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平成１５年度 国立天文台ALMA共同開発研究 研究成果報告書

１．研究課題名　外乱に強い高速高精度アンテナ制御技術の開発　　　２．区分　B

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４．研究成果の概要（１０００字程度で、ALMA計画に関連して重要であると思われる成果を重点的に記入してください。必要に応じて図表等は別紙として添付してください。また、主要な購入物品との関係についても記載してください。）

ALMAのアンテナでの課題は、「鏡面精度＜２０ミクロン」「Pointing/Tracking精度＜０．６”」「Fast Switch < 3 deg within 1.5 second」という性能の達成である．後者2項目について、新10m鏡に載せた加速度計や角度エンコーダで、計測を中心にして基礎的な評価が行われた．その結果，風外乱等に対して主鏡部は十分に剛構造であるが，通常追尾時のPointing/Trackingはほぼ仕様を満足するものの，Fast Switching時に発生する振動の収束が十分ではないためTracking精度が仕様を満たさず，Fast Switching観測での時間効率が高くないなどの問題点が指摘されている．つまり，新10mアンテナは，制御部の性能が不十分であり，これを改善すれば観測性能の向上が期待できる．

本研究の目的は新10mアンテナの駆動制御性能の向上である．このためにニューラルネットワークを用いたアンテナシステムの同定･制御を取り入れた高性能な制御系の開発を行う．これにより，アンテナの特性診断･解析，アンテナ系の同定，最適制御回路の設計，その実装と一連の技術開発が完成すれば，単に新１０mアンテナのみならず，他の高速スイッチング性能が必要なアンテナにも開発技術が応用できる．

上記目的を達成するために

(1) 新１０mアンテナの加速度計並びにエンコーダ出力データからアンテナシステムの同定･解析を行い，同定したアンテナモデルをPower PCにダウンロードすることにより実装し，同定したモデルをもとにFast Switching時の追尾誤差の収束の早い入力軌道と制御系の設計を行った．

(2) 最初に制御対象の順モデルや逆モデルを獲得するために階層型ニューラルネットワークの応用を考え，特に，強い非線形性を持つために従来の同定技術ではモデル化が困難であったアンテナシステムのような制御対象に対しても，学習を重ねることによって有効なモデルを得ることができるのではないかと考えた．

(3) そこで，階層型ニューラルネットワークを応用し，与えられたアジモス軸とエレベーション軸のエンコーダデータと加速度計の入出力データから学習によって対象モデルを任意の関数として表現させることを考えた．

(4) これに対し，制御系の目的は多くの場合，実際の出力結果を望ましい出力結果に一致させるような制御信号を見つけ出すことにあり，ニューラルネットワークは学習により最適な制御信号を獲得できるものと考えられ，制御器と制御対象の組み合わせが恒等変換であるようなフィードフォワード制御システムを構成させる場合，制御器は制御対象の逆モデルでなければばない．そこで，フィードフォワード制御器にニューラルネットワークを用いて逆モデルを獲得させる学習方法を試み，振動が少ない有効な軌道制御が行えることを数値シミュレーションで検証した．

5． 成果発表 （学会発表、研究会集録などを含みます。印刷中、投稿中なども可。）

著　者　名	論　文　標　題
村瀬卓弥，佐々木実，浮田信治	アンテナシステムのニューラルネットワークによる同定
発行年、雑誌・研究会名、巻・号、ページ	
計測自動制御学会システムインテグレーション部門（ＳＩ部門）講演会 SI2003（2003 年 12 月 19 日（金）～21 日（日））で発表	

著　者　名	論　文　標　題
Minoru Sasaki, Takuya Murase and Nobuharu Ukita	Neural Networks Based Identification and Control of a Large Flexible Antenna
発行年、雑誌・研究会名、巻・号、ページ	
2004 International Conference on Control, Automation, and Systems, August 25-27, 2004, The Shangri-la Hotel, Bangkok, Thailand.	

著　者　名	論　文　標　題
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6． 別刷り （各1部を添付してください。コピーも可。）

アンテナシステムのニューラルネットワークによる同定

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Neural Networks Based Identification of Antenna Dynamics

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Nobuharu Ukita　　National Astronomical Observatory of Japan

Abustruct: This paper presents identification of a 10-m antenna dynamics using accelerometers and angle encoders data. Artificial Neural Networks is capable of identifying underlying relations between input and output data. Some identification results are shown and compared with the results of conventional prediction error method. The results show the validation of the ANN approach for identification of the 10-m antenna dynamics.

1.　はじめに

ニューラルネットワーク(以下，NN)は，非線形処理能力，学習能力，並列分散処理能力を有することが知られている．近年，これらの能力を積極的に利用しようとする動きが活発に行われ，パターン認識，画像処理，音声認識，システム同定などの面で多くの論文が報告されてきている．

本研究では，アンテナに取り付けた加速度計およびモータ軸の角度エンコーダ・データを用いて，ALMA(Atacama Large illimeter/submillimter Array，アタカマ大型ミリ波サブミリ波干渉計)の 10m のアンテナの同定・解析を行う．アンテナシステムはモード間の干渉や非線形成分を含み，多入力多出力系であるために従来のシステム同定手法では，同定精度を上げることが困難であった．そこで，ニューラルネットワークを多入力多出力系への同定に応用することにより同定精度を上げることを試みる．また，その有効性の検証のために従来の予測誤差法とニューラルネットワークの同定結果について比較・検討を行う．

2.　ニューラルネットワークによる同定

Fig.1 に本研究で用いたアンテナの構造を示す．モータ軸の角度エンコーダは AZ(Azimuth) 軸，EL(Elevation)軸にそれぞれ，加速度計は副鏡に 3 箇所，

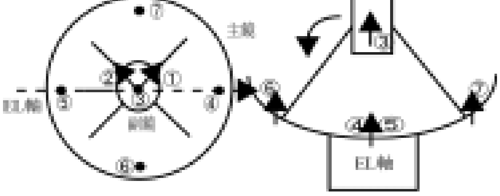


Fig.1 Sensor and encoder

主鏡に 4 箇所配置されており，2 入力 7 出力のシステムとなっている．データサンプリング時間は 10(msec)である．

Fig.2 に本研究で用いた階層型 NN の構造を示す．2 入力 7 出力の 4 層構造で，信号は層内の結合を含まないフィードフォワード型とする．4 層構造は入力層(Input layer)，2 層の隠れ層(Hidden layer)，出力層(Output layer)からなり，各隠れ層の各ユニット数は 30 とした．ニューロン i の内部信号 net_i は，入力信号の荷重和として次式で与えられる．

$$net_i = \sum_j w_{ij} out_j - \theta_i \tag{1}$$

ここで，w_{ij} はニューロン j からニューロン i への結合荷重，out_j はニューロン j の出力値，θ_i はニューロン i のしきい値である．各ニューロンの出力関数 $f(net_i)$ はシグモイド関数で，

$$out_i = f(net_i) = \frac{1}{1+\exp(-net_i)} \tag{2}$$

で与えられる．但し，出力層でのニューロンは線形関数とし，教師信号を $o(k)$，k 時間での出力信号を $d(k)$ とする．NN の結合荷重の学習は，同定目的を達成するために次式の評価関数

$$E(k) = \frac{1}{2}(o(k) - d(k))^2 \tag{3}$$

が最小になるように，最急降下法にもとづく誤差逆伝播法を用いて結合荷重の更新を行う．

$$w_{ij}(k+1) = w_{ij}(k) - \eta \frac{\partial E(k)}{\partial w_{ij}(k)} \tag{4}$$

ここで，η は学習定数であり，学習定数の値は 0.08

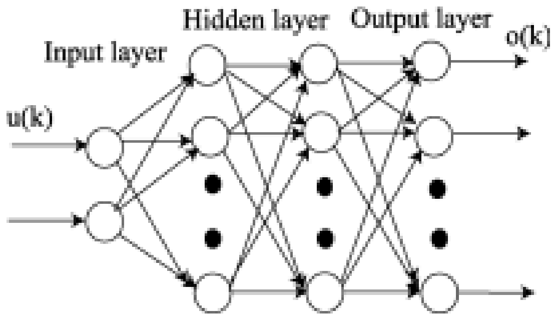


Fig.2 Multiple layers neural networks

を用いた．

3. 同定結果

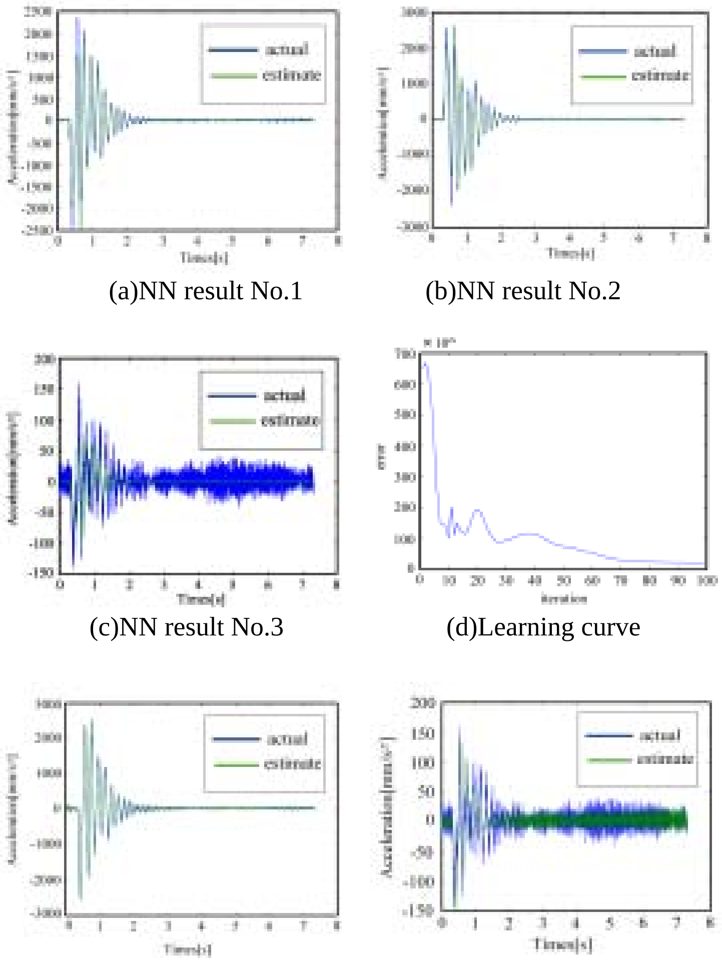
Fig.3 に同定結果を示す．入力に用いたデータは EL 軸 10 度に固定し，駆動角が AZ 軸を 0.3 度回転させた時の角度エンコーダと加速度計のデータを用いる．ここで，(a)，(b)，(c)は NN による同定結果，(d)が NN の学習曲線, (e), (f)は予測誤差法での同定結果を示す．青い線が実際の計測データで，緑の線が同定で得られた結果を示している．

NN は 2 入力 7 出力で同定しているが，紙面の関係上センサ 4 から 7 までの結果は省略してある. (d)の学習回数は，逐次的に学習しているため，iteration×733 回の更新を行っている．また，この場合，誤差値は

$$error = \sum_{i=1}^{7}\left(\sum_{k=1}^{733}(yd_i(k) - y_i(k))^2\right) \qquad (5)$$

を用いている．また，(5)の yd_i は目標値で y_i は同定器で求められた値である．(a)，(b)，(c)の NN の同定結果より，低周波の振動成分は同定精度が良く，高周波の振動成分は，同定精度が低い．(e)，(f)に NN の同定結果との比較のため，従来の予測誤差法による同定結果を示す．同定多項式モデルとして ARMAX 法を用い，同定には MATLAB のシステム同定ツールボックスを用いて計算を行った．また，予測誤差法による同定は 2 入力 1 出力の条件で行い，エンコーダ入力から各センサ出力ごとに同定モデルをもとめた．

従来のシステム同定法と NN による同定結果の比較を行う．評価としては式(5)の誤差値 error を用いた．従来のシステム同定法の誤差は実際値と同定したデータの，1 サイクルの 2 乗誤差の和を使い，NN 法では同定した 1 つのセンサ出力に対して 1 サイクルの 2 乗誤差の和を使用する．ARMAX 法のセンサ 1 の誤差値 error は 7.666×10^6 に対し，NN 法では 1.9×10^6 である．また，センサ 3 の ARMAX 法の誤差値は 4.8794×10^5 に対して，NN 法では 3.898×10^5 である．条件の細かな違いはあるものの，NN を用いた同定結果は



(a)NN result No.1　(b)NN result No.2

(c)NN result No.3　(d)Learning curve

(e)ARMAX result No.1　(f)ARMAX result No.3

Fig.3 Identification results

従来のシステム同定法よりも誤差が少ない結果を示している．また，NN の 7 つのセンサの誤差の 2 乗和の値は 21.1732×10^6 である．

4. 結言

従来のシステム同定法においては，多入力多出力系の同定においては部分空間法以外では適用が難しくまだ十分とは言い難い．NN による同定法は非線形の多入力多出力系においても同定モデルを得ることができ，また，従来のシステム同定法と比較してより高い同定精度が得られた．パラメータの最適調整や収束速度の向上による同定精度の向上は，今後の課題である．

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Neural Networks Based Identification and Control of a Large Flexible Antenna

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Abstract: This paper presents identification and control of a 10-m antenna via accelerometers and angle encoder data. Artificial Neural Networks can be used effectively for the identification and control of nonlinear dynamical system such as a large flexible antenna. Some identification results are shown and compared with the results of conventional prediction error method. And we use a neural network inverse model for control the large flexible antenna. In the neural network inverse model, a neural network is trained, using supervised learning, to develop an inverse model of the antenna. The network input is the process output, and the network output is the corresponding process input. The control results show the validation of the ANN approach for identification and control of the 10-m flexible antenna.

Keywords: Neural networks, Identification, Control, Inverse model, Antenna

1. INTRODUCTION

This paper presents identification and control of a 10-m antenna dynamics using accelerometers and angle encoders data.

ALMA - the Atacama Large Millimeter Array - will be a single instrument composed of 64 high-precision antennas located on the Chajnantor plain of the Chilean Andes in the District of San Pedro de Atacama, 16,500 feet (5,000 meters) above sea level(shown in Fig. 1). ALMA's primary function will be to observe and image with unprecedented clarity the enigmatic cold regions of the Universe, which are optically dark, yet shine brightly in the millimeter portion of the electromagnetic spectrum.

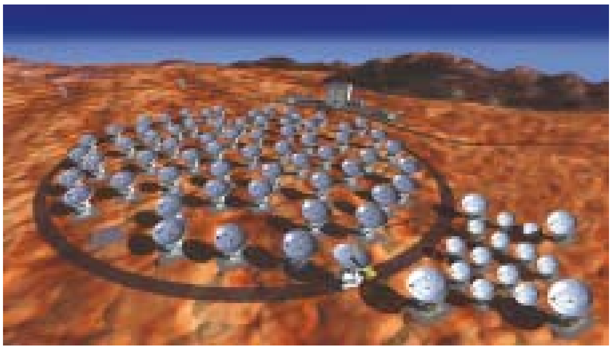


Fig. 1 Rending of ALMA.

The ALMA is an international collaboration between Europe and the North America to build a synthesis radio telescope that will operate at millimeter and sub-millimeter wavelengths. Japan also becomes a partner, making this a truly global collaboration.

Its main targets include planetary system formation and galaxy formation/evolution. The Technical challenges to key instruments for such arrays are now performed; i.e., developments of high precision antenna, low-noise sub-millimeter mixers, high-power sub-millimeter LO sources, and very high-speed samplers and wideband spectro-correlators. The specifications imposed for recent sub-millimeter antennas of a 10/12-m size in the open air are demanding and challenging. For example, 12-m antennas for Atacama Large Millimeter/sub-millimeter Array (ALMA) have a surface accuracy of better than 25 μm and pointing/ tracking accuracy of better than 0.6" under a wind velocity of 9 m s-1. They must also be able to slew to new position 1.5 degrees away and settle to within 3 arcsec in less than 1.5 sec to cope with phase errors caused by fluctuations in the atmosphere.

Loads on antenna structure due to wind cause elastic deformations, which deteriorate antenna's pointing and surfaces accuracies. The structural behavior of the telescope is typically measured at the encoders of azimuth and elevation axes, while the critical performance is the actual pointing on the sky. We need to make direct measurements of vibration motion of the main-dish and sub-reflector with a resolution of typically 3 - 5 μm. Seismic accelerometers serve this purpose for a frequency range from 0.1 to 100 Hz. A laser metrology system can also serve for a frequency range < 1 Hz. The low frequency component (< 1 Hz) is presumably due to wind load, and the high frequency (> 1 Hz) due to modal oscillation induced by a servo controller. It is very hard to identify and control of the antenna system [1-9].

With all advanced control schemes, mathematical knowledge of the dynamics of the process of interest is necessary. System identification refers to the process of developing a mathematical process model from experimental data. System identification in control engineering is a key element for understanding and controlling unknown dynamical systems. Traditional System identification techniques such as least square estimation, quasi-linearization and stochastic modeling have been successfully used in nonlinear dynamical systems. In traditional system, model structure must be defined a priori to estimate all required system parameters. In case of antenna dynamics, defining a priori model is difficult to get. Given input and output data, Artificial Neural Networks (ANN) is capable of identifying underlying relationship between the input and output data. Some identification results are shown and compared with the results of conventional prediction error method. The results show the validation of the ANN approach for identification of the 10-m antenna dynamics.

We use a neural network inverse model for control the large flexible antenna. In the neural network inverse model, a neural network is trained, using supervised learning, to develop an inverse model of the antenna. The network input is the process output, and the network output is the corresponding process input. The control results show the validation of the ANN approach for identification and control of the 10-m flexible antenna.

2. ANTENNA STRUCTURE AND MEASUREMENT SYSTEM

10-m antenna structure is shown in Fig. 2. Ukita and Ikeda made experiments on a 10-m antenna of Nobeyama Radio Observatory with accelerometers and angle encoders. The angle encoders have a 25-bit resolution (LSB = 0.039") and were measured to have an accuracy of 0.03" rms. The drive system of the antenna under no wind disturbance has been measured to have servo errors of typically 0.04" and 0.10" rms for rotational velocities < 0.001 deg s-1 and 0.1 – 0.001 deg s-1, respectively. The telescope was located at a highland of 1350 m elevation. There are three piezoelectric seismic sensors (PCB Model 393B12) at a sub-reflector mount chassis, four beneath a panel support board of the backup structure (BUS), normal to the surface, one at a reference point near the center of the BUS, and four capacitive accelerometers (PCB Model 3701G3) at yoke arm ends (horizontal directions, perpendicular and parallel to the elevation axis). These data sampled simultaneously are combined to figure out the oscillations of antenna global structure. For example, differences between pairs of sensors in the BUS tell us a tilt motion of the dish in the reflector axis. The system had a noise floor of 3 - 8 x 10-4 [m s-2 /root Hz] in the 0.1 to 1 Hz band and 2 x 10-4 [m s-2 /root Hz] in the frequency range from 1 to 20 Hz under a condition of no wind. Our 16-bit ADC has 16 single-ended input channels with a bipolar input range of ±5 Volt, and makes negligible contribution to the noise floor. Comparisons between Fourier spectra of the sensor outputs under windy and no-wind conditions suggest that the components below 0.7 Hz seem to be due to noise (poor stability) of the sensors and/or measurement system. Sensor outputs and angle encoder readouts were simultaneously recorded at a rate of 100 Hz, while the antenna was driven at a rotational speed of 10-5 deg s-1 and was pointed at various wind attack angles under a windy condition of typically 10 m s-2.

Fig. 2 Antenna structure.

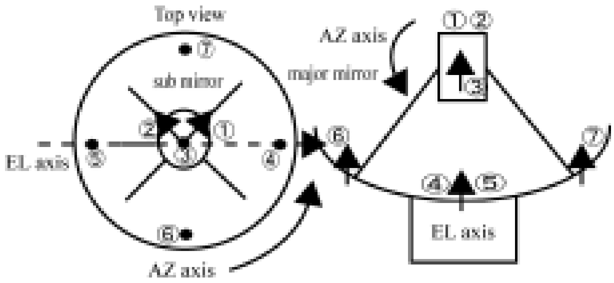


Fig. 3 Sensors and encoders position.

3. IDENTIFICATION USING PREDICTION ERROR METHOD

Control requirements can narrow the regions of time frequency over which an adequate model fit is necessary.

Therefore, if the control requirements are incorporated in the parameter estimation problem, it becomes possible to obtain improved models over the frequency band which is of importance to the control problem.

This is the objective of the control-relevant parameter estimation problem.

In a more generalized mathematical sense, the control-relevant parameter estimation problem is interpreted an optimization problem which requires minimizing a functional of the weighted error between the true and estimated plant models.

Parametric identification methods are techniques used to estimate parameters in given model structures.

It is basically a matter of finding those numerical values of parameters that give the best fit between the model output and the measured one.

System identification is concerned with the building of dynamic models which describe the relationships between measured signals. The system identification problem is to estimate the model of a system based on observed input-output data. Here, the parametric identification methods are used. Parametric identification methods are techniques used to estimate parameters in given model structures. It is basically a matter of finding those numerical values of parameters that give the best fit between the model output and measured one. The applied parametric model is the ARMAX (Auto - Regressive Moving Average eXogeneous) model which corresponds to the description

$$A(q)y(t) = B(q)u(t-nk) + C(q)e(t) \tag{1}$$

where q^{-1} is the delay operator, n_k is the time delay, and $A(q)$, $B(q)$ is

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \\ B(q) &= b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b} \\ C(q) &= 1 + c_1 q^{-1} + \cdots + c_{n_c} q^{-n_c} \end{aligned} \tag{2}$$

A time domain description of the system is given:

$$y(t) = G(q)u(t) + H(q)e(t) \tag{3}$$

Given a description Eq. (1) and having observed the input-output data u, y, the prediction errors $e(t)$ in Eq. (1) can be computed as:

$$e(t) = H^{-1}(q)y(t) - H^{-1}(q)G(q)u(t) \tag{4}$$

These errors are, for given data y and u, functions of G and H. The prediction error method is used in order to determine estimates of G and H by minimizing

$$V(G,H) = \sum_{t=1}^{N} e(t)^2 \tag{5}$$

4. NN IDENTIFICATION

The most popular control system application of neural networks is also the most straightforward conceptually. The supervised learning capabilities of neural networks can be used for identifying process models from input/output data. The process data are the training set for the network, the weights of which are adjusted until the network model output accurately predicts the actual process output. Once the training process is successfully concluded, the neural network constitutes a black-box, nonparametric process model [10].

Fig. 4 is an identification system used in this paper. This system produces output $yd(k)$ which approximates $y(k)$ when subjected to the same input $u(k)$ as the plant. $u(k)$ are AZ axis and EL axis angle data. $yd(k)$ are accelerometer's output data on the sub mirror and the major mirror of the antenna. $y(k)$ is the prediction value of the output in the identification model. $e(k)$ is an error which $yd(k)$ is compared with $y(k)$. Identification model structure is multiple layers artificial neural networks (ANNs). The ANNs have an input layers, an output layer, and two hidden layers as shown in Fig. 5. This ANNs have two inputs and seven outputs. The ANNs is a feed forward type including no combination inside the layers. Each hidden layers have thirty units. Each neuron activation function $f(net_i)$ is the sigmoid function given as

$$out_i = f(net_i) = \frac{1}{1+\exp(-net_i)} \tag{6}$$

The neuron activation function of output layer is assumed to be the linear function.

$$f_0(net_i) = net_i \tag{7}$$

To minimize the cost function

$$E(k) = \frac{1}{2}(yd(k) - y(k))^2 \tag{8}$$

the updating equation of the weights is defined

$$w_{ij}(k+1) = w_{ij}(k) - \eta \frac{\partial E(k)}{\partial w_{ij}(k)} \tag{9}$$

where w_{ij} is the weight value located between nodes i and j, t is the present iteration and η is the learning rate parameter. The learning rate parameter is 0.08. The thresholds is 0.01.

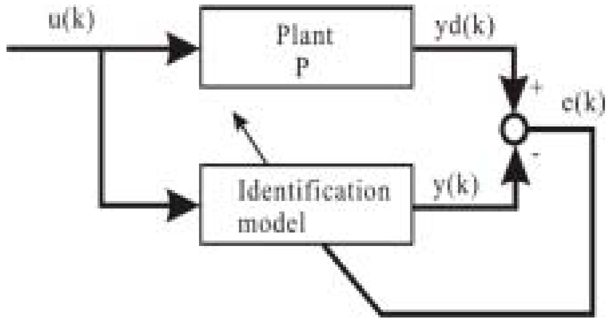


Fig. 4 Identification system.

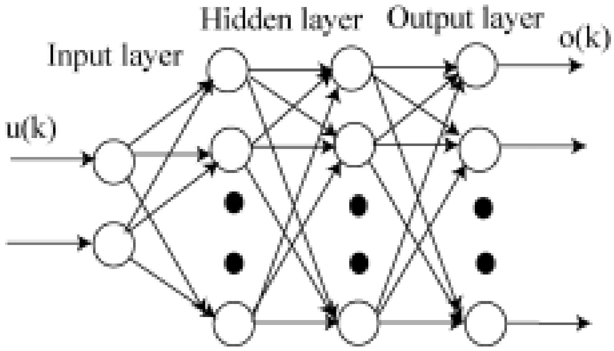
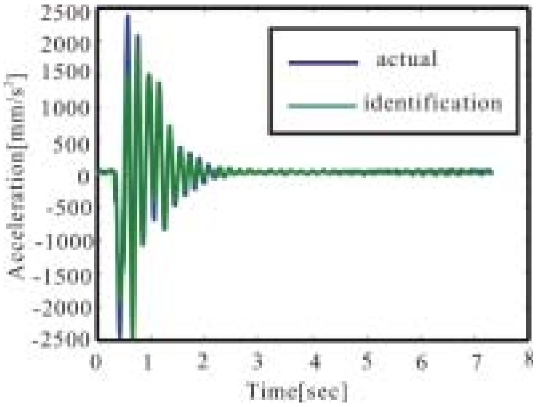


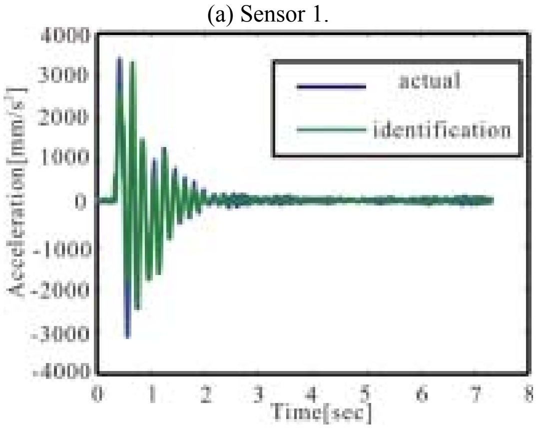
Fig. 5 Multiple layers neural networks.

5. IDENTIFICATION RESULTS

Identification results are shown in Fig. 6 and Fig. 7. Sensor outputs and angle encoder readouts is simultaneously recorded at a rate of 100 Hz, while the antenna is driven that the EL axis is fixed at 10 deg and the AZ axis is turned around from 0 deg to 0.3 deg,. 2 angle encoders data and 7 accelerometers data are used for the input data. NN identification results are shown in Fig. 6 (a) and (b). Identification results of the prediction error method are shown in Fig. 7 (a) and (b). The blue line shows the actual experimental result and the green line shows the identification result. Lower frequency vibration modes have good accuracy but Higher frequency vibration modes have not good accuracy. We carried out a computation by using MATLAB system identification toolbox. Identification in prediction error method is two inputs and 1 output. Identification model is determined in encoder input and each accelerometer sensor output. Compared with prediction error method and NN identification method, one cycle squared estimation error of the NN method is smaller than that of the prediction error method. One cycle squared estimation error of the prediction error method of the sensor No.1 is 7.666×10, that of NN identification method of the senor No.1 is 1.9×10, that of the prediction error method of the sensor No.3 is 4.8794×10 and that of the NN identification of the sensor No.3 is 3.898×10, respectively. The total squared error of the seven sensors of NN identification method is 21.1732×10.

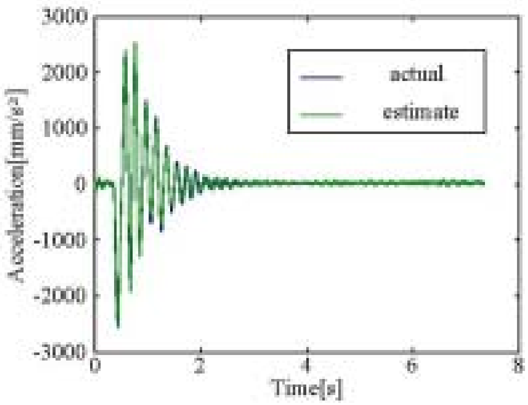


(a) Sensor 1.

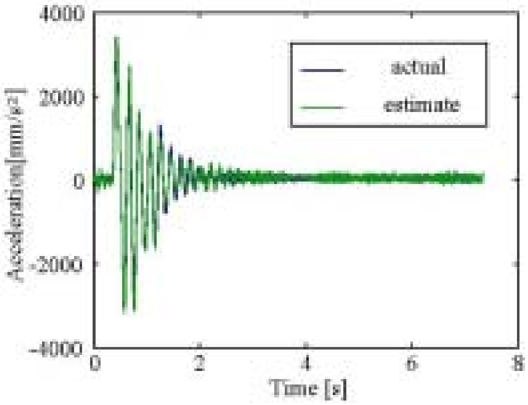


(b) Sensor 5.

Fig. 6 NN identification results.



(a) Sensor 1.



(b) Sensor 5.

Fig. 7 Identification using PEM.

6. NN CONTROLLER

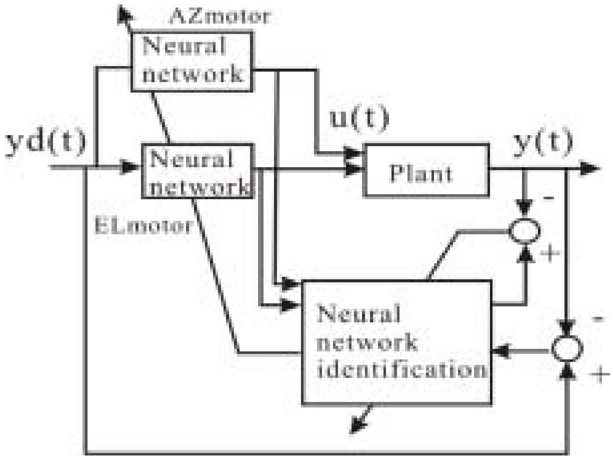


Fig. 8 Control system.

The inverse model of a dynamical system yields input for given out put. The model is a crucial role in a range of control structures. Conceptually the simplest approach is direct inverse modeling. A synthetic training signal is introduced to the system. The system output is then used as input to the network. The network output is compared with the system input and this error is used to train the network. This structure will clearly tend to force the network to represent the inverse of the plant [11]. Fig. 8 shows the control system using NN. For precise tracking the desired trajectory, a new cost function for the learning the networks is presented as follows:

$$E(k)=\sum_{i=1}^{7}\{\frac{1}{2}q(yo_i(k)-y_i(k))^2+\frac{1}{2}p(uo(k)-u(k))^2\} \quad (10)$$

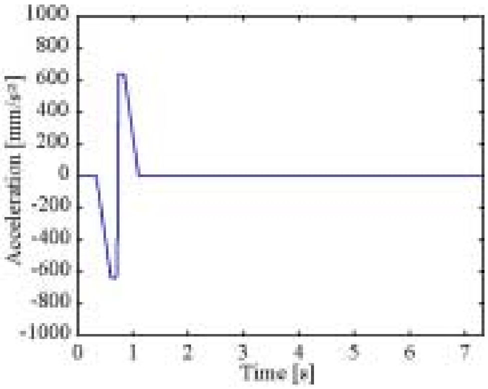
where q is a weight of acceleration output, p is a weight of desired trajectory input. We can rewrite the updating equation as

$$\frac{\partial E(k)}{\partial w_{ij}(k)}=\frac{\partial E(k)}{\partial u(k)}\frac{\partial u(k)}{\partial w_{ij}(k)} \quad (11)$$

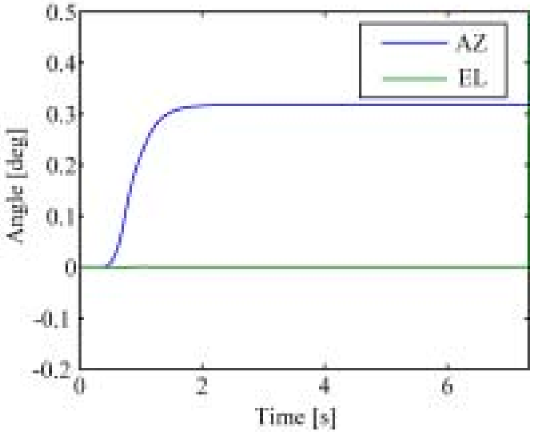
$$\frac{\partial E(k)}{\partial u(k)}=-q(yo_l(k)-y_l(k))\frac{\partial y(k)}{\partial u(k)}-pu(k) \quad (12)$$

where $\frac{\partial y(k)}{\partial u(k)}$ is the system Jacobian.

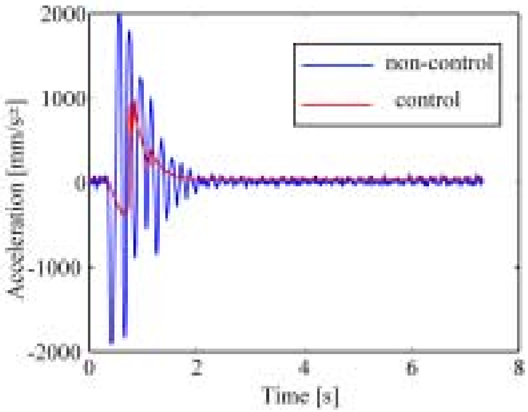
Figs. 9 and 10 show the controlled and non controlled results of the accelerometers output of the sensor No. 1 and No. 5. Fig. 9 shows the results of the conventional error learning. Fig.10 shows the results of the Jacobian learning. Fig. (a) shows the desired acceleration of the sensor No.1 and No.5. Fig. (b) shows the desired trajectory of the Azimuth axis and the Elevation axis. The residual vibration with the NN feed-forward controller is suppressing more quickly than that without the controller. Compared with the results of he conventional cost function Eq. (8) and those of the new cost function Eq. (10), the new cost function is more effective for suppressing the residual vibration and tracking the desired trajectory.



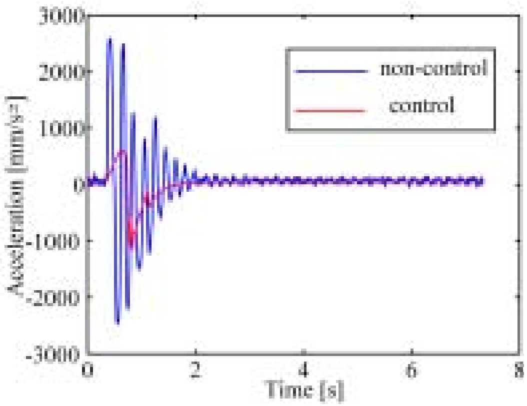
(a) Desired acceleration of sensor1



(b) Input trajectory

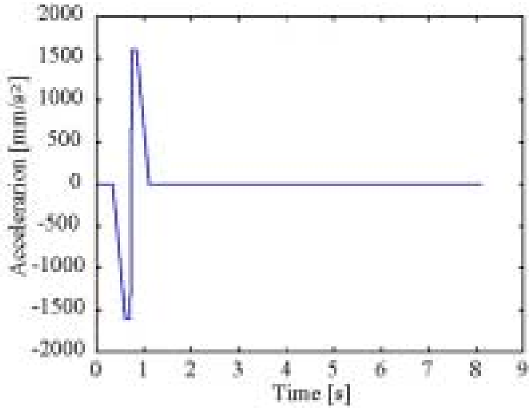


(c) Sensor1

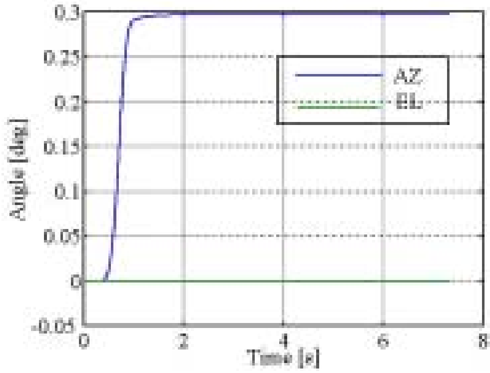


(d) Sensor5

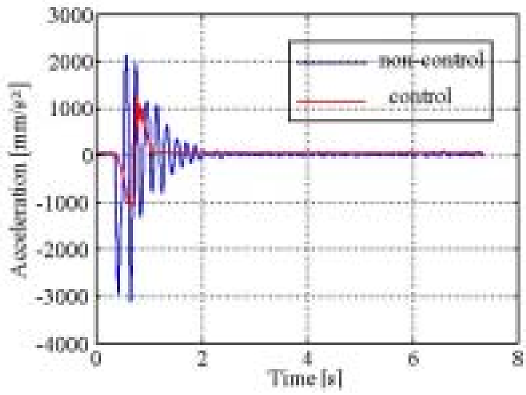
Fig. 9 Simulation result using error learning.



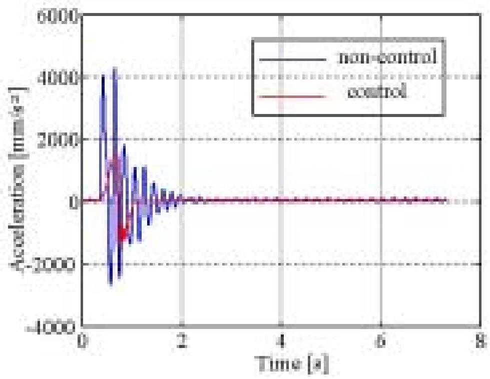
(a) Desired acceleration of sensor1



(b) Input trajectory

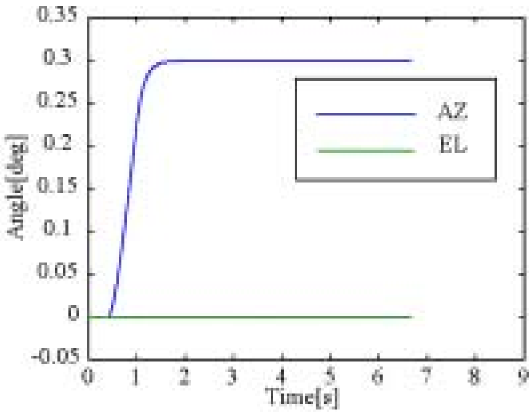


(c) Sensor1

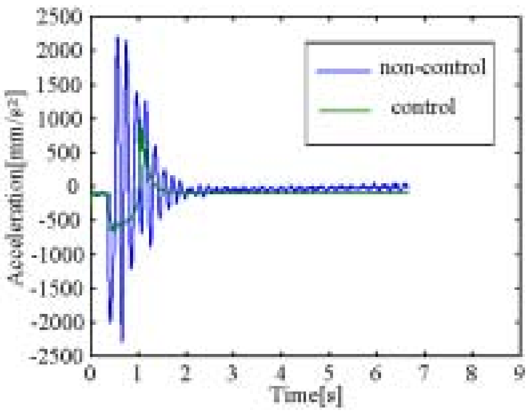


(d) Sensor5

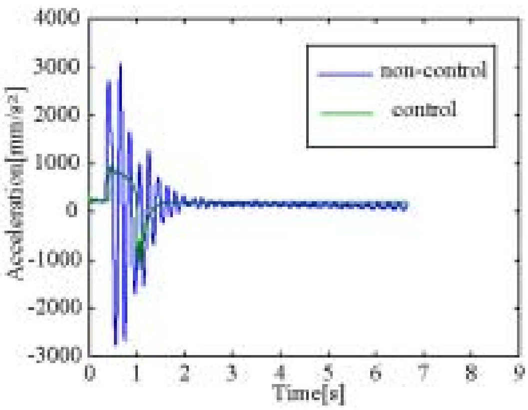
Fig.10 Simulation result using Jacobian learning



(a) Input trajectory



(b) Sensor1



(c) Sensor2

Fig.11 Simulation results using vector and acceleration value

7. CONCLUSION

Identification and control of a 10-m antenna dynamics for the Atacama Large Millimeter Array project using accelerometers and angle encoders data were presented. Compared with prediction error method and NN identification method, one cycle squared estimation error of the NN method was smaller than that of the prediction error method.

A neural network inverse model was used for control of the large flexible antenna. In the neural network inverse model, a neural network was trained, using supervised learning, to develop an inverse model of the antenna. The network input was the process output, and the network output was the corresponding process input. The control results showed the validation of the ANN approach for identification and control of the 10-m flexible antenna, especially the system Jacobian learning.

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