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ANN Approach to Solve Inverse Kinematics of Industrial Robot

Kshitish Kumar Dash[1], Jagdish Pradhan[2], Dr Prabhu Prasad Mishra[3]
[1]*Assistant Professor, Department of Mechanical Engineering, Gandhi Institute For Technology (GIFT), Bhubaneswar*
[3]*Professor, Department of Mechanical Engineering, Gandhi Institute For Technology (GIFT), Bhubaneswar*
[2] *Assistant Professor, Department of Mechanical Engineering, Gandhi Engineering College, Bhubaneswar*

ABSTRACT: An organized artificial neural-arrange (ANN) approach has been proposed here to control the movement of a robot controller. Numerous neural-organize models use edge units with sigmoid exchange capacities and angle plunge type learning rules. The learning conditions utilized are those of the back propagation calculation. In this work, the arrangement of the kinematics of a six- degrees-of-opportunity robot controller is actualized by utilizing ANN. Work has been embraced to and the best ANN congurations for this issue. Both the situation and direction points of a robot controller are utilized to the reverse kinematics arrangements.

I. INTRODUCTION

The robot control issue can be isolated into two fundamental zones: kinematics control (the coordination of the connections of kinematics chain to deliver wanted movements of the robot), and dynamic control (driving the actual- pinnacles of the system to follow the directed positions/speeds). In the essential plan methodology of a modern robot, the originator ought not just develop an optimal math for the controller, yet in addition needs to plan the control calculation, including the formulation of both the kinematics conditions and the dynamic conditions. The control techniques utilized in most robots include positions coordination in Cartesian space by an immediate/reverse kinematics strategy. Backwards kinematics (IK) contain the calculations expected to and the joint plots for a given Cartesian position and direction of the end-effectors. principal to the control of robot arms, yet it is very di • cult to compute an IK answer for a robot. It is, all in all, a non-direct logarithmic calculation, which has been appeared for the overall instance of a six- degrees-of-opportunity (DOF) arm to require the arrangement of a sixteenth-request polynomial condition. Most indispreliminary robot arms are planned so that the guideline of wrist parcelling can be utilized, where the three wrist-joint tomahawks cross at a solitary point, diminishing the issue to that of a second-request solution. IK detailing has for quite some time been an extremely intriguing favourable to problem for kinematicians. Pieper scientifically tackled the opposite issue for robots with three con- current joint tomahawks. Duey (1980) further discovered a few uncommon mathematical controllers, which can explain the same issue diagnostically. From that point forward, numerous strategies have been introduced to tackle the IK issue: Paul homogeneous change; Lee by a mathematical technique; Yang and Pennock (1985) by a double number methodology; and Tsai and Morgan (1984) by a continuation technique. Be that as it may, the issue includes the illuminating of exceptionally non-direct conditions. Numerous papers have introduced calculations giving analytically

1. The Denarit–Hartenberg method .

One of the most fundamental problems in describing a working environment in which one or more robots operate together with supporting equipment, is how to explain the relative positions of the various pieces of equipment. For example, a robot has to pick up a part from a certain location, put it down in another lo- cation, change-end eRectors by collecting a diRerent gripper from yet another location, and so on. The study of kinematics reveals that a method exists which allows these positions to be defined in a consistent and unambiguous manner. The method consists of attach- ing coordinate frames to each object or location of interest, so that when the object moves, so does the frame. In the analysis of kinematics structures consist- ing of serial links and joints, accepted methods for defining the position and orientation of one link with respect to another are in common use. In this way, the spatial orientation of quite complex kinematics struc- tures may be specified in a unified, straightforward method. The Denavit−Hartenberg method involves the allocation of coordinate frames to each link, using a set of rules to locate the origin of the frame and the orientation axes (Mooring et al., 1991). The positions of subsequent links are then defined by the homo- geneous transformation matrix, which transforms the frame attached to link i 1 into a frame fixed to link

i. This transformation is obtained from simpler trans- formations representing the three basic translations along, and three rotations about, the frames' x-, y-, and z-axes.

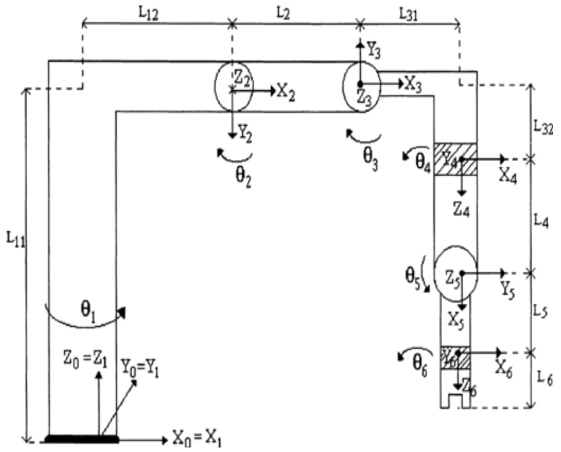

Fig.1

geneous transformation matrix, which uses four link parameters (Paul, 1981). This transformation is known as the Denavit−Hartenberg notation A = Rot(z, 8)Trans(0, 0, d)Trans(a, 0, 0)Rot(x, a).These equations show the forward kinematics that describe the position and orientation of the manipula- tor with respect to the world coordinate frame. Joint coordinate frames are used to describe the position and orientation of the manipulator.

There is no general procedure for H solution. That is why it is very useful to use an ANN. For this problem, the models of the Denavit−Hartenberg parameters used here are , where E denotes the tool frame Although the Denavit−Hartenberg model has been popular for use in the modeling of manipulator kin- ematics, several problems arise when using this model in a calibration procedure. The link coordinate frames are located at the intersection of the joint axis and the common normal. This implies that the location of these coordinate frames is a function of the manipula- tor geometry, and that small variations in this geome- try will cause these frames to shift. For example, the 'zero position' of the manipulator is not arbitrary.

ANN approaches to the inverse kinematics .

Recently, it has been shown that neural networks have the ability to solve various complex problems. IH is a transformation from a world coordinate frame (X, Y, X) to a link coordinate frame 8_1, 8_2, 8_3, 8_4, 8_5, 8_6). This transformation can be performed on input]output work that uses an unknown transfer function. This approach used here for the ANN is suitable for finding an ANN solution, and implementation.

An artificial neural network's neuron is a simple work element, and has a local memory. A neuron takes a multi-dimensional input, and then delivers it to the other neurons according to their weights. This gives a scalar result at the output of a neuron. This neuron has only one output but it can be increased. The transfer function of an ANN, acting on the local memory, uses a learning rule to produce a relationship between the input and output. For the activation input, a time function is needed (Harlik, 1994).

Studying the IH of a manipulator by using an ANN has two problems. One of these is the selection of the appropriate type of neural network, and the other is the generation of a suitable training data set (Funaha- shi, 1989). Uhen the kinematic parameters of a manip- ulator are known, then a kinematic model can be made (forward kinematics). After that, Eqs. (1) and (6) can be used to prepare the data set. These sets are used to teach the ANN. If the joint parameters are not known, then the experimental results obtained for the manipulator are used to prepare the data set. smost of the notable modern robots' joint standard ameters are known. The achievement of the ANN approach is estimated by the preparation mistake rate. For future examinations, it will be conceivable to set up the informational collections from straightforwardly the yields of sensors. One of the issues with an ANN is to decide the structure of the neural system, which requires an appraisal of the quantity of layers and the hubs in each layer. In this investigation, different neural-arrange structures have been examined, and it was discovered that when there is one yield in the yield layer and two shrouded layers in ANN, it gives better outcomes, as delineated in Fig. 2(b). Then again, where there are numerous yields in the yield layer and one shrouded layer, the ANN gives better outcomes. For both neural-organize structures, when the quantity of neurons in the covered up layer(s) is equivalent to the quantity of neurons in the info layer, the ANN creates better outcomes. As indicated by references (Hrishnaswamy et al., 1991; Hornik, 1991), depicting the hypothesis of ANN estimation, a back-propa-gation ANN will give the best guess accu-suggestive. Back-engendering was along these lines a characteristic decision as the preparation calculation for learning the reverse family. IK detailing has for some time been an extremely fascinating favorable to problem for kinematicians. Pieper (1968) scientifically most of the notable modern robots' joint standard ameters are known. The accomplishment of the ANN approach is estimated by the preparation blunder rate. For future investigations, it will be conceivable to set up the informational indexes from straightforwardly the yields of sensors. One of the issues with an ANN is to decide the structure of the ematics. Then again, a multi-layered feed-for-ward arrange has a superior capacity to gain proficiency with the correspondence between the information examples and educate ing values got from numerous information tests by methods for the mistake back-spread calculation. Along these lines, in this paper, three-layer feed-forward neural system was utilized, clarify by utilizing the mistake back-engendering calculation.

In this investigation two diRerent designs of ANN are utilized. In the main arrangement, there are 12 information neurons, 12 shrouded neurons and six yield neurons. In the subsequent design, there are 12 info neurons, 12 neurons in the primary shrouded layer, 12 neurons in the second concealed layer, and 1 yield neuron. The neural-organize design of this configur-ation is appeared in Fig. 2(a). The neurons are completely con-nected in this system. A sigmoid capacity is utilized as an exchange work among neurons, and there are 12 el-ements of the system input. The initial three of these speak to the Cartesian position (X, Y, X) .

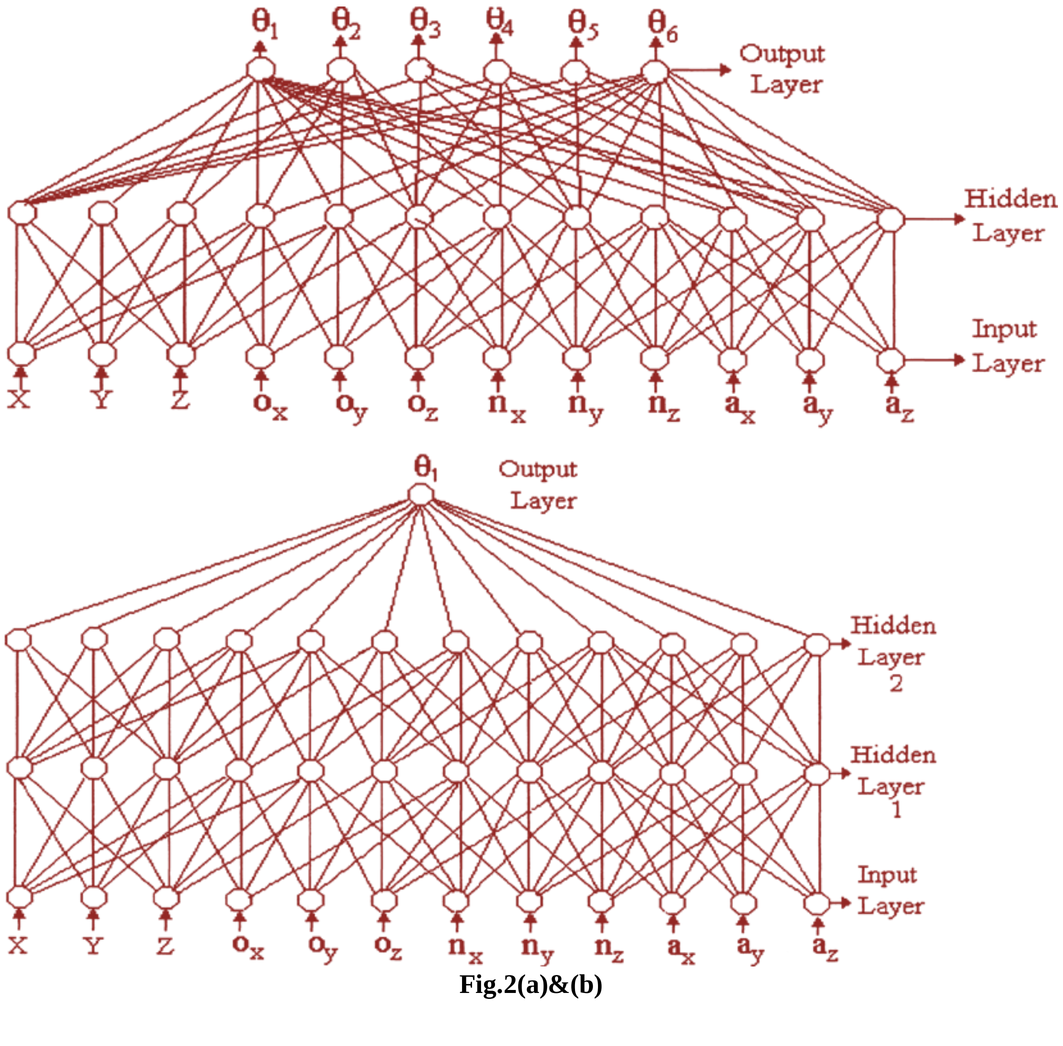

Fig.2(a)&(b)

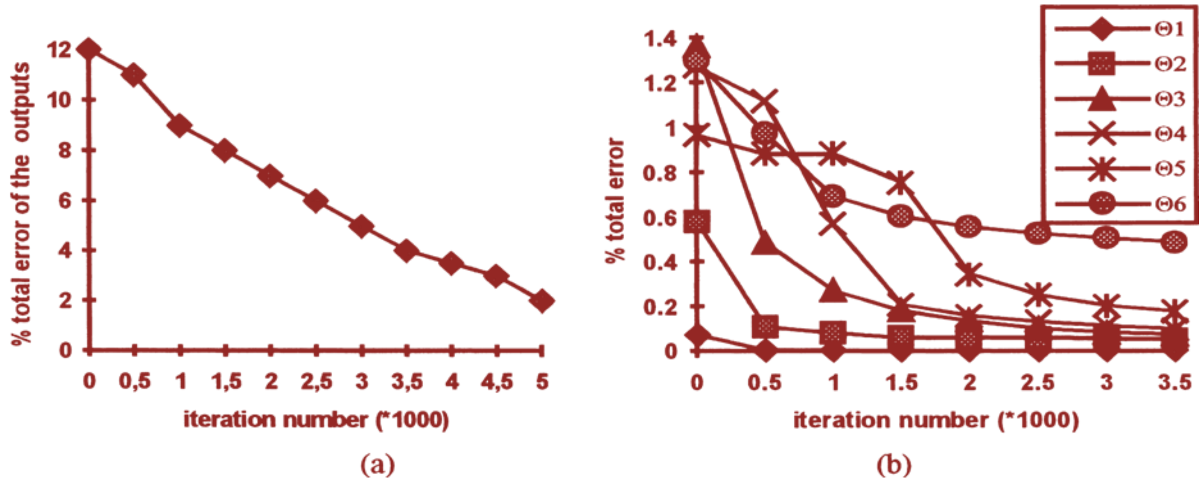

Fig-3(a) &(b)

controller as indicated by the world organize outline. The others are the nine components of the Z6 network . The RPY edges can likewise be utilized legitimately; in the event that RPY edges are utilized, at that point there will be six information standard ammeters (X, Y, X, $x, $y, $z). The encouraging informational index was set up so as to show just that an ANN can be utilized for the IH arrangement of a controller. The informational index components (inputs and out- puts) are determined from the systematic conditions as indicated by the limitations given in Table 1. For the investigative counts, a PC program has been created in the Borland C+ language. A sum of 4000 informational indexes are utilized in this paper, looked over all the potential edges of the joints. This implies an enormous informational collection was utilized in this examination. cable to the IH solution of a manipulator, and only the orientation links need to be improved further, as shown in Fig. 3(b). The results with the ANNs are bet- ter than for the other model mentioned earlier. The computation using an ANN is particularly useful where shorter calculation times are required, such as in this problem. In the future, data obtained from sensors will be able to be fed directly to the ANN, to carry out these calculations.

II. CONCLUSIONS

An appropriate computer program has been developed in the Borland C++ language for the ANN architectures considered in this study. Iterations were performed on a PC P-90 computer, and 6000 iterations were used for teaching the ANN. In Fig. 3(a) and (b) the mean teaching errors are given for the first and second configurations, respectively. Fig. 3(a) involves all of the link angles. As shown in Fig. 3(b), the position link values.

As a result, this study shows that ANNs are appli- cable to the IH solution of a manipulator, and only the orientation links need to be improved further, as shown in Fig. 3(b). The results with the ANNs are bet- ter than for the other model mentioned earlier. The computation using an ANN is particularly useful where shorter calculation times are required, such as in this problem. In the future, data obtained from sensors will be able to be fed directly to the ANN, to carry out these calculations.

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