optimal parameter estimation theory is used to design a neural predictive control Kalman filtering algorithm. As a result, the problems of neural network training and predictive control are viewed and treated in an integrated way as stochastic optimal linear parameter estimation problems.
In the second part of this paper, the feasibility of the proposed algorithm in the design of a geostationary satellite attitude control system is tested. Control and stabilization of a double-gimbaled momentum wheel three-axes stabilized geostationary satellite example configuration (Kaplan, 1976, Barret, 1992) is investigated. Attitude control torques for this application can be produced by momentum wheel exchange. The double-gimbaled momentum wheel offers control torques about all three-vehicle axes through wheel speed control and gyrotorquing.
To illustrate design considerations, attitude simulations of a double-gimbaled momentum wheel satellite with initial off nominal disturbances and solar pressure torques are presented. Results show excellent performance of the proposed scheme with satellite attitude being kept well inside limits of orientation of expected spacecraft attitude for one-day attitude simulation.

2 - CONTROL PROBLEM AND NEURAL NETWORK PREDICTORS

The problem at hand is that of controlling a dynamic system represented by

$$\dot{x} = f(x,u) \tag{2.1}$$

for which discrete time nonlinear input-output models can be taken to predict approximate responses

$$y(t_j) = f\left(y(t_{j-1}),\ \ldots,\ y(t_{j-n_y});\ u(t_{j-1}),\ \ldots,\ u(t_{j-n_u})\right) \tag{2.2}$$

where $t_j = t + j\Delta t$.
The adopted neural predictive control scheme uses a feedforward neural network which can uniformly and with the desired accuracy learn a mapping as that of Eq. (2.2) (Chen and Billings, 1992) to model the dynamic system of Eq. (2.1). The fundamental idea in predictive control is to predict the vector of future tracking errors and minimize its norm over a given number of future control moves. To accomplish this, the internal model neural network will provide the response model that will be used to determine a smooth and reference trajectory tracking control actions. These actions are obtained by minimizing a predictive quadratic index of performance of the type usually adopted in predictive control schemes

$$J = \frac{1}{2}\left\{\sum_{j=1}^{n}\left(y_r(t_j)-\hat{y}(t_j)\right)^T R_y^{-1}(t_j)\left(y_r(t_j)-\hat{y}(t_j)\right) + \sum_{j=0}^{n-1}\left(u(t_j)-u(t_{j-1})\right)^T R_u^{-1}(t_j)\left(u(t_j)-u(t_{j-1})\right)\right\} \tag{2.3}$$

where as before $t_j = t + j\Delta t$; $y_r(t_j)$ is the reference response, n defines the horizon over which the tracking errors and control increments are considered; $R_y(t_j)$ and $R_u(t_j)$ are positive definite weight matrices, and $\hat{y}(t_j)$ is the output of the feedforward neural network, trained to approximately model the dynamic system of Eq. (2.1) and which can be formally represented as

$$\hat{y}(t_j) = \hat{f}\left(\hat{y}(t_{j-1}),\ \cdots,\ \hat{y}(t_{j-n_y});\ u(t_{j-1}),\ \cdots,\ u(t_{j-n_u});\ \hat{w}\right) \tag{2.4}$$

Here $\hat{w}$ represents the neural network parameter vector, adjusted or estimated along training. Thus, in summary, for the solution of the resulting neural predictive control problem it is needed:

(i) to choose a feedforward neural network with appropriate architecture and size. Then, in a process usually involving both off line and on line supervised training, learn from dynamic system input-output data sets, how to represent the mapping of the considered nonlinear discrete model (Eq. 2.2);

(ii) to solve with respect to the control actions, on line and in a small fraction of Δt, the nonlinear programming problem of minimizing an objective function as that in Eq. (2.3) subjected to the constraint of Eq. (2.4).

3 - KALMAN FILTERING INTEGRATED SOLUTION

The problem of supervised training of the feedforward neural network used in the predictive control scheme can be treated using Kalman filtering algorithms. Versions of these algorithms, with different levels of approximation, can be found in the literature. These versions may vary from full non parallel algorithms, mostly suitable for off line use, to simplified parallel processing algorithms (Rios Neto, 1997) for on line use. Here, a method is proposed where the problem of determining the predictive control actions is also treated as one of stochastic optimal linear parameter estimation. This allows the derivation and use, in a given iteration, of the same Kalman filtering type of algorithms as in the neural network training.

The method starts by assuming that the problem of control determination can be viewed, in a more general stochastic framework, as a stochastic parameter estimation problem such as

$$y_r(t_j) = \hat{f}\left(\hat{y}(t_{j-1}), \cdots, \hat{y}(t_{j-n_y}), u(t_{j-1}), \cdots, u(t_{j-n_u}), \hat{w}\right) + n_y(t_j) \tag{3.5}$$

$$0 = u(t_{j-1}) - u(t_{j-2}) + n_u(t_{j-1}) \tag{3.6}$$

$$E[n_y(t_j)] = 0; \qquad E[n_y(t_j) n_y^T(t_j)] = R_y(t_j); \tag{3.7}$$

$$E[n_u(t_j)] = 0; \qquad E[n_u(t_j) n_u^T(t_j)] = R_u(t_j); \tag{3.8}$$

where $j = 1,2,..,n$. The errors $v_y(t_j)$ and $v_u(t_j)$ are considered to be constituted of uncorrelated components as well as, uncorrelated for different values of t_j. A first consequence of this more general stochastic framework is that the weight matrices in the objective function, Eq. (2.3), have now the meaning of covariance matrices. This certainly facilitates their definition.

In order to iteratively solve the problem of Eqs. (3.5) and (3.6) as one of linear parameter estimation, one takes in a given ith iteration the linearized approximation of Eq. (3.5)

$$\alpha(i)\left[y_r(t_j) - \bar{y}(t_j,i)\right] = \sum_{k=k_0}^{j-1} \left[\frac{\partial \hat{y}(t_j)}{\partial u(t_k)}\right]_{\{\bar{u}(t_k,i)\}} \left[u(t_k,i) - \bar{u}(t_k,i)\right] + n_y(t_j) \tag{3.9}$$

where $k_0 = \max[0, (j - n_y - n_u)]$. The parameter α, $0 < \alpha(i) \le 1$, is to be adjusted to guarantee the linear perturbation approximation hypothesis. The partial derivatives indicated above, are to be calculated recursively using the backpropagation rule and the trained feedforward neural network (Chandran, 1994, Soloway and Haley, 1997). This observation type of condition is then processed, taking as a priori information, based on Eqs. (3.6) and (3.9), the following equation (Rios Neto and Da Silva, 2000)

$$\alpha(i)\left[\hat{u}(t_{-1}) - \bar{u}(t_l,i)\right] = \left[u(t_l,i) - \bar{u}(t_l,i)\right] + \sum_{k=0}^{l} n_u(t_k) \quad (3.10)$$

where $l = 0, 1, \ldots, n-1$ and $i=1, 2, \ldots, I$. The control variable $\hat{u}(t_{-1})$ is the estimated solution from last control step and for a new iteration it is assumed that: $\alpha(i) \leftarrow \alpha(i+1)$ and $\bar{u}(t_l, i+1) = \hat{u}(t_l, i)$. For i=1 estimates or extrapolations of the control variables are used.
For $j=1,2, \ldots, n$ and $l=0,1, \ldots, n-1$, the problem represented by Eqs. (3.9) and (3.10) is one of stochastic linear parameter estimation. In a more compact notation,

$$U(t,i) = \left[u^T(t_0,i) : u^T(t_1,i) : \cdots : u^T(t_{n-1},i)\right]^T; \qquad \hat{U}_l(t_{-1}) = \hat{u}(t_{-1})$$

$$\alpha(i)\left[\hat{U}(t_{-1}) - \bar{U}(t,i)\right] = U(t,i) - \bar{U}(t,i) + V_u(t) \quad (3.11)$$

$$\alpha(i)\bar{Z}^u(t,i) = H^u(t,i)\left[U(t,i) - \bar{U}(t,i)\right] + V_y(t) \quad (3.12)$$

The meanings of the compact notation variables becomes obvious if Eqs. (3.11) and (3.12) are identified with Eqs. (3.10) and (3.9), respectively. Using a Kalman filtering estimator, results

$$\hat{U}(t,i) = \bar{U}(t,i) + \alpha(i)\left[\hat{U}(t_{-1}) - \bar{U}(t,i)\right] + K(t,i)\alpha(i)\left\{\bar{Z}^u(t,i) - H^u(t,i)\left[\hat{U}(t_{-1}) - \bar{U}(t,i)\right]\right\} \quad (3.13)$$

$$K(t,i) = R_u(t)H^{u^T}(t,i)\left[H^u(t,i)R_u(t)H^{u^T}(t,i) + R_y(t)\right]^{-1} \quad (3.14)$$

$$\hat{R}_u(t,I) = \left[I_u - K(t,I)H^u(t,I)\right] R_u(t) \quad (3.15)$$

$$\bar{U}(t,\ i+1) = \hat{U}(t,i); \quad \hat{U}(t) = \hat{U}(t,I); \quad \alpha(i) \leftarrow \alpha(i+1) \quad (3.16)$$

The matrices $R_u(t)$, $R_y(t)$ and $\hat{R}_u(t,I)$ are error covariance matrices of $V_u(t)$, $V_y(t)$ and $(\hat{U}(t,I) - U(t))$, respectively and I_u is an identity matrix. A way of showing that convergence is guaranteed is by considering the algorithm in the equivalent form (Eq. (3.13))

$$\hat{U}(t,i) = \bar{U}(t,i) + \left[R_u^{-1}(t) + H^{u^T}(t,i)R_y^{-1}(t)H^u(t,i)\right]^{-1} \cdot \alpha(i)\left\{R_u^{-1}(t)\left[\hat{U}(t_{-1}) - \bar{U}(t,i)\right] + H^{u^T}(t,i)R_y^{-1}(t)\bar{Z}^u(t,i)\right\} \quad (3.13a)$$

and noticing that this is the result of applying Newton's Method to the functional (Luenberger, 1984)

$$J_P = \frac{1}{2}\left\{Z^{u^T}(t)R_y^{-1}(t)Z^u(t) + \left[U(t) - \hat{U}(t_{-1})\right]^T R_u^{-1}(t)\left[U(t) - \hat{U}(t_{-1})\right]\right\} \quad (3.17)$$

In a way completely analogous to that adopted for the problem of neural network training (Rios Neto, 1997), one can obtain approximated versions of Eqs. (3.11) and (3.12) which can be paralleled processed for each value of $l=0,1, \ldots, n-1$. To get this simplified version one can approximate the values of $U_k(t,i), k \neq l$, in Eq. (3.12) by $\bar{U}_k(t,i)$. These approximations lead to a problem, which can be locally processed, and which also converges to a smooth control that tracks the reference trajectory.

4 - SATELLITE ATTITUDE CONTROL

As an example of application a control scheme of a three-axes stabilized, actively attitude controlled, geostationary satellite is investigated. At synchronous altitude gravity gradient and magnetic moment methods do not produce sufficient torques to permit satisfactory correction of orbit attitude errors and solar pressure perturbation effects. Significant perturbing torques result from solar pressure torques, which are sinusoidal in nature with period equal to that of the orbit. Mass expulsion, momentum exchange or other practical technique must generate orbit control forces. Specific torque producers and thrusters are several in type and have been the subject of study in the past decades. In particular, techniques using double-gimbaled momentum wheel have been investigated for satellite attitude maintenance (Kaplan, 1976, Barret, 1992).
The double-gimbaled momentum wheel system is of particular interest because of its unique combination of advantages over other momentum devices. It offers control torques about all three-vehicle axes through wheel speed control and gyrotorquing. This system can be used both for satellite maneuvering and attitude stabilization. They maintain attitude by momentum exchange between the satellite and the wheel. As a disturbance torque acts on the satellite along one axis, the wheel reacts, absorbing the torque and maintaining the attitude. The wheel spin rate increases or decreases to maintain a constant attitude. Momentum wheel control systems are particularly suited for attitude control in the presence of cyclic or random torques. An example control system using the double-gimbaled momentum wheel is presented to illustrate design and feasibility of the proposed Kalman filtering predictive control algorithm.

4.1 - Equations of Motion

The vehicle considered was selected based on specifications suggested by Kaplan, 1972, and Barret, 1992. The satellite is assumed to have 716 kg of mass and moments of inertia equal to Ix=Iz=2000 kg.m^2 and Iz=400 kg.m^2. Attitude accuracy requirements indicate that pitch and roll angles should not exceed 0.05^0 and yaw angle values should be less than 0.40^0. Then, consider a satellite initially placed and deployed in geostationary orbit. The control system initiates operation with nominal wheel momentum, H_o, zero gimbal deflections and small attitude errors. A rigid body model with internal momentum is used for this preliminary analysis. Consider a body reference frame, x, y, z, which is actually rotating with respect to an inertial frame at the rate of the orbit, w_0. The z or yaw axis points towards earth center and the x or roll axis is in the orbital plane with the same direction of the velocity vector. The y or pitch axis completes the orthogonal system of reference. Euler's equations for the rigid satellite and wheel are given by

$$T + G = \frac{dh}{dt} = \left[\frac{dh}{dt}\right]_b + \omega \times h \qquad (4.1)$$

where T is the disturbance torque due to solar pressure and thrust misalignment, G is the gravity gradient torque and h is the total angular momentum, including wheel. Thus, considering that h_v is the vehicle angular momentum and h_w is the wheel angular momentum results that

$$h = h_v + h_w \tag{4.2}$$

Expressed in terms of components along the principal axes,

$$h_v = I_x\omega_x i + I_y\omega_y j + I_z\omega_z k \tag{4.3}$$

where the unit vector i, j, and k correspond to body x, y, z, principal axes, respectively. Also, the momentum wheel components are

$$h_{\omega x} = \cos\delta\sin\gamma h_\omega \qquad h_{\omega y} = -\cos\delta\cos\gamma h_w \qquad h_{\omega z} = -\sin\delta h_w \tag{4.4}$$

where δ, γ are the roll and yaw gimbal angles, respectively. Combining these expressions leads to the following set of nonlinear ordinary differential equations

$$\dot{\omega}_x = \frac{1}{I_x}\Big[T_x + G_x + \dot{\delta}\sin\delta\sin\gamma h_w - \dot{\gamma}\cos\delta\cos\gamma h_w - \cos\delta\sin\gamma\dot{h}_\omega - \omega_y\left(I_z\omega_z - \sin\delta h_\omega\right) + \omega_z\left(I_y\omega_y - \cos\delta\cos\gamma h_\omega\right)\Big] \tag{4.5}$$

$$\dot{\omega}_y = \frac{1}{I_y}\Big[T_y + G_y - \dot{\delta}\sin\delta\cos\gamma h_\omega - \dot{\gamma}\cos\delta\sin\gamma h_\omega + \cos\delta\cos\gamma\dot{h}_\omega - \omega_z\left(I_x\omega_x + \cos\delta\sin\gamma h_\omega\right) + \omega_x\left(I_z\omega_z - \sin\delta h_\omega\right)\Big] \tag{4.6}$$

$$\dot{\omega}_z = \frac{1}{I_z}\Big[T_z + G_z + \dot{\delta}\cos\delta h_\omega + \sin\delta\dot{h}_\omega - \omega_x\left(I_y\omega_y - \cos\delta\cos\gamma h_\omega\right) + \omega_y\left(I_x\omega_x + \cos\delta\sin\gamma h_\omega\right)\Big] \tag{4.7}$$

The attitude rates and body rates are related by

$$\omega = \omega_0 + \omega_{\psi\theta\phi} \tag{4.8}$$

where ω_0, ω and $\omega_{\psi\theta\phi}$ are the orbital, absolute and relative angular velocities, respectively. In the sequel, (ψ, θ, ϕ) are the yaw, pitch and roll Euler angles of the body with respect to a local vertical reference system. Then, in terms of their components Eq. (4.8) becomes

$$\begin{bmatrix}\dot{\phi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix} = \frac{1}{\cos\theta}\begin{bmatrix}\cos\theta & \sin\phi\sin\theta & \sin\theta\cos\phi\\ 0 & \cos\phi\cos\theta & -\sin\phi\cos\theta\\ 0 & \sin\phi & \cos\phi\end{bmatrix}\begin{bmatrix}\omega_x + \omega_0\sin\psi\cos\theta\\ \omega_y + \omega_0(\cos\psi\cos\phi + \sin\psi\sin\theta\sin\phi)\\ \omega_z + \omega_0(\sin\psi\sin\theta\cos\phi - \cos\psi\sin\phi)\end{bmatrix} \tag{4.9}$$

The gravity gradient torque components are approximated by

$$G_x = \frac{3}{2}\omega_0^2\sin 2\phi\cos^2\theta\left(I_z - I_y\right) \tag{4.10}$$

$$G_y = \frac{3}{2}\omega_0^2 \cos\phi \sin 2\theta (I_z - I_x) \quad (4.11)$$

$$G_z = \frac{3}{2}\omega_0^2 \sin\phi \sin 2\theta (I_x - I_y) \quad (4.12)$$

and the solar pressure torque components for t=0 at 6 A.M. or 6 P.M. orbital position are approximated by

$$T_x = 2.0\times10^{-5}(1 - 2\sin\omega_0 t) \quad T_y = 1.0\times10^{-4}\cos\omega_0 t \quad T_z = -5.0\times10^{-5}\cos\omega_0 t \quad (4.13)$$

4.2 - Simulation and Results

The plant, represented by the set of nine ordinary differential equations, that describes the satellite attitude motion, was initially identified with a feedforward neural network. The net was chosen with 12 neurons at the input layer, 20 at the hidden layer and 9 at the output layer, all layers having a bias of +1. Patterns used for training were created by numerical integration of the set of differential equations during a 1.0-second interval. This interval also defines the frequency of control actualization. Initial conditions were randomly chosen between the limits: angles ϕ, θ and ψ, ± 0.0573 deg, angle rates, $\dot{\phi}$, $\dot{\theta}$ and $\dot{\psi}$, ± 0.0573 deg/s, gimbal angles, δ and γ, ± 2.2918 deg, gimbal angle rates, $\dot{\delta}$ and $\dot{\gamma}$, ± 0.0286 deg/s, angular momentum, h_w, 200 ± 2 kg.m^2/s, angular momentum rate, $\dot{h}_\omega$, ± 0.10 kg.m^2/s^2.

The gimbal angle rates $\dot{\delta}$ and $\dot{\gamma}$ and the momentum rate $\dot{h}_\omega$ were chosen as control variables. A set of 1500 patterns were created by choosing a set of initial conditions given by $\{\dot{\phi}, \dot{\theta}, \dot{\psi}, \phi, \theta, \psi, \delta, \gamma, h_\omega, \dot{\delta}, \dot{\gamma}, \dot{h}_\omega\}$, numerical integration over the 1.0-second interval and by getting the state variables at the end of the interval $\{\dot{\phi}, \dot{\theta}, \dot{\psi}, \phi, \theta, \psi, \delta, \gamma, h_\omega\}$. With a set of conveniently chosen dimensional variables, those two groups of variables were further converted into values ranging from –1 to +1 and represented the inputs and desired outputs of the neural network. From the total of 1500 patterns, 1250 were used for training and 250 for verifications. Neural training was performed until a mean square error of 1.0×10^{-3} was obtained.

After neural network training, a one-day satellite attitude simulation was performed. Initial satellite attitude was considered as being: $\psi=\theta=\phi=1.0$ degrees and $\dot{\psi}$, $\dot{\theta}$ and $\dot{\phi}$ negligibly small. The objective of the simulation was control the satellite's attitude in order to lead it to nominal values, in the presence of unmodeled solar perturbations. Reference trajectory was actually set as a function of attitude's angles and rates current values:

$$\psi_r = \psi(t)e^{-t/7000} \quad \theta_r = \theta(t)e^{-t/7000} \quad \phi_r = \phi(t)e^{-t/7000}$$
$$\dot{\psi}_r = \dot{\psi}(t)e^{-t/50} \quad \dot{\theta}_r = \dot{\theta}(t)e^{-t/50} \quad \dot{\phi}_r = \dot{\phi}(t)e^{-t/50}$$

It should be noted that for the satellite attitude control simulation, dimensional variables related with attitude angles and angle rates were conveniently chosen so that, angles and rates absolute values never exceed a 1.0-value. Simulation results for attitude's angles and rates as well as control variables are shown on Figures 1(a) to 1(c), 2(a) to 2(c), 3 and 4, respectively. Results show excellent performance of the proposed scheme. It can be observed that for one-day

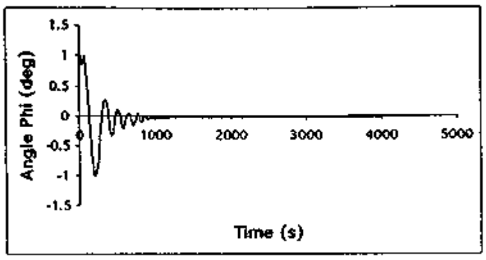

Fig. 1(a)

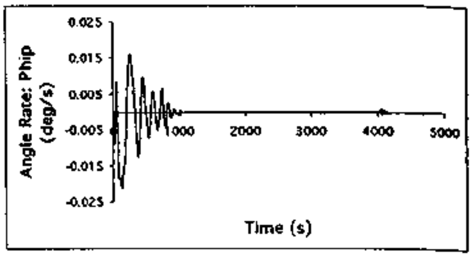

Fig. 2(a)

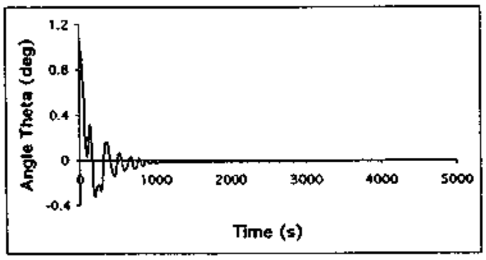

Fig. 1(b)

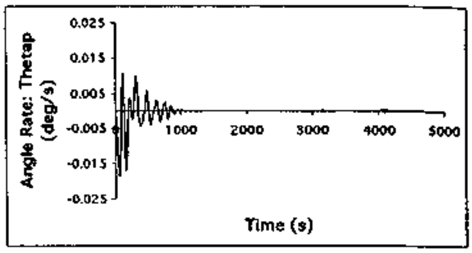

Fig. 2(b)

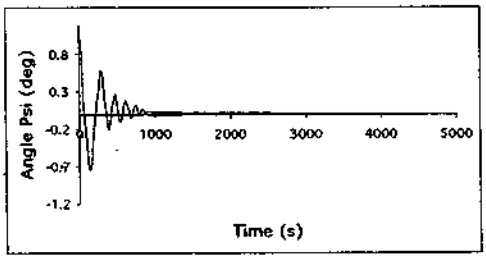

Fig. 1(c)

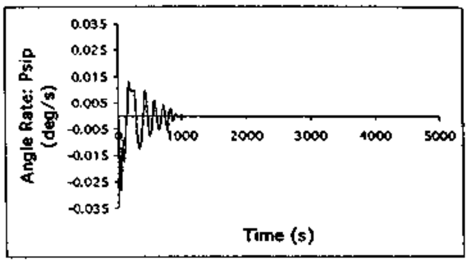

Fig. 2(c)

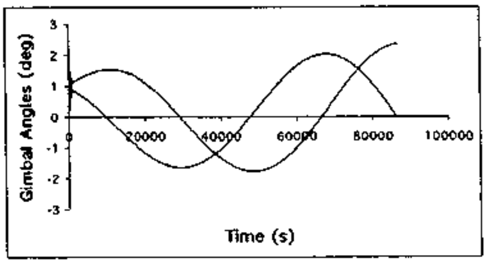

Fig. 3

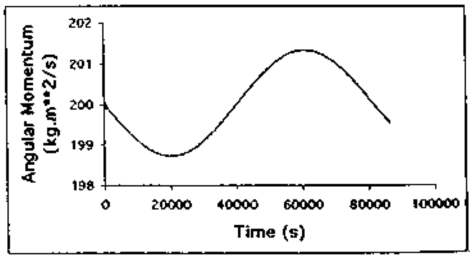

Fig. 4

simulation the values of satellite's attitude angles and rates are kept well inside limits of orientation of expected spacecraft attitude.

5 - CONCLUSION

The use of Kalman filtering as an optimal parameter estimation tool allows design of a method to solve neural predictive control problems. This method can be shown to converge to Newton's Method solution of minimizing functionals which constraint smooth and reference trajectory tracking controls.

A numerically simulated test was considered by applying the proposed methodology to the control of a geostationary satellite attitude. Nonlinear equations of motion were used, neural network training patterns were created, a feedforward neural network was trained and then, the control actions were obtained. Satellite attitude control was obtained with attitude errors maintained well inside specified limits. The results obtained are excellent, relative to those found in the literature and although a 1.0-degree initial attitude angles were considered, supplementary simulations demonstrated that control of larger initial angle values are also possible.

The simulation demonstrated that the algorithm's performance is equivalent to that of the correspondent neural network training Kalman filtering algorithms because they are completely similar algorithms used to solve numerically equivalent parameter estimation problems.

Acknowledgement

This research has been partially supported by CNPq and FAPESP grants.

REFERENCES:

[Bar 92] - Barret, C.: " Spacecraft Flight Control System Design Selection Process for a Geostationary Communication Satellite", *NASA Technical Paper* 3289, 1992.

[Chen 92] - Chen, S., Billings, S. A.: "Neural networks for nonlinear dynamic system modeling and identification", *International Journal of Control*, Vol. 56, No. 2, 1992, pp. 319-346.

[Chen 93] - Chen, G. and Ögmen, H.: "Modified Extended Kalman Filtering for Supervised Learning", *International Journal of Systems Sciences*, 24(6), 1993, pp. 319-346.

[Cyb 89] - Cybenko, G.: "Approximation by superpositions of a sigmoidal function", *Mathematics of Control, Signals and Systems*, Vol. 2, No. 3, 1989, pp. 303-314.

[Sil 99] - Da Silva, J. A., Rios Neto A.: "Preliminary testing and analysis of an adaptive neural network training Kalman filtering algorithm", *Proceedings of IV Brazilian Conference on Neural Networks*, July 20-22, 1999, ITA, São José dos Campos, SP, Brazil, pp. 247-251.

[Fun 89] - Funahashi, K.: "On the approximate realization of continuous mappings by neural networks", *Neural Networks*, Vol. 2, No. 3, 1989, pp. 183-192.

[Horn 89] - Hornik, K., Stinchcombe, M. White, H.: "Multilayer feedforward networks are universal approximators", *Neural Networks*, Vol. 2, No. 5, 1989, pp. 359-366.

[Iig 92] - Iiguni, Y., Sakai, H., Tokumaru, H.: "A real-time learning algorithm for a multilayered neural network based on the extended Kalman filter", *IEEE Transactions on Signal Processing*, 40(4), 1992, pp. 959-966.

[Kapl 76] - Kaplan, M: "Modern Spacecraft Dynamics and Control", John Wiley and Sons, 1976.

[Lang 95] - Lange, F.: "Fast and accurate training of multilayer perceptrons using an extended Kalman filter (EKFNet)", *Internal paper, DLR (German Institute Aerospace Research Establishment), Institute for Robotics and Systems Dynamics*, 1995.

[Liu 98] - Liu, G. P., Kadirkamanathan, V., Billings, S. A.: "Predictive control for nonlinear systems using neural networks", *International Journal of Control*, Vol. 71, No. 6, 1998, pp. 1119-1132.

[Mill 94] - Mills, P. M., Zomaya, A. Y., Tadé, M. O.: "Adaptive model-based control using neural networks", *International Journal of Control*, Vol. 60, No. 6, 1994, pp. 1163-1192.

[Nare 90] - Narendra, K. S, Parthasarathy, K.: "Identification and control of dynamical systems using neural networks", *IEEE Transactions on Neural Networks*, Vol. 1, No. 1, March 1990, pp. 4-27.

[Rios 97] - Rios Neto, A.: "Stochastic optimal parameter estimation and neural nets training in systems modeling", *RBCM – Journal of the Brazilian Society of Mechanical Sciences*, Vol. XIX, No. 2, 1997, pp. 138-146.

[Rios 00] - Rios Neto, Da Silva, J. S.: "Neural Predictive Control Based on Kalman Filtering Algorithms". To be published on *ICONNE 2000 – The Third International Conference on Nonlinear Dynamics, Chaos, Control and Their Applications in Engineering Sciences*, July 31 – August 07, 2000, Campos do Jordão, SP, Brazil.

[Sann 92] - Sanner, R. M., Slotine, J. J. E.: "Gaussian networks for direct adaptive control", *IEEE Transactions on Neural Networks*, Vol. 3, No. 6, November 1992, pp. 837-863.

[Sing 92] - Singhal, S. Wu, L.: "Training multilayer perceptrons with the extended Kalman algorithm", *Advances in neural Information Processing Systems*, Vol. 1, Morgan Kaufman Pub. Inc., 1989, pp. 133-140.

[Solo 97] - Soloway, D., Haley, P. J.: "Neural generalized predictive control: a Newton-Raphson implementation", *NASA Technical Memorandum* 110244, February 1997.

[Su 93] - Su, H., McAvoy, T. J.: "Neural model predictive control of nonlinear chemical processes", *Proceedings of the 1993 International Symposium on Intelligent Control*, Chicago, Illinois, USA, August 1993, pp. 358-360.

[Zhu 99] - Zhu, K. Y. Qin, X. F., Chai, T. Y.: "A new decoupling design of self-tuning multivariable generalized predictive control", *International Journal of Adaptive Control and Signal Processing* 13, 1999, pp. 183-196.

[Wata 91] - Watanabe, K. Fukuda, T. Tzafestas, S. G.: "Learning algorithms of layered neural networks via extended Kalman filters", *International Journal of System Science*, 22(4), 1991, pp. 753-768.