ADVANCES in NATURAL and APPLIED SCIENCES

ISSN: 1995-0772
EISSN: 1998-1090
2016November10(16):pages 115-119

Published BY**AENSI Publication**
http://www.aensiweb.com/ANAS
Open Access Journal

GRNN Based Inertia Parameters Identification of Robot Dynamics

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Received 23 August 2016; Accepted 21 November 2016; Published 30 November 2016

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ABSTRACT

Background: In a robot dynamics the important fields are modeling and controlling of parameters. The Parameters involved in modeling must be improved to have precision control. Here for inertia parameter identification, the robotic arms dynamics were considered and its parameter were transformed in to linear equation for to have accurate model. Generalized regression neural network (GRNN) is used for identification, in which the input and output parameters were generated just by operating the robotics arms by particular degree of freedom (DOF). Every connecting rod and its inertia parameters are used as the weights for the neural networks. Based on the error the weight for the GRNN was adjusted. **Objective:** To simulate the initial parameter for training the GRNN two degree of freedom robot arms. Every connecting rod and its inertia parameters are used as the weights for the neural networks. Based on the error the weight for the GRNN was adjusted **Conclusion:** Finally with the identification results the accurate model parameter was developed and verifies the validity based on the GRNN.

KEYWORDS: GRNN, Inertia parametes, Weights, Robot dynamics

INTRODUCTION

The robot arm is a complex system with strong coupling and non linear characteristics. For any design in particular for off-line programming the modeling of robot dynamics with appropriate parameters are very-very important. In a robotic modeling, the accuracy and precision is achieved just by fixing the values of inertia parameters. Usually robot has connecting rod which straight away links with many physical parameters such as mass, the centre of mass and inertia tensors in all the coordinates.

The robot dynamics and its parameter estimation ate areas which most of the researchers were concentrating. To estimate the parameters particularly the inertia parameters of space robots were done by using momentum conservation law algorithm [1]. The parameters extracted don't have that much accurate value as this could not be generalized. So for each and every task separate modeling and parameters need to be identified. The same momentum of conservation law has been used to identify the inertia parameters in robot pedestal, which faces same set of issue as seen in earlier literature [2].The issues discussed earlier were some extend overcome by just by using genetic algorithm with momentum of conservation law [3] and improved the efficiency. To improve furthermore, torque based robot inertia parameters were identified by adapting the least square method and the Newton-Gausse iterative method according to the inverse dynamics model [4].

In some of the circumstances the independent inertia parameters are needed to perform some specific task. The extraction of independent parameter is been identified with the connect in assembly method [5].As these kind of parametes cannot be used as it is, as a parameters required for online. The artificial neural network is

been used to handle these kind of inertia parameters , as neural network has adaptive self-learning capability with the non-linear approximation characteristics, which are all very much needed for identification of inertia parameters related with robot arm.

Here GRNN is been used which A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function [6].The GRNN is used not to estimate dynamic model with concrete inertia parameters, it is used just to estimate the inertia parameter without the concrete inertia parameters, as it will lead to faster training which will help to get faster response.

Here the conventional model is transformed in to a linear identification model, which is much needed for inertial parameter identification [9]. For to simulate the initial parameter for training the GRNN two degree of freedom robot arms been used in a case study. The results simulated by trained GRNN verify the accuracy of the neural network parameter identification. The paper is organized as follows in section II robot dynamics are briefly introduced. In section III, the GRNN were briefly introduced, in IV results and discussion and the conclusion is presented in section V.

Robot Dynamics:

Based on the degree of freedom (DOF) the robotic structures have been defined. Based on the number of DOF the robotics can be classified as simple and complex robot. In any robot the movement especially the arm movement is considered to be major part which is simulated by friction, settling time, rise time and motions of joints. Figure 1 is considered as for the analysis mainly to extracting initial inertia parameters.

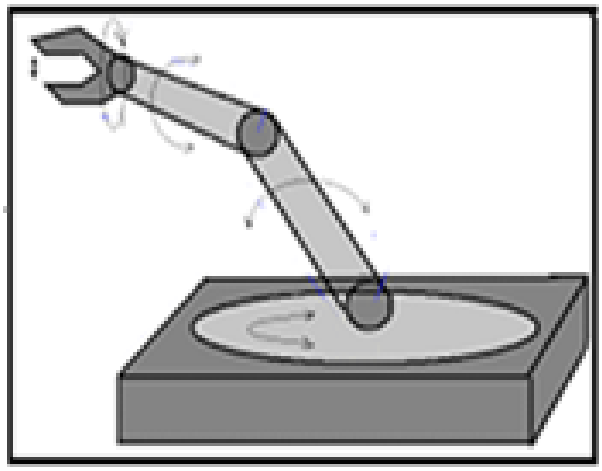

Fig. 1: Robot arm

The dynamics of a serial n-link rigid robot can be written as equation (1)

$$M(\dot{q})\ddot{q} + C(q,\dot{q}) + g(q) = \tau \quad (1)$$

Where q is the n x1 vector of joint displacement.

$\dot{q}$ is the nx1 vector of joint velocity.

τ is the nx1 vector of actuator applied for M(q) is the nxn symmetrical positive definite manipulator inertia matrix.

$C(q,\dot{q})$ is the nx1 vector of centripetal and coriolis torques.

$g(q)$ is the nx1 vector of gravitational torques. Here the electrical parameters of the actuator are assumed by comparing the size and power of the motors

Generalized regression neural network:

Generalized regression neural network is introduced by Donald F. Specht [6] [7] and [8]. According to him it is one kind of radial basis function with effective feed forward neural network which has a capability of having both situation approximation and optimum approximation which is much needed from any kind of neural network. It consists of input layer, a layer with RBF network and an output layer with linear characteristics as shown in figure 2.

In this the ‘P’ is the input vector where inputs for training, validation and for testing has been carried, ‘R’ is the input dimensionality of the network, which varies based on the number of inputs and outputs based on the

task, precision and accuracy. 'Q' tells about the nerve cells and number of nerve cells needed by each layer to perform various task as training did in the initial pahse. 'LW' is the weight matrix which will decides the priority to be given to particular link between the layers to achieve certain task with high accuracy rate. The hidden nodes are assigned by the radial basis function unit to have radial basis function property such as with better training and performance. The output nodes are just summations to have various manipulations.

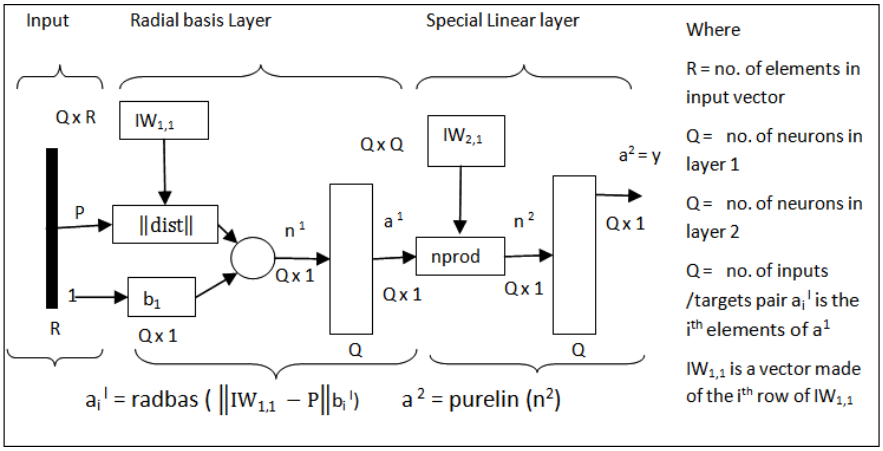

Fig. 2: Architecture of GRNN

The input layer is designed with 'newrbe' which is a RBF network with radial basis nerve nodes with same number of input sample. The weight and adjustment of weight has been updated just by transposition of the input vector, the threshold value is estimated by using the given equation 2.

$$b = [-\log(0.5)]^2/spread \quad (2)$$

The hidden layer which is a radial basis layer has the same number of nodes as that of the number of either samples. The Gaussian function which is most widely used one with their consistency in performance was used here as a transfer function for the hidden layer. The function is shown in equation 3.

$$R_i(x) = \exp\left(\left(\frac{\|x-c^2\|}{2\sigma_i^2}\right)\right) \quad (3)$$

Where σ_i is the smoothing factor which decides the basic functions shape in the hidden layer. The basis function will be much smoother for the higher value of σ_i.The last layer is the output layer with linear charateristics. Its weight function is mostly used to estimate network vector n^2.This n^2 has the capability of giving the results to linear transfer function mainly to calculate the output of the network.

RESULT AND DISCUSSION

In any ANN approach, the main difficulty is that, if the number of input parameter increases, ANN will take more time to train the network. Hence, selection of parameters and number of parameters is necessary to the ANN approach for the real time problems. The performance of the network can be improved in terms of accuracy and time consumption, by reducing the number of parameters. In this analysis, the data sets of kinematic parameters of the 2DOF arm are used from [9] to validate the GRNN. In that the dynamic model is established with Newton-Euler method. By operating robot arm, we get 12 groups of sample data as the training samples. Give some small enough initialization values to the 20 weights randomly. The parameters used and the theoretical values are shown in Table 1.for both the arm i.e. link 1 and link 2.

Table 1: Data for Training

Link	M_i (kg)	P_{icx} (mm)	P_{icy} (mm)	P_{icz} (mm)	I_{icxx} (Kg mm^2)	I_{iyy} (Kg mm^2)	I_{izz} (Kg mm^2)	I_{icy} (Kg mm^2)	I_{icx} (Kg mm^2)	I_{iyz} (Kg mm^2)
1	3.12	125	0	0	1768	17914	16354	0	0	0
2	2.50	100	0	0	1414	9651	8430	0	0	0

All together for both the links 20 initial parameters are used. For training purpose 0.1 is chosen as learning rate and in each iteration the weights been updated, based on the weight the error surface and error contour has been shown in the figure 3, which normally tells about how the sum squared error , bias and weights been settled while the network is in the learning phase.

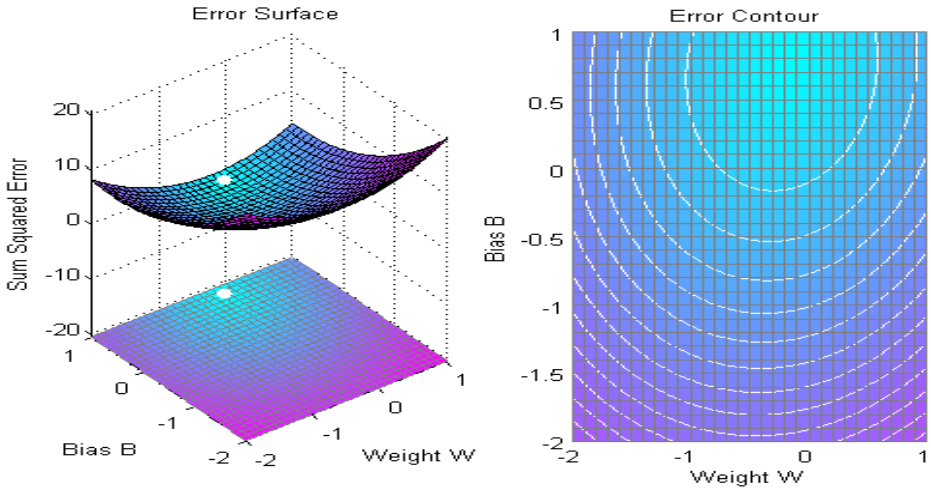

Fig. 3: Error during the Training process

Input signals for training are selected randomly at a time. The training is set for learning rate 0.01 and target error 0.001. Each network is trained with 15 input data, of each class and 30 data of each class are considered for testing. Weights are updated in each and every iteration, in this way new training input is given to the network. The randomly selected signal from 30 samples of each power quality problem is used to test GRNN. The desired output and the training, testing and validation errors are obtained from the toolbox itself is shown in figure 4. The identified results by GRNN are shown in table 2.

From the two tables, it is observed that the results are so close to the theoretical values simulated by the GRNN which can be used to have performance in real time application without running with the help of hardware. In same way the results can be obtained for updating 20 other groups of sample data. That indicates the accuracy of inertia parameters identification based on GRNN.

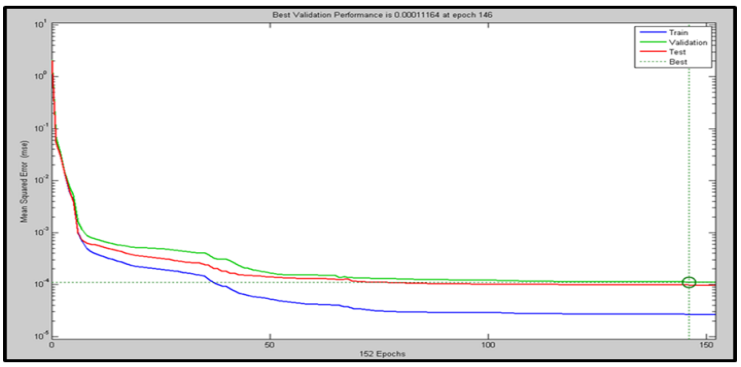

Fig. 4: Training, testing and validation

Table 2: Pridicted results

Link1	M_i (kg)	P_{icx} (mm)	P_{icy} (mm)	P_{icz} (mm)	I_{icc} (Kg mm^2)	I_{iyy} (Kg mm^2)	I_{izz} (Kg mm^2)	I_{icy} (Kg mm^2)	I_{icx} (Kg mm^2)	I_{iyz} (Kg mm^2)
1	3.11	124	0.001	0.014	1747	17867	16363	0.0014	0.006	0.0014
2	2.52	100.7	0017	0.006	1412	9632	8441	-0.022	0	0

Conclusion:

Modeling and controlling of parameters of robot arms for 2DOF was modeled by using inertia parameter considering the robotic arms dynamics and its parameter were transformed in to linear equation for to have accurate model. The Parameters involved in modeling has been improved with precisies control. Parameters were generated just by operating the robotics arms by particular degree of freedom which is been used as inputs to Generalized regression neural network for identification. Every connecting links and its inertia parameters are used as the weights for GRNN .Based on the error the weight for the GRNN were adjusted. Finally with the identification results the accurate model parameter was developed which can be used to perform any task.

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