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Atair Rios Neto, Kondapalli Rama Rao
National Institute of Space Research
São José dos Campos, São Paulo, Brasil

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A STUDY ON THE ON-BOARD ARTIFICIAL SATELLITE ORBIT PROPAGATIONS USING ARTIFICIAL NEURAL NETWORKS

Atair Rios Neto[1], Kondapalli Rama Rao[2]
National Institute of Space Research
São José dos Campos, São Paulo, Brasil

ABSTRACT

In this paper the possible application of artificial neural networks for on-board orbit propagation is studied, using perceptron type nets trained with a backpropagation method and data of the first Brazilian Satellite SCD1. Preliminary results show that neural nets with just one hidden layer of 20 neurons can learn how to propagate SCD1 orbits.

INTRODUCTION

The use of artificial neural networks[1,2,3] as computational tools with the characteristic of parallel signal processing and with the capacity that some of them have of learning and representing data mappings is already an established fact. The success in dynamic system modelling[4], specially in control systems related schemes, is a strong indication that their utility in orbital dynamics modelling, and specifically in the problem of on-board satellite orbit propagation, can be safely expected. The combination of space qualified parallel computational facilities that soon will be available with the convenience of having satellite autonomous missions give motivation to better study this possibility of use.

In this paper, using data of the first Brazilian Satellite SCD1, launched on the 9th of February of 1993, a preliminary study is done to evaluate the possible use of multilayer perceptron networks for on-board orbit propagations. A software called NETS, developed by the Software Technology Branch of NASA's Johnson Space Center and based on the generalized delta backpropapagation learning method[5] is employed to train the neural nets. Results of a previous study[6], where the different architetures and sizes of this type of neural net were tested in terms of the capacity of learning how to model typical arcs of the SCD1 orbit, are considered to select the simplest configuration to be used in this orbit propagation study.

MULTILAYER PERCEPTRON AND ORBIT PROPAGATION

The theory of artificial neural networks developed until now guarantees that a neural net built with artificial perceptron neurons with just one hidden layer, can represent mappings

$$f \in C : x \in D \subset R^n \rightarrow y \in R^m$$

uniformly and with the desired accuracy in the domain D, as long as the number of neurons in the hidden layer is large enough[2].

The multilayer perceptron neural network is formed of basic artificial neurons, like the one of Figure 1, where for a kth hidden layer, with n_k neurons:

$$s_i^k = \sum_{j=1}^{n_{k-1}} w_{ij}^k \, x_j^{k-1} + w_{io}^k \tag{1}$$

$$x_i^k = a(s_i^k), \; k = 1, 2, \ldots, \ell - 1 \tag{2}$$

with the activation function $a(s)$ being typically given by:

$$a(s) = 1/(1 + exp(-s)) \quad or \; a(s) = tanh(s) \tag{3}$$

The inputs to the first hidden layer are $x_i^0 = x_i, i = 1, 2, \ldots, n$, the network input vector. And for the neurons of the output layer, $k = \ell$, it is sufficient to have zero threshold weights and an identity activation function:

$$\hat{y}_i \equiv x_i^\ell = \sum_{j=1}^{n_{\ell-1}} w_{ij}^\ell \, x_j^{\ell-1}, \; i = 1, 2, \ldots, m \tag{4}$$

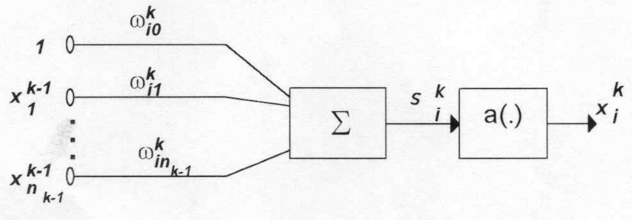

Figure 1: BASIC ARTIFICAL NEURON

For the orbit propagation application, after the experience acquired with a previous study[6], a perceptron

[1]Full Researcher

[2] Full Researcher

type neural net was chosen with just one hidden layer, as illustrated in Figure 2, where $x_i(t), i = 1,2,\dots,n$ represents the satellite motion state vector at time t, and

$$\hat{x}_k(t+\Delta t) = \sum_{i=1}^{n_1} \omega^2_{k_i}\left(tanh\left[\sum_{j=1}^{n} \omega^1_{ij} x_j(t) + \omega^1_{io} \right]\right) =$$

$$= \hat{f}_k(x(t), \omega, \Delta t), \quad k = 1,2,\dots,n \tag{5}$$

where ω is the vector of the ω^k_{ij} for $k = 1,2,$ and $i,j = 1,2,\dots,n.$

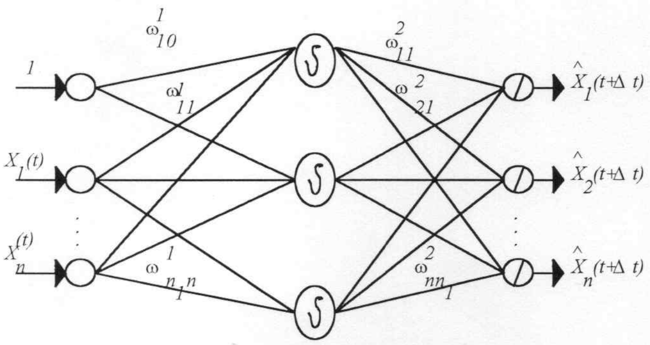

Figure 2: ORBIT PROPAGATION NEURAL NET

The theory guarantees that this neural net, with a large enough n_1 (the number of neurons in the hidden layer), can uniformly learn (by adjustment of the weights w^k_{ij}) how to approximate, with a given accurary a continuous and time invariant function

$$x(t+\Delta t) = f(x(t), \Delta t) \tag{6}$$

which for a given Δt discretizes the satelllite motion in a chosen state domain.

Notice that, if one assumes the orbital dynamics to be modelled by a state diferential equation with time invariant derivative function, then one can also assume, based on the theory of ODE numerical integrations, that this differential equation can always be discretized in a chosen domain with any given accuracy, as indicated in Equation (5).

To train the neural net to represent the satellite motion in the region of interest, a data set of pairs $(x(t_\ell), x(t_\ell+\Delta t)), \ell = 1,2,\dots,L,$ sufficiently distributed in this region is considered and, as usual, the adjustment (estimation) of the weights is done by minimization of:

$$J_L(w) = \sum_{\ell=1}^{L}\left(\sum_{k=1}^{n} \left(f_k\left(x(t_\ell), \Delta t\right) - \hat{f}\left(x(t_\ell), w, \Delta t\right)\right)^2 \right) \tag{7}$$

using, for example a back-propagation method[5], as is the case in this paper.

TESTS AND RESULTS

In a previous study[6], for the data of a short arc of the orbit of the first Brazilian satellite, five different network configurations, namely (i) one hidden layer with 10 neurons; (ii) one with 20 neurons; (iii) one with 40 neurons; (iv) two hidden layers with 10 neurons and (v) two with 20 neurons each, were chosen for training and testing. The results of that study showed that a perceptron neural net with one hidden layer of $n_1 = 20$ neurons can learn and represent the typical orbital arcs of SCD1 with the required accuracy.

The tests of this present study used the same neural net and were aimed at:

CASE 1: assessing the number of data pairs $(x(t), x(t+\Delta t))$ equally distributed along a nominal orbit of SCD1 (Table 1) necessary to allow the neural net to learn how to represent the complete orbit with a required accuracy;

CASE 2: assessing the neural net capacity of learning and propagating orbits inside a region around the nominal orbit of SCD1 (the same of Table 1) assuming some positive and negative variations in the nominal orbital elements, as in Table 2:

Table 1: Nominal orbit of SCD1

Orbital Elements		
a	=	7138139m
e	=	0.0
i	=	25°
Ω	=	185°
ω	=	350°
M	=	125°

Table 2: Orbits generated with some deviations in the nominal orbit of SCD1.

	Orbital Elements of Orbit 1		Orbital Elements of Orbit 2
a =	7138139 m	a =	7138139 m
e =	0.002	e =	0.004
i =	24°	i =	26°
Ω =	180°	Ω =	190°
ω =	345°	ω =	355°
M =	120°	M =	130°

202 points in each of these orbits were generated using a numerical integration procedure[7], so as to use as data sets for training.

Now, in Case 1, for SCD1 nominal orbit, after using various combinations of data sets, it was found that only 42 data pairs chosen in a systematic way $((n \times 10+1; n \times 10+2),\ n = 0, 1, ..., 20)$ from the large set of 202 points are enough for training the neural net to obtain an RMS error of the order of 10^{-4} in about four hundred thousand iterations. When the trained net was tested with some arbitrary data points from the large set of 202 points, the precision obtained also was of the same order. Results of some arbitrary input data values are shown in Table 3. The values shown in Table 3 are the normalized values of the state vector, generated as per the requirements of the software used.

Table 3: Propagation results of the nominal orbit of SCD1

Input value	**True output value**	**Network Estimate**	**Accuracy**
0.6913431	0.7004593	0.700306	10^{-4}
0.2102070	0.2165194	0.216159	10^{-4}
0.8073593	0.8019391	0.801652	10^{-4}
0.7930977	0.7869485	0.787230	10^{-4}
0.6962698	0.7052696	0.704903	10^{-4}
0.3326055	0.3230275	0.322333	10^{-4}
0.7506994	0.7582527	0.758266	10^{-5}
0.2600358	0.2681622	0.268032	10^{-4}
0.7633476	0.7559632	0.755588	10^{-4}
0.7443372	0.7363477	0.736370	10^{-5}
0.7547293	0.7621400	0.762091	10^{-5}
0.2695452	0.2613779	0.261065	10^{-4}
0.7180891	0.7265853	0.726574	10^{-5}
0.2299774	0.2371099	0.236824	10^{-4}
0.7902074	0.7839076	0.783591	10^{-4}
0.7738069	0.7668275	0.767019	10^{-4}
0.7226544	0.7310223	0.730876	10^{-4}
0.3044048	0.2953783	0.294866	10^{-4}
0.7265853	0.7348579	0.734870	10^{-5}
0.2371099	0.2445020	0.244253	10^{-4}
0.7839076	0.7773266	0.776994	10^{-4}
0.7668275	0.7595846	0.759736	10^{-4}
0.7310223	0.7391627	0.739062	10^{-4}
0.2953783	0.2865538	0.286097	10^{-4}

In case 2 also, it was found that only 42 data pairs of each of the the three orbits (given inTable 1 and Table 2) chosen in the same systematic way as in case 1 were enough to train the network and to obtain an RMS error of the order of 10^{-4}, in about four hundred thousand iterations as before. When the trained set was tested with some arbitrary data points from the large set of 606 points (202 points for each orbit), the accuracy obtained also was of the same order.

Now, two different orbits (given in Table 4) in the region comprising the three orbits (given in Tables 1 and 2) were considered to test the trained neural net. The results obtained for some arbitrary data points on these two orbits (orbits 3 and 4) are given in Table 5. It can clearly be seen that the RMS errors in all the propagation test cases are of the same order as that obtained in training the net.

Table 4: Orbital elements of two more orbits in the same region

Orbital Elements of Orbit 3	**Orbital Elements of Orbit 4**
a = 7138139m	a = 7138139m
e = 0.001	e = 0.003
i = 24.5^{o}	i = 24.5^{o}
Ω = 182.5^{o}	Ω = 187.5^{o}
ω = 347.5^{o}	ω = 352.5^{o}
M = 122.5^{o}	M = 127.5^{o}

Table 5 - Results of orbits 3 and 4

	Input Values	**True Value**	**Estimate**	**RMS Error**
Orbit 3	0.7102422	0.7189167	0.718827	10^{-4}
	0.2257829	0.2327436	0.232722	
	0.8027834	0.7971204	0.796945	
	0.7793186	0.7725883	0.772969	
	0.7182109	0.7266629	0.726859	
	0.3237214	0.3143399	0.314277	
	0.4188103	0.4081257	0.408008	10^{-4}
	0.8382275	0.8352234	0.835157	
	0.1524335	0.1539084	0.153958	
	0.1592707	0.1619666	0.162104	
	0.4110073	0.4003768	0.400596	
	0.5401594	0.5511174	0.551025	
Orbit 4	0.6329587	0.6430624	0.642355	10^{-4}
	0.1773240	0.1817425	0.181985	
	0.8288617	0.8249297	0.825169	
	0.8236615	0.8193259	0.819318	
	0.6358833	0.6459295	0.646284	
	0.3798882	0.3696268	0.369138	
	0.2810660	0.2725717	0.272220	10^{-4}
	0.7714322	0.7643381	0.764193	
	0.2191178	0.2258431	0.226074	
	0.2267777	0.2338155	0.233556	
	0.2791593	0.2707051	0.271009	
	0.7087188	0.7174890	0.717478	

CONCLUSIONS

The analysis of the results indicates that a perceptron type neural network with just one hidden layer of 20 neurons can be trained to learn orbital motion of a low orbit satellite and to become a numerical tool for on-board orbit propagation.

However, before a conclusion is taken that neural nets are not only feasible for this purpose but also competitive in terms of computational load and complexity, comparison studies will have to be done, considering the already available alternatives of orbit numerical integration and orbit analytical approximations. On the side of neural nets will be the advantages of:

- learning during operation;
- paralell processing; and
- fault tolerance.

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