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Inverse Kinematics of an Anthropomorphic Robotic Hand

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ABSTRACT

Solution of inverse kinematic equations is a complex problem, the complexity comes from the nonlinearity of joint space and Cartesian space mapping that has multiple solutions. This is a typical problem in robotics where it is required to control the fingers of an anthropomorphic robotic hand to perform the tasks, it is designated to do. Multi-fingered hands having multiple joints on every finger, creates more complexity to such problems making it theoretically intractable. This work is intended to capture the problem through use of ANFIS (Adaptive Neuro-Fuzzy Inference System) that needs limited mathematical expressions and gives reasonable good solution through number of iterative steps, which can be practically implemented. This method proves to be efficient, fast and has shorter response time. The proposed method has number of advantages such as ease of implementation time and better response with acceptable errors.

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1. INTRODUCTION

One of the major challenges faced by the researchers in design of multi-fingered robot hand is attaining greater autonomy and dexterity of the hands in the manipulation of objects. Each multi-jointed finger of a robotic hand can be regarded as an individual manipulator and hence a five-fingered hand may be regarded as a set of five manipulators in synchronise. These are required to be controlled as a single set to perform a given task. The fingertip position control is considered as one of those control schemes that achieve the contact position with the object using the inverse kinematics model. The soft contacts as in case of human hand are defined as a small area rather than a point [1]. Using this kind of contact, the required inverse kinematics system does not need to be too precise. However, the inverse kinematics scheme must be fast enough to allow the real time implementation.The inverse kinematics determines the joint variables that would result in a desired position of the end-effector of the manipulator with respect to a reference coordinate system. The inverse kinematics solution is difficult since the mapping between the joint space and Cartesian space isnon-linear and involves transcendental equations having multiple solutions. A unique solution may be obtained in such cases if a performance criterion, like total joint displacement minimization, is incorporated in the solution scheme.

During the late 80's and early 90's, the calculation of theinverse kinematics of manipulators has been widely studied. These studies provide several theoretical concepts such as the ill-conditioned Jacobian matrix. Physically, this means that the manipulator is at singularity configuration or in its neighbourhood. In this situation, a small deviation in the Cartesian space provides a high change in joint space variables which is not desirable. It is extremely important to ensure a good behaviour of the manipulator in this critical configuration. The different techniques used for solving inverse kinematics can be classified as algebraic [2], geometric [3] and iterative [4]. The algebraic methods do not guarantee closed form solutions. In case of geometric methods, closed form solutions for the first three joints of the manipulator must exist geometrically. The iterative methods converge to only a single solution depending on the starting point and will not work near singularities.If the joints of the manipulator are more complex, the inverse kinematics solution by using these traditional methods is quite time consuming. In other words, for a more generalized *m* degrees of freedom manipulator, traditional methods will become prohibitive due to the high complexity of mathematical structure of the formulation. To compound the problem further, robots have to work in the real world that cannot be modelled concisely using mathematical expressions.

There are several methods for solving Inverse Kinematics problemsin which Fuzzy Inference Systems are the most popular constituent of the soft computing area since they areable to represent human expertise in the form of IF antecedent THEN consequent statements. In this domain, the system behaviour is modelled through the use of linguistic descriptions. Although the earliest work by Prof. Zadeh on fuzzy systems has not been paid as much attention as it deserved in early1960s, since then the methodology has become a well-developed framework. The typical architectures of fuzzy inference systems are those introduced by Wang [5], [6], Takagi and Sugeno [7] and Jang [8]. In the work of Korein et al. [4], a fuzzy system having Gaussian membership functions, product inference rule and weighted average defuzzifier is constructed and has become the standard method in most applications. Takagi and Sugeno [7] change the defuzzification procedure where dynamic systems are introduced as defuzzification subsystems. The potential advantage of the method is that under certain constraints, the stability of the system can be studied. Yangsheng Xu, and Michael C. Nechgba [9], discusses the automatic genexafion of the Fuzzy Inverse Kinematic Mapping (FIKM) from specification of the DH parameters, the efficiency of the scheme in comparison to conventional approaches, and the implementation results for both redundant and non-redundant robots. Ramakrishnan M. [10] presents a novel single-pass algorithm that is fast and eliminates problems related with improper and large angle rotations. E. Sariyildiz and H. Temeltas [11], present a formulation based on screw theory with dual-quaternions for both forward and inverse kinematic equations. P. Kalra et al. [12] use real-coded genetic algorithms to obtain the inversekinematics solution of an articulated robotic manipulator. Samual R. Buss [13] discuss the solutionof inverse kinematic with jacobian transpose, pseudo inverse and damped least squares methods. Takehiko Ogawa and Hajime Kanada [14], propose a network inversion as a methodfor solvinginverse kinematics problem of a robot arm with multiple joints, where the joint angles areconjectured from the given end-effector coordinates.

2. KINEMATIC MODEL OF THE HAND

The multi-fingered robot hand acts as a multipurpose gripping device for various tasks. Since it is designed to mimic the human hands, most anthropomorphic robot hands duplicate the shape and functions of human hands. The anthropomorphic structure of a human hand is shown in Figure 1. The finger segments in human hand give us the inspiration to design an independently driven finger segment to construct a whole finger.

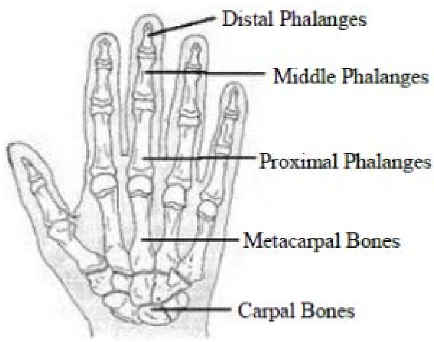

Figure 1. Anatomical View of Human hand

The structure of the proposed anthropomorphic robot hand is similar to that of a human hand as shown in Figure 2. The segmental lengths of the thumb and fingers are taken proportionately to hand length and hand breadth with a fixed wrist. Typically the hand motion is approximated to have 27 DoFs. In the present study only 25 DoFs are considered. The thumb is modeled with 5 DoFs. The index and middle fingers are modeled with 4 DoFs each. The ring and little fingers are modeled with 6 DoFs each considering two degrees of freedom each at Carpometacarpel (CMC) joint for palm arch. The Trapeziometacarpal (TM) joint, all five Mecapophalangeal (MCP) joints and two CMC joints are considered with two rotational axes each for both abduction-adduction and flexion-extension. The Interphalangeal (IP) joint on the thumb, the Proximal-Interphalangeal (PIP) and Distal- Interphalangeal (DIP) joints on the other four fingers possess 1 DoF each for the flexion-extension rotational axes. Figure 2 illustrates the proposed hand model while the parameters of the thumb and other fingers are given in our earlier paper [15].

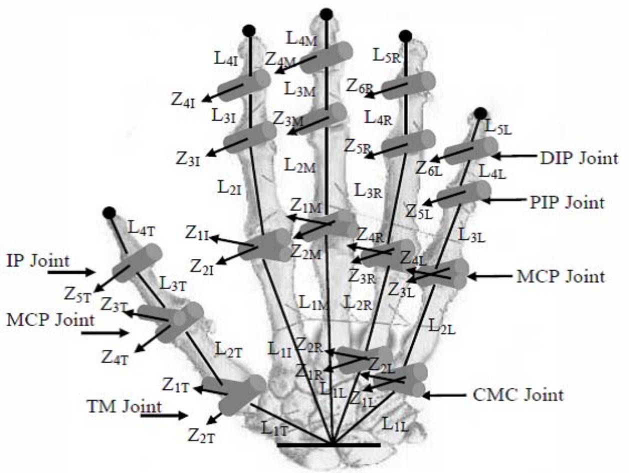

Figure 2. Kinematic Model of the proposed hand

2.1. Anthropometric Data and Joint Limits

It is difficult to get the exact anthropometric data for the segmental lengths of the human hand due to the fact that the shape and sizes of the human hand vary in an appreciable manner. However, for the purpose of our study, we have considered standard formulae such as given in Table 1 and Table 2.

Table 1. Segment Length for Metacarpal Bones

Finger	Metacarpal bones	Link
Thumb	$0.251*HL$	L_{2T}
Index	$\sqrt{(0.374*HL)^2+(0.126*HB)^2}$	L_{2I}
Middle	$0.373*HL$	L_{2M}
Ring	$\sqrt{(0.336*HL)^2+(0.077*HB)^2}$	L_{2R}
Little	$\sqrt{(0.295*HL)^2+(0.179*HB)^2}$	L_{2L}

Table 2. Segment Length for Phalangeals

Finger	Proximal	Link	Middle	Link	Distal	Link
Thumb	$0.196*HL$	L_{3T}	-	-	$0.158*HL$	L_{4T}
Index	$0.265*HL$	L_{3I}	$0.143*HL$	L_{4I}	$0.097*HL$	L_{5I}
Middle	$0.277*HL$	L_{3M}	$0.170*HL$	L_{4M}	$0.108*HL$	L_{5M}
Ring	$0.259*HL$	L_{3R}	$0.165*HL$	L_{4R}	$0.107*HL$	L_{5R}
Little	$0.206*HL$	L_{3L}	$0.117*HL$	L_{4L}	$0.093*HL$	L_{5L}

Where HL is Hand Length and HB is Hand Breadth [15] similarly the angle limits for different joints considered from our earlier work [15].

2.2. Kinematics Analysis

Forward kinematics is used to determine the position and orientation of the proposed hand model with respect to fixed point i.e. wrist. In order to do this a kinematic model is developed using the joint angles, the fingertip position in the palm frame is calculated with respect to MCP joints of Middle and Index finger, TM joint of thumb and CMC joint of ring and little finger. The DH method is implemented to determine the DH parameters for all the fingers which are tabulated and given in our earlier work [15]. The global coordinate system for hand is located in the wrist as shown in Figure 2. The transfer from a reference frame to the next one the general expression of the matrix can be written as follows:

$$ {}^{i-1}T_i = \begin{bmatrix} \cos q_i & -\sin q_i \cos\alpha_i & \sin q_i \sin\alpha_i & L_i \cos q_i \\ \sin q_i & \cos q_i \cos\alpha_i & -\cos q_i \sin\alpha_i & L_i \sin q_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1) $$

Where, i= Joint Number

T= Transfer matrix at a particular joint.

q= Joint angle.

α= Link twist angle.

L=Link or finger segment length.

d= Joint distance

By multiplying the corresponding transfer matrices of joints of each finger as presented:

$$ {}^{0}T_n = {}^{0}T_1\, {}^{1}T_2\, {}^{2}T_3 \cdots\cdots\cdots {}^{n-1}T_n \quad (2) $$

Where, n = Number of joints in one finger.

Hence by multiplying the corresponding transfer matrices written for every finger as in Equation (2), the kinematic equations describing the fingertip motion with respect to the local co-ordinate system (situated at TM joint of thumb, MCP joint of index and middle finger and CMC joint of ring and little finger) can be determined. While drawing analogy with a manipulator, the fingertip is considered as the grasping element of the hand. Hence, it is necessary to know the fingertip positions of all the fingers by solving the forward kinematic equations of the fingers. In the present problem there are five fingers including the thumb which are move simultaneously to grasp a desired object. Therefore all these fingers must have a common reference system for tracking the position of the fingertips which are supposed to make simultaneous movements. This is done by transferring reference system to that of the wrist which is considered to be fixed for the sake of convince in calculation. Equation (3) can be used for transferring every incidental finger matrix to the wrist reference system.

$$ {}^{0}T_1 = \begin{bmatrix} \cos\gamma_i & -\sin\gamma_i & 0 & L_i \cos\gamma_i \\ \sin\gamma_i & \cos\gamma_i & 0 & L_i \sin\lambda_i \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3) $$

Where: γ_i is the angle of the i^{th} finger with respect to reference axis [15].

L_i is the length of metacarpal bone of the i^{th} finger.

The equations so obtained have ben coded in MATLAB and the fingertip positions of all the fingers together have been traced. The loci of these points may also be considered as the workspace of the hand as a whole. From the result obtained by solving the forward kinematic problem, three different data sets are prepared for the purpose of training, testing and checking of the ANFIS structure for prediction and validation of the said structure.

3. ANFIS STRUCTURE

In order to activate and cause motion to them for grasping an object, it is essential to incorporate the inverse kinematics in to the motion program of the hand. Since the inverse kinematics does not have a unique solution, incorporating the inverse kinematics as such may not result in the desired and correct configuration of the fingers which is required for grasping and subsequent handling the objects for the intended task. Therefore it is essential that the fingers may be trained in a correct manner and then be allowed to move using the inverse kinematics logic for its proper functioning. As an obvious option neural network techniques may be gainfully utilized for getting such results. From the study of previous literature imperative thatthe neural network alone does not give the correct results due to restrictions of the results such as; only selected inverse kinematics solutions are acceptable and 100% training of the data is not possible. These have to be quite a large number of interpolation and extrapolation. Hence hybridizing this with fuzzy-inferencing should yield better result under the set conditions. Since ANFIAS (Adaptive Network-based Fuzzy Inference System) developed by Jang [16] can handle non-linear functions in even online mode, the same has been employed here to do away with complicated mathematical equations and obtain acceptable values for the desired tasks. ANFIS uses a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference system using the training input output data. The learning algorithm tunes the membership functions of a Sugeno-type Fuzzy Inference System using the training input-output data. In the present case, the input-output data refers to the coordinate-angle data base. The coordinates act as input to the ANFIS and the angles act as the output. The learning algorithm teaches the ANFIS to map the coordinates to the angles through a process called training. At the end of training, the trained ANFIS network would have learned the input-output map and get ready to be deployed into the larger control system solutions. The architecture of ANFIS structure selected for the problem is shown in Figure 3, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. The end-effecter position (X, Y, Z) are the inputs and the outputs are the joint variables angles. Among FIS models, the Sugeno fuzzy model is applied because it's high interpretability and computational efficiency. The learning algorithm tunes the membership functions using the training input-output data. Implementation of a representative fuzzy inference system using a BP neural network like structure. The fuzzy ifthenrules are expressed as:

If x is A and y is B and z is C then K= px + qy + sz + r

Where A, B and C are the fuzzy sets in the antecedent, and p, q, s and r are the design parameters that are determined during the training process.

The ANFIS architecture comprises of five layers. The role of each layer is briefly presented as follows:

Leto_i^ldenote the output of node i in layer l, and $x_i$is the i^{th}input of the ANFIS,

$i = 1;2;\ldots\ldots; p$ [17].

Layer1:

Every node i is employ a node function R given by:

$$O_i^1 = R_i(x_i)$$

Where $R_i$can adopt any fuzzy membership function (MF).

Layer 2:

Every node calculates the firing strength of a rule via multiplication:

$$O_i^2 = w_i = \min\,(R_i)$$

Where $w_i$represent the activation level of a rule.

Layer 3:

Fixed node i in this layer calculate the ratio of the ith rules activation level to the total ofall activation level:

$$O_i^3 = \overline{w}_l = \frac{w_i}{\sum_i w_i}$$

Where $\overline{w}_l$is referred to as the normalized firing strengths.

Layer 4:

Every node i has the following function:

$$O_i^4 = \overline{w}_l k_i = \overline{w}_i(p_i x + q_i y + s_i z + r_i)$$

Where $\overline{w}_l$ is the output of layer 3, and (p_i, q_i, s_i, r_i) are the parameter set. The parameters inthis layers are referred to as the consequence parameters.

Layer 5:

The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$O_i^5 = \overline{w}_l k_i = \frac{\sum_i \overline{w}_l k_i}{\sum_i w_i}$$

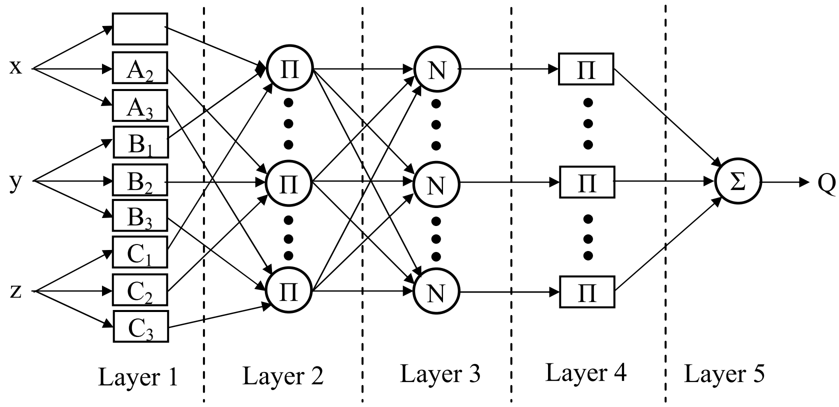

Figure 3. Neuro-fuzzy (ANFIS) architecture

ANFIS distinguishes itself from normalfuzzy logic systems by the adaptive parameters, i.e., in the way that both the premise and consequent parameters a readjustable. The most remarkable feature of the ANFIS is its hybrid learning algorithm. The process is carried out using the ANFIS toolbox of MATLAB and is presented by a flowchart in Figure 4.

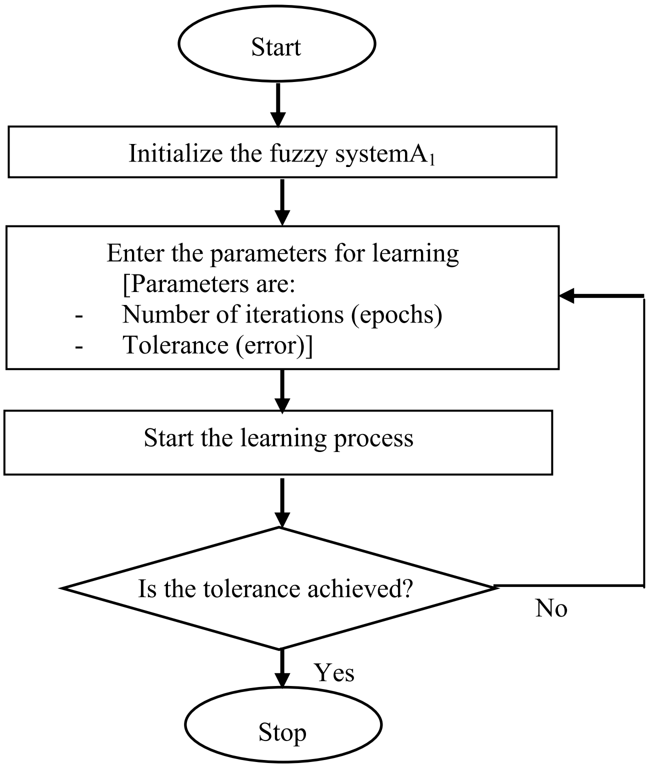

Figure 4. Flow chart for computations in ANFIS

The adaptation process of the parameters of the ANFIS is divided into two steps. For the first step of the consequent parameters training, the Least Squares method (LS) is used, because the output of the ANFIS is a line arc ombination of the consequent parameters. The premise parameters are fixed at this step. After the consequent parameters have been adjusted, the approximation error is back-propagated through every layer to update the premise parameters as the second step. This part of the adaptation procedure is based on the gradient descent principle, which is the same as in the training of the back propagation (BP) neural network. The consequence parameters identified by the LS method are optimal in the sense of least squares underthe condition that the premise parameters are fixed. Therefore, this hybrid learning algorithm is more effective than the pure gradient decent approach, because it reduces the search space dimensions of the original back propagation method. The pure BP learning process could easily be trapped into local minima. When compared with employing either one of the above two methods individually, the ANFIS converges with a smaller number of iteration steps with this hybrid learning algorithm.

4. SIMULATION AND RESULTS

Twenty five different ANFIS structures are designed for the simulation, for solving the inverse kinematics parameters of the 25-DOF proposed anthropomorphic hand model. Each structure having seven Gaussian membership functions in each input and 43 rules in the second layer. MATLAB 8 is used to implement the simulation code using ANFIS editor command. The ANFIS editor display is shown in Figure 5, which consists of 4 main sub displays as: Load data, Generate FIS, Train FIS and test FIS.

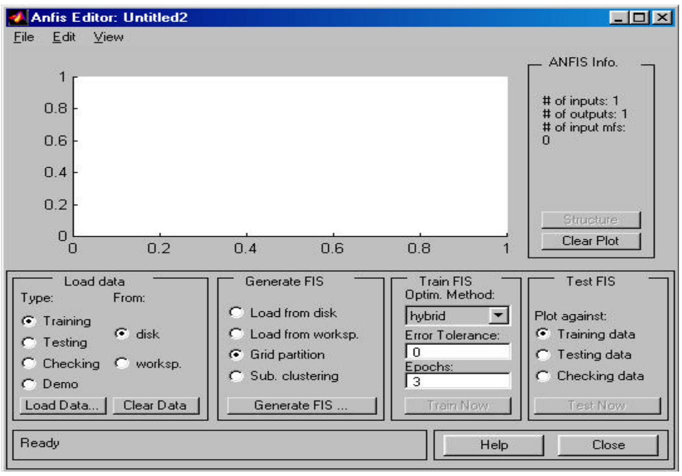

Figure 5. ANFIS editor display in MATLAB

Load data: Here the different type data such as training data, testing data and checking data are loaded into the system for the purpose of training, testing and checking the proposed structure. In the present case the data sets are generated using the forward kinematic and loaded input as coordinate of fingertip position and output as joint angle.

Generate FIS: Once data have been loaded, an initial fizzy interface system (FIS) can be generated using generate FIS. In this stage the number and type of membership function (MF) will vary to get the better FIS structure. In the present case seven number of MF, gussian type input MF and linear output MFs are chosen.

Train FIS: The main computing occurs in the Training block. Here the hybrid algorithm is used. The tolerance (Error) is at 0 by default. In practice, a complete fit is not achieved, hence it changed to 0.01. In the present case the epoch value is chosen to be 100. Now the system is ready for training. By clicking “Train now” option the FIS structure is trained as per the given training data set.

Test FIS: Here the performance of FIS can be tested against the testing data set. It will give the testing error. In this case 300 to 700 data are taken for training the FIS for thumb and fingers depending on the number of joints and 1000 to 1800 data are taken for testing.

After completion of the above four steps with very minimum acceptable testing error the FIS structure is ready for use this procedure is repeated for all 25 joint angles and 25 FIS structures are finalized, which are used for predicting the value of all 25 joint angles for a given position coordinate. Finally, the checking dataset is use for predicting the value of all joint angles for given position as inverse kinematic problem and the difference in the value of deduce value and predicted value is calculated using MATLAB programmer. The thumb consists of 5 DoFs and for all 5 joint angles i.e. q1, q2, q3, q4 and q5 the difference in the deduced value and predicted is calculated and is shown in five sub plots in Figure 6.

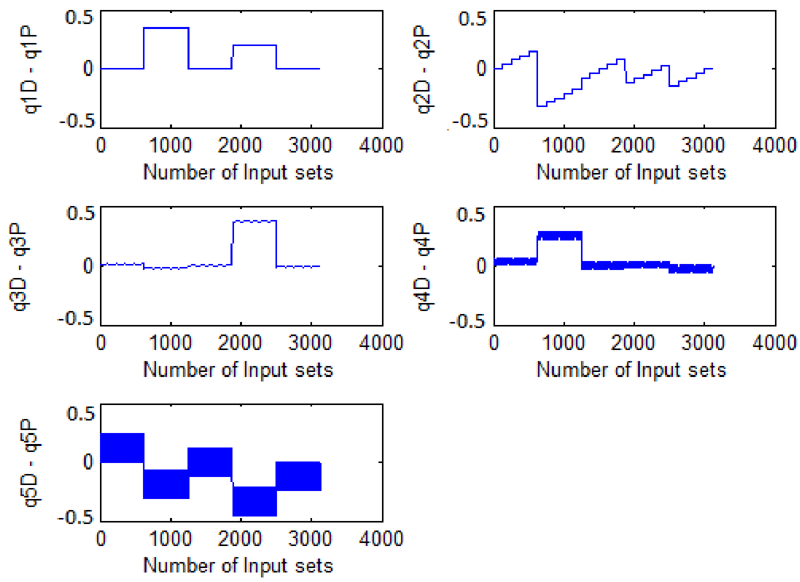

Figure 6. Difference in deduced values and predicted values for different joint angles of Thumb

The Index finger consists of 4 DoFs, the difference in deduced value and predicted value using trained ANFIS structure of all four joint angles i.e. q6, q7, q8 and q9 are calculated and the values are plotted in 4 sub plots as shown in Figure 7.

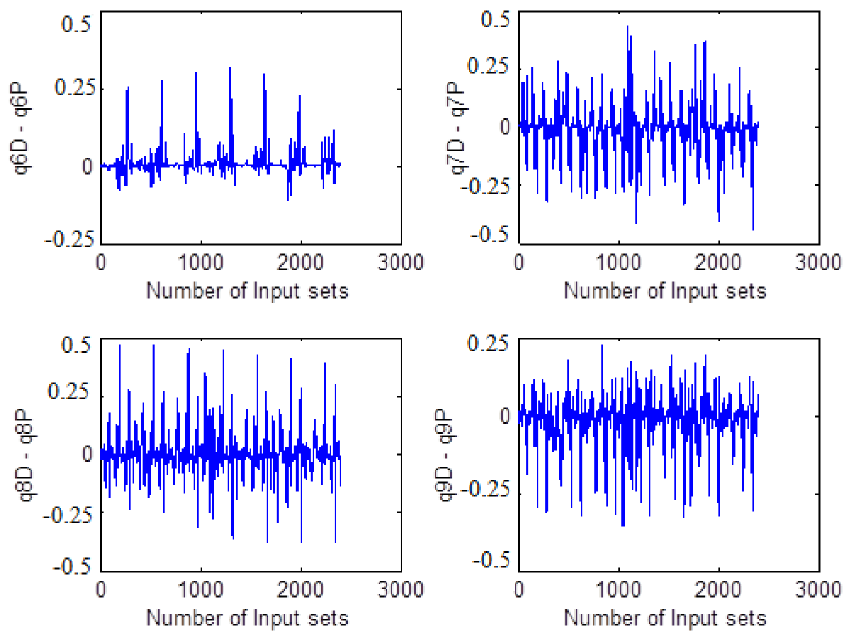

Figure 7. Difference in deduced values and predicted values for different joint angles of Index finger

The middle finger also consists of 4 DoFs like index finger and the difference in deduced value and predicted value for all four joint angles i. e. q10, q11, q12 and q13 of the proposed hand model are calculated and the values are plotted in 4 sub plots as shown in Figure 8.

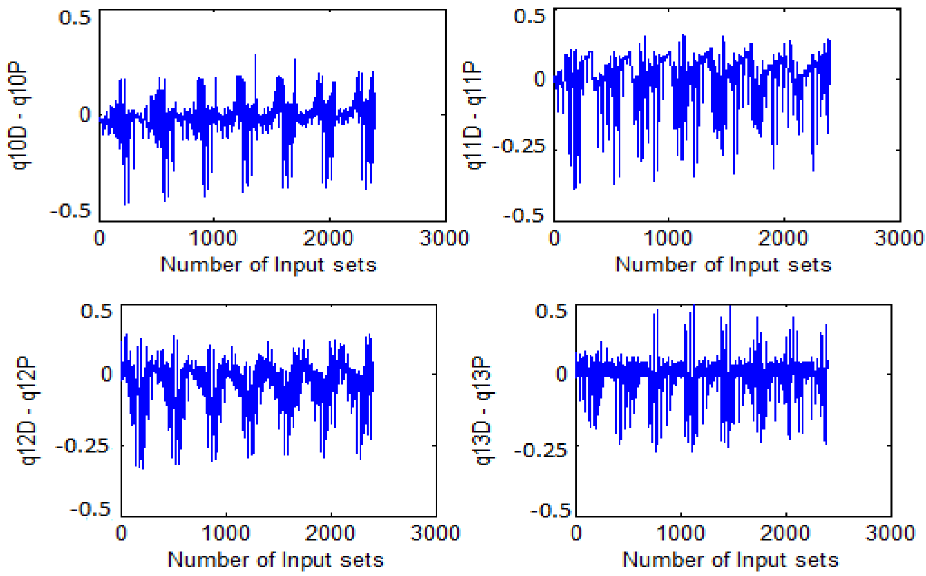

Figure 8. Difference in deduced values and predicted values for different joint angles of Middle finger

The ring finger consists of 6 DoFs in the proposed hand model and the difference in deduced value and predicted value for all six joint angles i. e. q14, q15, q16, q17, q18 and q19 are and the values plotted in 6 sub plots as shown in Figure 9.

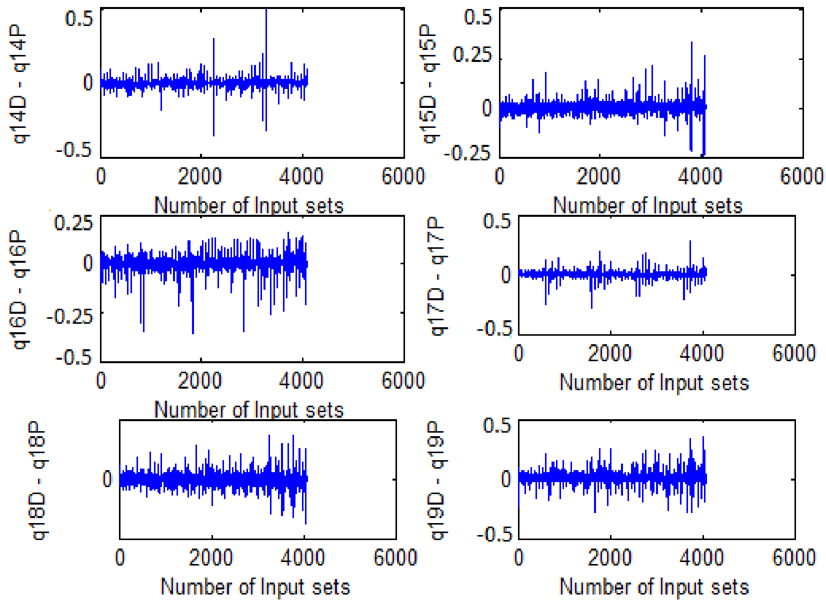

Figure 9. Difference in deduced values and predicted values for different joint angles of Ring finger

The little finger consists of 6 DoF like ring finger, so the difference in deduced value and predicted value using trained ANFIS structure for all six joint angles i. e. q20, q21, q22, q23, q24 and q25 of the proposed hand model are calculated and the value plotted in 6 sub plots as shown in Figure 10.

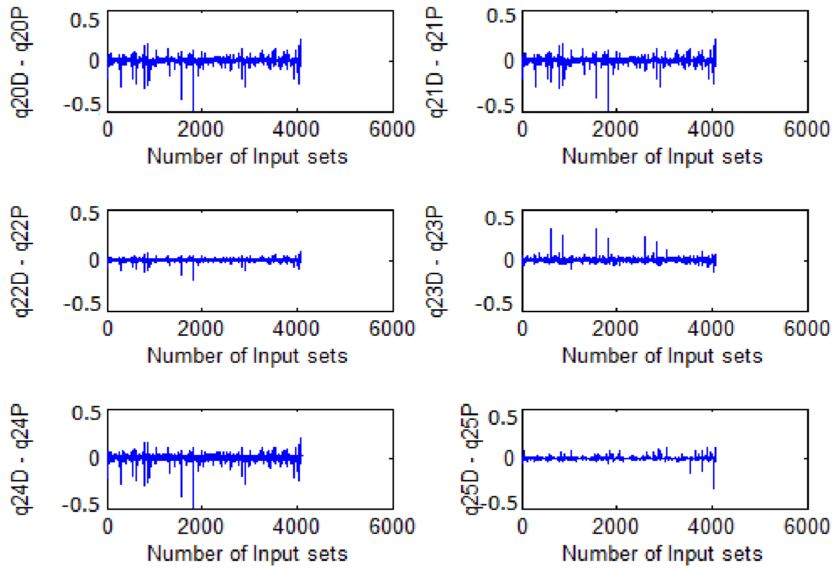

Figure 10. Difference in deduced values and predicted values for different joint angles of Little finger

5. CONCLUSION

The solution of inverse kinematics problem for a multi jointed finger of robotic hand is never unique. The set of solutions obtained through any known method essentially gives the various postures by which the end point (fingertip) can locate itself to the desired position. However, all these postures may not be acceptable for practical purposes considering the tasks and associated environment. Although, mathematical equations can produce all possible solutions to a problem, it will be difficult to short out the feasible one out of the lot. Therefore a programmatic method of obtaining the feasible set of values can be a better option. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is one such tool which has the capability of handling such problems and yielding desired results within the acceptable limits provided, the selection of its structure and the training process is carefully done. The difference in deduced value of the angle ‘q’ and the data predicted with ANFIS trained for all 25 joint angles of the proposed anthropomorphic hand model clearly depicts that the proposed method results in an acceptable error. As shown in Figure 6, Figure 7, Figure 8, Figure 9 and Figure 10 for all 25 joint angles the difference value is within the range of -0.5 to 0.5, which is very minimum error. Also the ANFIS converges with a smaller number of iteration steps with the hybrid learning algorithm. Hencetrained ANFIS can be utilized to provide fast and acceptable solutions of the inverse kinematics there by making ANFIS as an alternate approach to map the inverse kinematic solutions. Other techniques like input selection, tuning methods and alternate ways to model the problem may be explored for reducingthe error further.

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