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DIRECT INVERSE ROBOT CALIBRATION USING CMLAN (CEREBELLAR MODEL LINEAR ASSOCIATOR NET)

D. Y. Choi and H. Hwang*

Robotics Lab.
Automation Eng. Dept.
Korea Institute of Machinery and Metals, Korea

*Robotics & Automation Lab.
Dept. of Agricultural Machinery Eng.
Sung Kyun Kwan Univ., Korea

ABSTRACT

Cerebellar Model Linear Associator Net(CMLAN), a kind of neuro-net based adaptive control function generator, was applied to the problem of direct inverse calibration of three and six d.o.f. PUMA 560 robot. Since CMLAN autonomously maps and generalizes a desired system function via learning on the sampled input/output pair nodes, CMLAN allows no knowledge in system modeling and other error sources. The CMLAN based direct inverse calibration avoids the complex procedure of identifying various system parameters such as geometric(kinematic) or nongeometric(dynamic) ones and generates the corresponding desired compensated joint commands directly to each joint for given target commands in the world coordinate. The generated net outputs automatically handles the effect of unknown system parameters and dynamic error sources. On-line sequential learning on the prespecified sampled nodes requires only the measurement of the corresponding tool tip locations for three d.o.f. manipulator but location and orientation for six d.o.f. manipulator. The proposed calibration procedure can be applied to any robot.

1. INTRODUCTION

Engineering manipulator control problems have serious computational shortcomings in comparison with the simple or complex motor behavior performed by biological organisms. In spite of its high complexity for the trivial action performed by ordinary organisms, it is almost certain that biological organisms do not solve or model the complex mathematical formulation for such complicated behavior. Instead, it seems that biological organisms use some form of memory driven control system.

Anatomical and neurophysical study of the cerebellum has led to a theory concerning the functional operations of the cerebellum. Cerebellar Model Articulation or Arithmetic Controller(CMAC) proposed by Albus[1-5] is a schematical approximate modeling of information processing characteristics of the cerebellum. From the analysis and comparison of the CMAC net with the linear associator which is one of well known neural net models, CMAC is renamed as CMLAN(Cerebellar Model Linear Associator Net). Through a series of storages or learnings CMLAN works as a computational module generating weights in a distributed table look-up manner connected in parallel. Researches on CMLAN based control applications can be found in the references [1,2,6-8]. Details on the structural and functional characteristics of CMLAN refers to Hwang[9].

On the other hand, many researchers have attempted to solve various robot control problems by applying and modifying well known neural net models. A generalized back propagation(BP) delta rule is utilized as one of the dominent basic nets. In solving a robot inverse kinematic control problem, though it showed favorable results as expected from the privilege of the BP net[10-13], the kinematic accuracy of learned results obtained from BP was poor to use as direct joint commands. However, CMLAN gave excellent performance and could be used as a proper control function generator[9].

For a robot calibration, Shamma[14] attempted an inverse robot calibration using CMLAN, but failed stating CMLAN is not suitable as an approximation device for higher order surfaces because of its discrete linear interpolating property. Since CMLAN is a kind of linear associator which is one of well known neural nets it is true that it shows a discrete linear interpolating behavior from the property of generalization. However, CMLAN can approximate successfully higher order nonlinear function by introducing several sub-CMALANs and adjusting the CMLAN input space. The required number of discrete points situated between the training points can be properly controlled via adjusting CMLAN input offset and the size of quantizing block according to the task requirement.

In this paper, simulated results of successful CMLAN based direct inverse calibration for three and six d.o.f. PUMA 560 manipulator and applied learning strategy were presented.

2. INVERSE ROBOT CALIBRATION

Robot calibration is a process which minimizes the worktool location error and gets much more importance as robot off-line task teaching increases. Off-line task programming improves the production rate and can easily access partial robot route change. Moreover it can adopt the CAD/CAM data directly. However, it has a problem of total dependence of its performance on the worktool positional accuracy.

The worktool positioning error is mainly caused by the model difference with static and dynamic effect between the internal robot controller and actual robot. A model used for the internal robot controller is called a nominal model and it can not avoid errors due to the unmodeled or incomplete phenomena in the actual. Calibration requires a certain way of measuring worktool position and is usually divided into forward and inverse.

Forward calibration is understood similarly as forward kinematics such that given set of joint commands it is a problem of finding the actual worktool position. Forward calibration involves modeling, measurement, identification, and compensation.

Identification is determining kinematic and /or dynamic parameters of functional relationship(model) between joint tranceducer readings and actual end-effector positions. Compensation is correcting joint variable commands according to the identified parameters to position the worktool accurately. Researches on various process of forward calibration can be found in many references[17-21]. They all have a significant difficulty when modeling of nongeometric or dynamic parameter error is considered.

On the other hand, inverse calibration is finding set of joint commands from given worktool positions. Shamma[14] stated well about the privileges of inverse calibration over forward calibration and other relative works on this field.

In Shamma's work, modeling of inverse calibration process was avoided using a black box method because the inverse modeling is in fact almost impossible. By evaluating the coefficients of approximate function of each joint which does a curve fitting of the errors observed between desired and actual worktool locations, inverse calibration was performed. As an approximating function, multivariable orthonormal polynomials were used, and the data points were selected via method of Tchebychev spacing.

Kozakiewicz and et. al.[22] attempted to reduce the locational error caused by the static deflection of a four d.o.f. direct drive SCARA robot under loading using a variational approach of Shamma's. Least square approximation of multivariate polynomial function was used to fit the joint correction data and for interpolation. The joint correction value is function of variables such as nominal joint angle, arm tip load, and moment. The degree of polynomial was determined in an ad hoc basis. The calibration was performed in the partial(approximately 15%) workspace ,which denotes standard working area.

They also attempted BP to store the joint correction data. Relatively poor result was obtained compared to the least square approximation method.

Takanashi[23] implemented BP to improve the absolute positioning accuracy of six d.o.f. PUMA robot. Two sets of two dimensional endpoint was used as a reference data for learning. Deviation between the actual and ideal model was specified using only the differnce of the shoulder link. The orientation was fixed during the learning and net performance test.

...There is a difficulty in comparing the performance of the calibration methods mentioned above and this paper's scheme because the actual and nominal arm models of simulated robot and testing condition is different. However, it is true BP with relatively small size of processing elements is not proper to a desired function generator. BP has an inherent local minima problem and long cpu time for learning as processing elements gets greater.

On the other hand, CMLAN method in this paper is the simplest and it shows excellent calibration performance because it does not require any coefficient determination of polynomial approximation function and any system modeling.

2.1 CMLAN Based Inverse Direct Calibration

First, it is allowed to assume the positional error of worktool caused by the kinematic and dynamic difference between the nominal and actual models forms a smooth, continuous nonlinear error surface in the manipulator workspace.

Shamma stated CMLAN is not proper as a black box for approximating higher order surface because of its discrete linear interpolating behavior. Since CMLAN is a kind of linear associator, one of well known neural nets, it is true that it shows a discrete linear interpolating behavior from the property of generalization due to the unique structured mapping. Its learning performance is degraded when sparse discrete nodes are sampled for training and gets worse when the CMLAN input space grid is formed with relatively low offset.

However, CMLAN can approximate successfully higher order nonlinear function by introducing several sub- CMLANs[9]. And the required number of discrete points situated between the training points can be properly controlled via adjusting CMLAN input space and the size of quantizing block according to the task requirement. Moreover, CMLAN does handle large sizes of input/output pairs efficiently, if necessary, via LMS(Least Mean Square) error learning.

CMLAN was successfully implemented to the inverse robot calibration process without doing any complex procedure for setting approximation polynomial and evaluating corresponding coefficients. Selected training points were spaced regularly in the CMLAN input space. And they are actually around the neighbor of CMLAN input grids.

A scheme of generating desired compensation joint variable movement was adopted from Shamma. Considering measurement of worktool position and orientation, main three d.o.f.

calibration was performed for PUMA 560 with a measurement of worktool location only. Six d.o.f. PUMA was also calibrated with simulated measurements of worktool position(location and orientation). Three and six sub-CMLANs were used for each calibration respectively.

Same nominal and actual parameters of PUMA 560 including geometric and non-geometric effects were adopted as Shamma's for its performance comparison. Instead of measuring actual worktool locations, measured values were computed from the actual model.

<u>2.2 Three D.O.F. Calibration</u>

Ranges of calibrated workspace for three d.o.f. were chosen in $R\theta Z$ cylindrical coordinate such as

$R \in [300, 840]$ in mm unit
$\theta \in [0, 90]$ in degree unit
$Z \in [-495, 495]$ in mm unit

The XYZ measurement of worktool location is only fed through the main three axes while keeping other axes fixed. Given target XYZ worktool location, three sub-CMLANs generate corresponding sets of delta joint movements which compensate nominal joint command.

Seven data points were selected with a uniform interval of 15 unit on each input range resulting 343 sampled data in the workspace. One major advantage of CMLAN is once quantizing size is kept, CMLAN net weights can be easily adapted for new sets of input/output pairs due to its learning capabilty. For a learning algorithm, on-line type sequential error correction was used.

CMLAN input space was set up 90 grids for each range resulting total of $90 \times 90 \times 90$ grids. Quantizing size K and learning gain were chosen 30 and 0.4 respectively. To investigate the learned generalization effect of CMLAN net, the errors over the extended nodes were also tested by adding an intermediate node between two sampled nodes with an interval of 7.5 unit apart on each input range.

Trend of learning performance is shown at every five epochs of learning in fig. 1. The rapid convergence of the learned rms and maximum errors over sampled and extended nodes can be seen at the early stage.

Initially the simulated rms and maximum worktool location errors of PUMA 560 due to the geometric and nongeometric effects were 3.90mm and 4.37mm over 343 sampled nodes respectively. The initial rms and maximum errors over the extended nodes were 3.92mm and 4.37mm.

After 20 epochs of on-line type sequential training over the sampled nodes, the rms and maximum errors were reduced to 7.21E-02mm and 1.78E-01mm over the sampled and 7.60E-02mm and 2.35E-01mm over the extended. After 30 epochs, the errors were reduced to 6.25E-02mm and 1.73E-01mm over the sampled and 7.33E-02mm and 2.36E-01mm over the extended. As fig.2 shows, the rate of learninng is almost negligible after 30 training epochs.

Considering the practical difficulty of worktool orientation measurement, this process can be extended to six d.o.f. calibration as Shamma did. However, additional sub-CMLANs are only required to learn the proper compensation tool transformation which yields a different desired location.

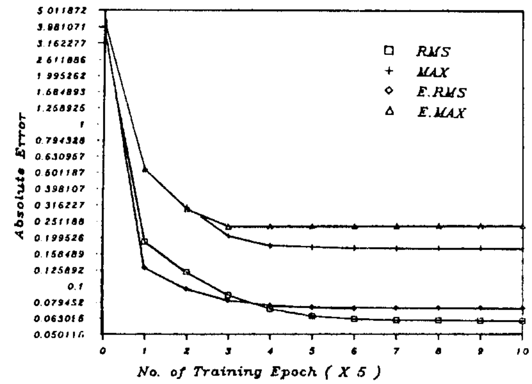

Fig.1 The learned performance of three axis robot inverse calibration over the sampled(15 deg) and extended(7.5 deg) input nodes(K=30 and Gain=0.4)

<u>2.3 Six DOF Calibration</u>

The inverse calibration of six d.o.f. PUMA 560 was also performed using six sub-CMLANs under the assumption of measurement on worktool positions (location and orientation). Ranges of the calibrated workspace were selected in the joint space since the worktool space of the articulated arm is best defined in that space. Selected workspace ranges were represented in degree.

$\theta_1 \in [0, 60]$
$\theta_2 \in [-75, -15]$
$\theta_3 \in [105, 165]$
$\theta_4 \in [15, 75]$
$\theta_5 \in [15, 75]$
$\theta_6 = 0$

Total CMLAN input space was constructed as six dimensional space whose axis has 60 units each. The last wrist joint was fixed at the desired worktool pose. However, CMLAN net makes it move to compensate the orientation error. For each joint input space, 5 data points were selected with an interval of 15 unit. The offset of exch input was one unit resulting one degree in the real joint space. Total sampled data points were 3125. Quantizing size K was selected as 30 and learning gain was selected as 0.5.

The worktool orientation error was computed using matrix norm defined such that

$$\|\Delta R\| = \max_{1 \le i \le 3} \sum_{j=1}^{3} |\Delta r_{ij}|$$

,where ΔR = 3 by 3 orientation difference matrix. The same kinematic and nongeometric error sources were used for the three main joints. For the wrist three joints, the kinematic error source was only simulated since the precise nongeometric model of the wrist joints was not available. However, the process of simulation does not make any difference since it concerns only the error reading of the measuring device.

The initial simulated rms and maximum worktool location errors of PUMA 560 were 2.75mm and 4.00mm over the sampled nodes. The inital rms and maximum orientation errors were 3.65E-2 and 4.86E-2.

The trend of learing on the sampled nodes at every three epochs was shown in Fig.2. After 30 epochs of learning, the rms and maximum location errors were 4.72E-02mm and 1.44E-01mm. the rms and maximum orientation errors were 1.34E-04 and 5.83E-4.

The extended nodes were also chosen to show the generalized effect of CMAC net. The extended nodes were selected similarly as three axis inverse calibration. Resulting rms and maximum location errors over the extended nodes were 8.22E-02mm and 4.64E-01mm. the rms and maximum orientation errors were 1.75E-04 and 1.87E-03.

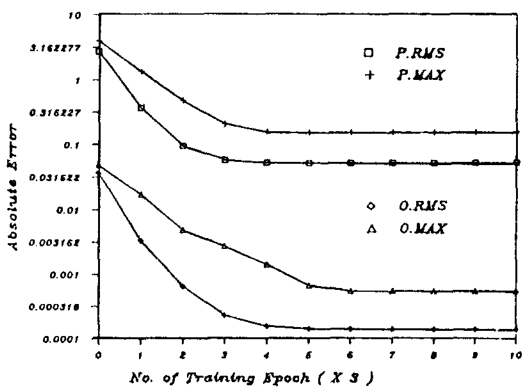

Fig.2 The learned performance of six axis inverse robot calibration over the sampled input nodes of 30 degree interval.(K=30 and Gain=0.5)

3.CONCLUSION

The trained CMLAN network using the sampled input pattern vectors automatically generates a linear interpolating results for the untrained input nodes located among sampled nodes. With the proper number of sampled input nodes, CMLAN can learn the desired system behavior arbitrarily close.

As we expected, CMLAN successfully generates the proper desired functional values to the problems of a direct inverse calibration of a manipulator without any priori knowledge in system modeling, detailed dynamic parameters, and other error sources such as deflection under loading.

The performance of the CMLAN based learning was quite good enough to implement the memory driven control system. The required system memory for distributed trained data storage was enourmously small compared to normal table look-up type storage.

Presented results will accellerate and extend application of CMLAN to robotics field such as motion planning and control, sensor fusion, and obstacle avoidance. CMLAN system controller can be extendeded to contol the integrated system behavior employing several sub-CMLANs of different function generator and controller hierarchically connected each other in a closed loop. Research and application of this concept for the task of the sensor integrated robot system control is widely open.

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