A INVERSE KINEMATIC SOLUTION OF A 6-DOF INDUSTRIAL ROBOT USING ANN

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ABSTRACT

An inverse kinematics problem of a robotic manipulator solved using Artificial Neural network is presented. This paper represents the Inverse kinematics problem which is really intricate in nature for robotic manipulators. Many conventional methods are insufficient to find the solution, though the joint arrangement of the manipulator is more complicated , so the neural computation are used to find the joint angles to set a particular Cartesian space and direction of the end effectors. A number of end effecter position and corresponding joint angle are calculated analytically in the work volume for a robotic manipulator. The entire real-world coordinates (x, y, z) as per the angles recorded in a file named as training set of ANN model. The designed neural model has specified the correct coordinates according to the certain angles of Cartesian coordinate. By using the ANN it is very effective to know the errors in joint angles.

KEYWORDS: Inverse Kinematics, Artificial Neural Network, 6-D.O.F Industrial Robot

The ANN approaches are applied in the inverse kinematics technique leads many and particular problem. It is apposite for real time adaptive manageable of robot arm manipulators with a tolerable error. The Neural networks are competent with learning and building of complex functions, which are used in different applications like pattern recognition, approximation and fitting of data dynamic errors for checking. The Nonlinear dynamic systems are included with the robots for executing tasks repetitively. The literature confirmed the results which are found that, the neural network is valuable for various problems of inverse kinematics problem. The Artificial neural network solution of an inverse kinematics case is analyzed with addition to the background of theoretical neural representation. The neural networks are the data processing frame of interest in neuron computing. Simultaneously different sequence dispensation frame collected of a number of plain dispensation elements and to be interconnected with similar neurons like the nerve system of a human body. The fundamentals are processed and are act together locally with a bunch of inline weight connectors. The ANN arrangement trains itself in broad by the mapping and the practical association with set of participation data and consequent productivity data. The ANN model supplies up the association strength or weights linking the dispensation unit. During the learning process the weights correspond to the potency among neuron are in tune. The neural model is in contrast with establishing technique where the exact relationship between in and out to be abounding by user distinct algorithm. In this neural network behavior self-organization for tolerance of fault, association, optimization, and generalization etc. are allowed in the neural network.

RELATED WORK

Hariharan et al., [2015] developed an instantaneous inverse kinematics of odd no DOF hyper-redundant manipulator arm with a mutual arithmetical as well as methodical approach. The work presents a novel, computationally competent method of performing inverse kinematics for universal odd no of DOF manipulators with a spherical joint at the wrist. Kinematic and dynamic uncertainties found the solution. Wei et al. [2014] proposed a common move towards for inverse kinematics of nR robots. This paper uses of a semi-analytic method and a general method to solve the spatial nR robot inverse kinematics problem. It overcomes the numerical method's limits associated to accurateness. The conformal geometric space theory is used to set up general kinematic equations. Based on that, the biased breathing space vector melancholy method is used to find the relation between the angles of robot spatial rotation and the data of the space vector. Kucuk et al. [2014] developed an inverse kinematics problem for industrial robot arm with balance wrist. A new numerical algorithm is proposed for the opposite kinematics of the robot arm that cannot be solved in closed form. In direct to illustrate the presentation of the New Inverse Kinematics .A simulation results attained from NIKA are compared with those obtained from well-known Newton–Raphson Algorithm (NRA). Ras it Koker [2013] presented a genetic algorithm come close to ANN base inverse kinematics of robotic arm base on inaccuracy reduction. ANN and genetic algorithms are used to solve the problem of inverse kinematics a six-joint Stanford robotic arm to minimize the error at the end effectors'. The end-effectors' location error is to defined the suitability function, and the hereditary

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algorithm is implemented. Fahmy et al. [2013] develop Neuro-fuzzy inverse model control structure of robotic arm utilize for rehabilitation applications. They presented a new neuro-fuzzy regulator for robot arm. The inductive knowledge method is applied to make the necessary inverse model rules from in/out data set record in the off-line arrangement learn stage. The manage structure show high-quality result compare to the predictable techniques. Aggarwala et al., discussed the ANN for the improvement of an inverse kinematic problem with optical detection of spectacle zone. This method shows a non-conventional method to solve the inverse kinematics problem using ANN. The technique gives an idea to promising, since it requires little computation time over other traditional methods. Fang et al. [2015] proposed paper neural networks based adaptive decoupling control for three-axis gyro stabilized platform. The nonlinearity and coupling system is full-state-linear zed using feedback linearization, and neural networks are used to compensate for the disturbances and uncertainties. The stability of the proposed scheme is analyzed by the Lyapunov criterion. Comparative simulations and experiments results show the effectiveness of the proposed control approach compared with the conventional control.

INVERSE KINEMATICS FOR SIX AXES ROBOTS

It is very important for industrial robot manipulators to know the kinematic behaviour. To describe the kinematic model of robot arm cartesian space and joint space are generally required in the workspace. This two can be may be decomposed in form of rotation motion and a translation motion. Different path are there to represent rotation, with the following: Euler angles, Gibbs vectored. Denavit-Hartenberg algorithms require four parameters for general transformation between two joints, which may called as the Denavit-Hartenberg parameters. It becomes a standard method to describing robot kinematics. Forward kinematic solution is more easer then to the inverse kinematics problem.

$$x = f(v) \qquad (1)$$

f is known as non-linear function having frame of structure and different parameters are known. They are associates with each v a sole to x and usually an inverse mapping can have many v's related with each x. Closed form solutions and mathematical solutions are used to solve inverse and forward kinematic problem. Closed forms solved by taking the spatial geometry of manipulator and followed by the matrix of algebraic equation (1). The Mathematical technique are iterative algorithms is known as Levenberg-Marquardt (LM) and iterative in nature a mathematical solution which is generally slower than the corresponding closed form solution. This is very vital to note that the joint angle vector or the specification of the Cartesian vector can obtain with the equations (1) and (2), but to find the Cartesian velocity and acceleration we use equation (1), if f(q.) at least once differentiable, then

$$v = f^{-}(x) \qquad (2)$$

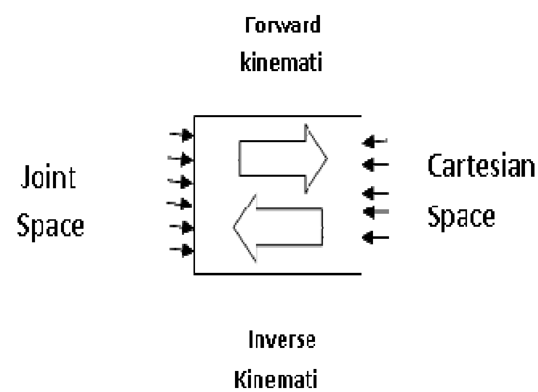


Figure 1: Kinematics architecture

$$ {}^0_6T = \begin{bmatrix} q11 & q12 & q13 & px \\ q21 & q22 & q23 & py \\ q31 & q32 & q33 & pz \\ 0 & 0 & 0 & 1 \end{bmatrix} = {}^0_1T(v1)\,{}^1_2T(v2)\,{}^2_3T(v3)\,{}^3_4T(v4)\,{}^4_5T(v5)\,{}^5_6T(v6) $$

For joint one (v1) the inverse kinematic solution have a elements of T base end-effectors, the transformation of link as follows.

$$ \left[{}^0_1T(v1)\right]^{-1}\,{}^0_6T = \left[{}^0_1T(v1)\right]^{-1}\,{}^0_1T(v1)\,{}^1_2T(v2)\,{}^2_3T(v3)\,{}^3_4T(v4)\,{}^4_5T(v5)\,{}^5_6T(v6) $$

$$ \left[{}^0_1T(v1)\right]^{-1}\,{}^0_6T = {}^1_2T(v2)\,{}^2_3T(v3)\,{}^3_4T(v4)\,{}^4_5T(v5)\,{}^5_6T(v6) $$

$$ \left[{}^0_1T(v1)\,{}^1_2T(v2)\right]^{-1}\,{}^0_6T = {}^2_3T(v3)\,{}^3_4T(v4)\,{}^4_5T(v5)\,{}^5_6T(v6) $$

$$ \left[{}^0_1T(v1)\,{}^1_2T(v2)\,{}^2_3T(v3)\right]^{-1}\,{}^0_6T = {}^3_4T(v4)\,{}^4_5T(v5)\,{}^5_6T(v6) $$

$$ \left[{}^0_1T(v1)\,{}^1_2T(v2)\,{}^2_3T(v3)\,{}^3_4T(qv4)\right]^{-1}\,{}^0_6T = {}^4_5T(v5)\,{}^5_6T(v6) $$

$$ \left[{}^0_1T(v1)\,{}^1_2T(v2)\,{}^2_3T(v3)\,{}^3_4T(v4)\,{}^4_5T(v5)\right]^{-1}\,{}^0_6T = {}^5_6T(v6) $$

Neural Networks Structures

Artificial neural networks are a type of model that can perform capably multifarious non linear system in nature. The artificial neural networks have different benefits in comparison to predict computational systems in robotics. When a artificial neural networks map the three-dimensional robot between joint angle and Cartesian space by using only a back propagation algorithm. The 6R robot is chosen as one kind industrial robot manipulator due to dimensional configuration and the robot is not permit to solve inverse kinematics problems rationally.

The ANN derived from the nerve system of a human brain. Now a day's ANN starts as an important method for sorting and optimization of different kinematic problem. It is emerge as a leading learn method to perform different multifarious odd jobs in highly nonlinear vigorous environmental problem. The ANN is appropriate for designing nonlinear mapping among the in and out data set because of its large parallel interconnection between multiple patterns and the nonlinear meting out features. The Fig. 2 shows an artificial neuron network pattern, which generally include a computing element. The total is added to bias or threshold then the resultant signal is n passed through a nonlinear function known as log sigmoid function.

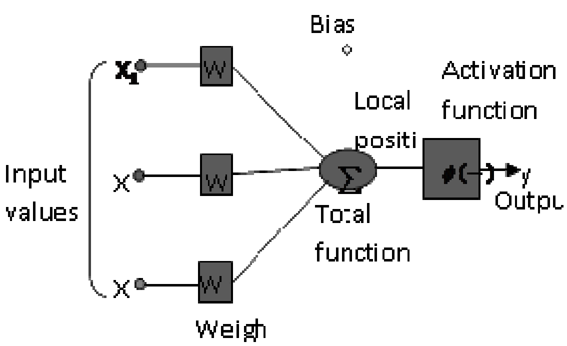


Figure 2: Artificial Neuron Network Pattern

ANN Applied on Inverse Kinematics Problem

ANN has created two problems while solving inverse kinematics of a robot arm manipulator i.e is collection of the appropriate type of artificial neural network and another one generation of perfect trained dataset. A kinematic model can develop after knowing the kinematic factors of a robot manipulator. For preparing data set experimental results gained for the manipulator are consider but it is more difficult to train it. If joint parameters are known for an industrial robot then accomplishment of this loom is measured as per the training error rate.

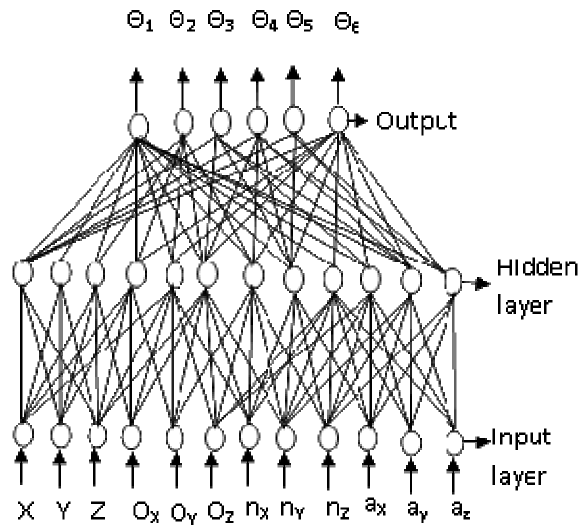


Figure 3: Three Layer Perception with six outputs

$$AHi(y) = \sum_{j=1}^{i} WTjIj + \sum_{j=1}^{n} WH_{ij} f(AHj(y-1));$$
$$i = 1,2,3 \ldots\ldots\ldots\ldots\ldots\ldots n$$

The starting function is used here in the unknown layer and the output of the network is a weighted sum of the unknown unit o/p.

$$O_i(y) = \sum_{j=1}^{n} WO_{ij} f(AH_j(y)); i = 1,2 \ldots\ldots\ldots\ldots n \quad (6)$$

$$E(y) = \sum_{p=1}^{pp} \left(\frac{1}{2} \sum_{j=1}^{n} e_{jp}(y)^2 \right) \quad (7)$$

$$E(y) = \sum_{p=1}^{pp} \left(\frac{1}{2} \sum_{k=1}^{n} \left(T_{jp}(y) - O_{jp}(y)^2 \right) \right) \quad (8)$$

SIMULATION RESULTS

The simulations are done here by using ANN with MATLAB tool box to match the input date target value i.e joint angle for industrial robot. In this analysis a 138 data sets are created and the input parameter in Cartesian position. The training and estimation the models are done here using these data sets. From the data sets having 138 data points, 99 are used as training data network, and for modernizing the desired weights. In the problem, the capacity models of the joint angles are required here as shown in Table 1. The distance between adjacent links with their ranges is mentioned in Table 2. Table 3 shows the normal positioning vector in all direction.

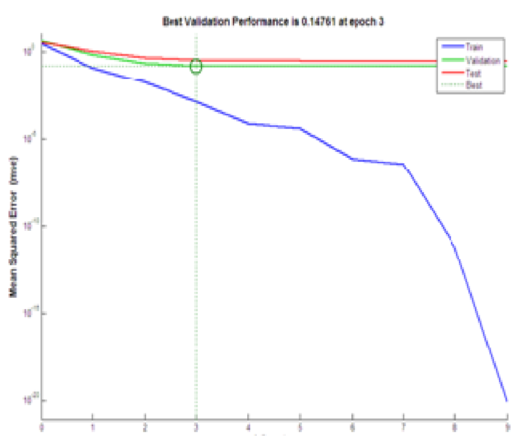
Extreme value	Range	Joint
320	(-160 to 160)	Waist Joint
220	(-110 to 110)	Shoulder Joint
270	(-135 to 135)	Elbow Joint
532	(-266 to 266)	Wrist Roll
200	(-100 to 100)	Wrist Bend
532	(-266 to 266)	Wrist Swivel

d_1	d_2	d_3	d_4	d_5	d_6
184	158	300	150	378-5	640

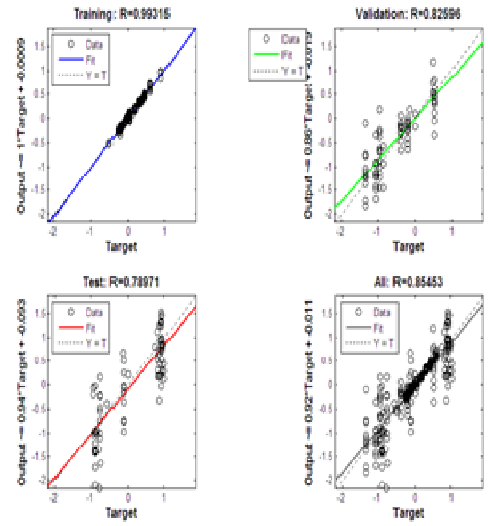
The above date set i.e. Joint angle and link parameter are calculated from the Ariosto Industrial robot which is available in our lab. For different position of the joint angle the end-effectors position are calculated .similar procedure we follow for other joint angle i.e. $\theta_1 to \theta_6$. While we change the joint angle we careful about the maximum and minimum range of it,

SIMULATION CURVE

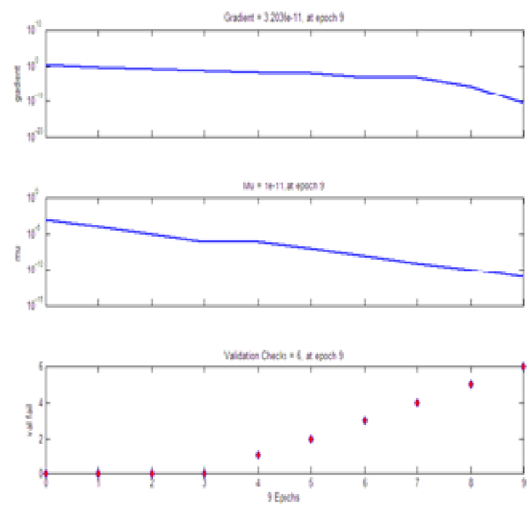
The effectiveness of neural network is analysed and 38 nodes are nominated in the unknown layer and only 20 nodes are presented in Table 3. For the θ_1 to θ_6 are symbolized in 103 epochs for mean square error model which shows in Fig.3. In this figure the best validation performance is analysed properly



It conclude that the performance of the net work is 2.87 by choosing data division and the random test performance is 350.8441e-003,train performance is 1.2368e-003 and 147.614e-003.



In Figure-4, P_x, P_y, Pz shows the training convergence graphs. From this figure it is clearly visible that convergence is achieved using very few epochs. In our case multilayer neural network structure is used. Log sigmoid function is used in the unknown layer and output layer uses a linear activation function. Twenty nos. of hidden neurons have been used for simulation



The number of epochs used in every graph and learning of the proposed network is done using Levenberg Marqdt (LM) algorithm which is very fast. Here the graph shows both input data and output data are matching each other and also vary with mean line.

RESULTS AND DISCUSSION

From the result it conclude that ANN will not give good result with less no of data set but it need more number sample data set for training to attain an satisfactory accuracy. With training 60 % of the input and output data set , the matching point will very much closer to each other. For best testing 20% of data set which are not incorporated in the training set are used and got very marginal error and for validation another 20% are data set are used. For validation of the artificial neural network calculation, the errors of joint angles for 38 test points are found near mean point. Though inaccuracy result are very near by the mean line so effective error and root mean square error is calculated for each angle i.e $\theta_1, \theta_2, \theta_3, \theta_4, \theta_5$ *and* θ_6 respectively. Here we found that the errors in θ_4 and θ_5 are found to be higher as comparison to other joint angles.

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