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Research Article

A Dynamic Effective Fault Tolerance System in Robotic Manipulator using a Hybrid Neural Network based Controller

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Abstract: Robot manipulator play important role in the field of automobile industry, mainly it is used in gas welding application and manufacturing and assembling of motor parts. In complex trajectory, on each joint the speed of the robot manipulator is affected. For that reason, it is necessary to analyze the noise and vibration of robot's joints for predicting faults also improve the control precision of robotic manipulator. In this study we will propose a new fault detection system for Robot manipulator. The proposed hybrid fault detection system is designed based on fuzzy support vector machine and Artificial Neural Networks (ANNs). In this system the decouple joints are identified and corrected using fuzzy SVM, here non-linear signal are used for complete process and treatment, the Artificial Neural Networks (ANNs) are used to detect the free-swinging and locked joint of the robot, two types of neural predictors are also employed in the proposed adaptive neural network structure. The simulation results of a hybrid controller demonstrate the feasibility and performance of the methodology.

Keywords: ANN, co-operation, fault tolerance, fuzzy SVM, neural network, robotics

INTRODUCTION

In the recent years various Neural network based controller are developed for robotic manipulator. Fault detection, diagnosis and accommodation play a key role in the operation of autonomous and intelligent robotic systems. System faults, which typically result in changes in critical system parameters or even system dynamics, may lead to degradation in performance and unsafe operating conditions. Robotic manipulators have been deployed in an ever growing number of unstructured and/or hazardous environments, such as in outer space and in deep sea. Robots are used in these environments to limit or eliminate the presence of human beings in such dangerous places, or due to their capability to execute repetitive tasks very reliably. Faults, however, can put at risk the robots, their task, the working environment and any humans present there.

Faults in robots are mainly due to their inherent complexity. There are several sources of faults in robots, such as electrical, mechanical and hydraulic (Visinsky *et al*., 1995). In fact, the mean-time-to-failure of industrial robots can be considered small for their intended life expectancy and cost. According to studies published in the decade of 1990, the recorded mean-time-to-failure of industrial robots was only 500-2500 h (Dhillon and Fashandi, 1997). This number is probably smaller in unstructured or hazardous environments due to external factors, such as extreme temperatures, moving obstacles and radiation. Therefore, there are good reasons to research and develop Fault Detection and Isolation (FDI) systems for robots.

Robotic systems with actuation redundancy are interesting in applications where fault tolerance is needed because the number of Degrees of Freedom (DOF) in these systems is generally higher than the DOF required to execute the task. Furthermore, as in the human case where the use of two arms means an advantage over the use of only one arm in several cases, two or more robots can execute tasks that are difficult or even impossible for only one robot (Vukobratovic and Tuneski, 1998).

Fault tollerent systems for single manipulators generally employ the residual generation scheme. The residual vector is generated by comparing the measured states of the arm with their estimates obtained by a mathematical model of the fault-free arm. This method, however, does not work well in the presence of modeling errors, generating false alarms or hiding the fault effects. Robust techniques (McIntyre *et al*., 2005) and Artificial Intelligence techniques (Schneider and Frank, 2008) have been used to avoid these problems. In the approach presented in Vemuri and Polycarpou (2004), the off-nominal behavior due to faults is mapped utilizing an ANN trained using a robust observer, based on the robot's physical model. Overall, one problem with FDI methods which rely on the mathematical system

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model is that, for some real robots, detailed modeling is difficult.

The major advantage of the neural network approaches over the traditional control methods is that they requires less prior knowledge about the controlled system. Rather, they involve using neural networks to complete modeling and control task autonomously. Kiguchi and Fukuda (2000) proposed a fuzzy vector method that enables the controller to deal with force sensor signals including noise and/or unknown vibrations caused by working tool.

This type of controller exploits the possibilities of neural network for learning nonlinear functions as well as for solving certain types of problems where massive parallel computation is required. The 'learning' capability of NN's is used to make the controller learn a certain function, highly nonlinear most of the time, representing direct dynamics, inverse dynamics or any other characteristics of the process. This is usually done during a, normally long, training period when commissioning the controller is supervised or unsupervised manner (Psaltis *et al*., 1998). If the learning capability of the NN is not switched off after the training period, once the controller is commissioned the NN based hybrid controller is worked as an adaptive controller. The ability of NNs for parallel computation has been exploited to implement controllers which require a substantial amount of computation (Quero and Camacho, 1990).

PROPOSED HYBRID ADAPTIVE CONTROLLER

This study investigates the problem of fault diagnosis in decouple joints of robotic manipulators. A learning architecture, with neural networks as on-line approximations of the off-nominal system behavior, is used for monitoring the robotic system for faults. The approximation (by the neural network) of the off-nominal behavior provides a model of the fault characteristics which can be used for detection and isolation of faults. In the proposed system the decouple joints are identified and corrected using fuzzy SVM, here non-linear signal are used for complete process and treatment, the Artificial Neural Networks (ANNs) are used to detect the free-swinging and locked joint of the robot, two types of neural predictors are also employed in the proposed adaptive neural network structure. The following Fig. 1 shows the simple architecture of NN's.

The NN controller system consists of PD feedback controller and a multilayer neural controller. In the feedback loop, the fixed gain PD controller makes the overall system stable along a desired trajectory. The NN is used to approximate the un-modeled dynamics. The overall block diagram of NN controller is shown in Fig. 2.

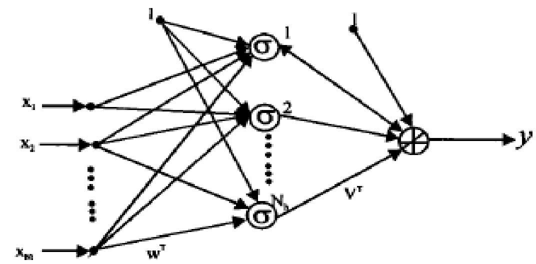


Fig. 1: Neural network architecture

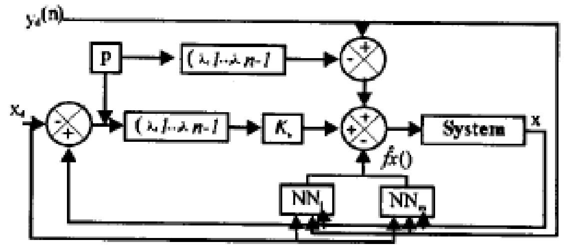


Fig. 2: Neural network controller

In the proposed system the inverse dynamics of a rigid link n degrees of freedom manipulator is described by:

$$\omega(t) = M(r)\ddot{r} + D(r,\dot{r})\dot{r} + h(r)$$

where,

$r \in R^n$ = The vector of joint displacements
$\omega \in R^n$ = The vector of applied joint torques
$M(r) \in R^{n\times n}$ = The symmetric manipulator inertia matrix
$h(r) \in R^n$ = The vector of gravitational torques

The dynamic structure can be expressed as a linear function of a suitable selected set of robot and load parameters:

$$\omega(t) = W(r,\dot{r},\ddot{r}).\phi$$

where, $W(r, \dot{r}, \ddot{r}) \in R^{n\times m}$ and $\phi = (\overset{1}{\phi}, \overset{2}{\phi}, \overset{3}{\phi}, \ldots\ldots, \overset{n}{\phi})^T \in R^n$ is a function of robot parameters.

For a nonlinear function can be formulated by a two layer NN with a sufficiently large number of neurons.

Fuzzy SVM: Let us consider a set of N tyrined NN's that model the inverse dynamics of the robot for different payload conditions. The hybrid adaptive controller was design using fuzzy logic based support vector machine and artificial neural networks. In 2002 Fuzzy SVM (FSVM) has been developed, which is an effective supervised classifier and accurate learning technique. Which was first proposed by Lin and Wang, Here Fuzzy membership function is applied to each input data of SVM (Vapnik, 1982).

The fuzzy training set can be expressed as the following equation:

$$\left\{\left(x_i, y_i, s\right), i = 1,2,...n; x_i \in R^d; y_i \in \left\{1,-1\right\}; \lambda < s_i < 1\right\}$$

Here λ is a small positive number.

All hyperplanes in R^d are parameterize by a vector (w) and a constant b. Can be expressed as w•x + b = 0.

FSVM follows the structural risk minimization principle from the statistical learning theory. Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs (Zhang *et al*., 2006). A Fuzzy support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space (Kim and Park, 2003).

The Lagrange multiplier function is:

$$L(w,b,\xi,\beta) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} f_i\xi_i - \sum_{i=1}^{n}\alpha_i(y_i(wz_i + b) - 1 + \xi_i) - \sum_{i=1}^{n}\beta_i$$

Which satisfies the following parameter condition:

$$w - \sum_{i=1}^{n}\alpha_i y_i z_i = 0$$

$$-\sum_{i=1}^{n}\alpha_i y_i = 0$$

$$f_i C - \alpha_i - \beta_i = 0$$

In Nonlinear data, m the input space X can be mapped into higher dimensional feature space ψ. It's become linearly separable. The mapping function ψ should be in accordance with Mercer's theorem (Huang and Chen, 2005):

$$K(x, x_i) = \psi(x)^t \psi(x_i)$$

where, $K(x, x_i)$ is Kernel function.
It can be chosen from the following functions.

Polynomial learning machine kernel function:

$$K(x, x_i) = (x.x_i + 1)^i, i = 1,2,3....,n$$

Linear network kernel function:

$$K(x, x_i) = x^T x_i$$

Radial-Basis Function (RBF) kernel function:

$$K(x, x_i) = \exp(-g\|x - x_i\|^2), i = 1,2,3....,n, g > 0$$

In FSVM the cost C is multiplied by the fuzzy membership function. It is the major difference between SVM and FSVM, different input points can make the result of SVM and FSVM.

Back propagation based ANN: An ANN is a mathematical model consisting of a number of highly interconnected processing elements organized into layers, geometry and functionality of which have been resembled to that of the human brain. The ANN (Kara and Dirgenali, 2007), may be regarded as a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and marking it available for use. The feed forward neural network which was employed as the classifier required in this study had three layers (after several trails for different hidden layers with different number of neurons). The first layer consisted of 7 input elements. The number of neurons in the hidden layer was five. The most frequently used training algorithm in classification problems is the back-propagation algorithm with the Levenberg-Marquart learning rule which is used in this study also. The neural network has been trained to adjust the connection weights and biases in order to produce the desired mapping. At the training stage, the feature vectors are applied as an input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship between the input patterns and outputs (Karibasappa and Patnaik, 2004).

In Back propagation algorithms modifying the weights and biases of the network in order to minimize a cost function. The cost function always includes an error term a measure of how close the network's predictions are to the class labels for the examples in the training set. Additionally, it may include a complexity term that reacts a prior distribution over the values that the parameters can take. The activation function considered for each node in the network is the binary sigmoidal function defined (with s = 1) as output = 1/ (1 + e - x), where *x* is the sum of the weighted inputs to that particular node. This is a common function used in many BPN. This function limits the output of all nodes in the network to be between 0 and 1. Note all neural networks are basically trained until the error for each training iteration stopped decreasing.

The inputs m and outputs of the j hidden layer neurons can be calculated as follows:

Step 1: $\boldsymbol{m_j^h} = \sum_{i=1}^{N+1} \boldsymbol{W_{jixi}}$
Step 2: $\boldsymbol{y_j} = f(\boldsymbol{m_j^h})$

Calculate the m inputs and outputs of the k output layer neurons are:

Step 3: $\boldsymbol{Z_k} = f(\boldsymbol{m_j^0})$
Step 4: $m_k^0 = \sum_{j=1}^{J+1} V_{kjyj}$

Updates the weights in the output layer ($\forall k, j$ pairs):

Step 5: $v_{kj} \leftarrow V_{kj} + c\lambda\,(d_k - Z_k)\,Z_k(1 - Z_k)\,y_j$

Updates the weights in the hidden layer ($\forall i, j$ pairs):

Step 6: $w_{ji} \leftarrow w_{ji} + c\lambda^2 y_i\,(1 - y_i)\,x_i(d_k - Z_k)\,Z_k(1 - Z_k)\,v_{kj}$

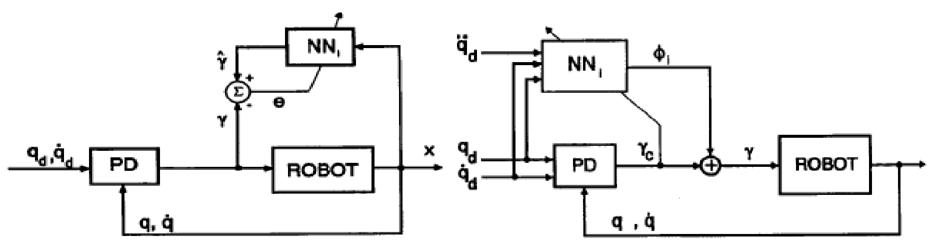
Update the error term:

Step 7: $E \leftarrow E + \sum_{k=1}^{k}(d_k - Z_k)^2$

and repeat from Step 1 until all input patterns have been presented. If E is below some predefined tolerance level, then stop. Otherwise, reset $E = 0$ and repeat from Step 1 for another epoch.

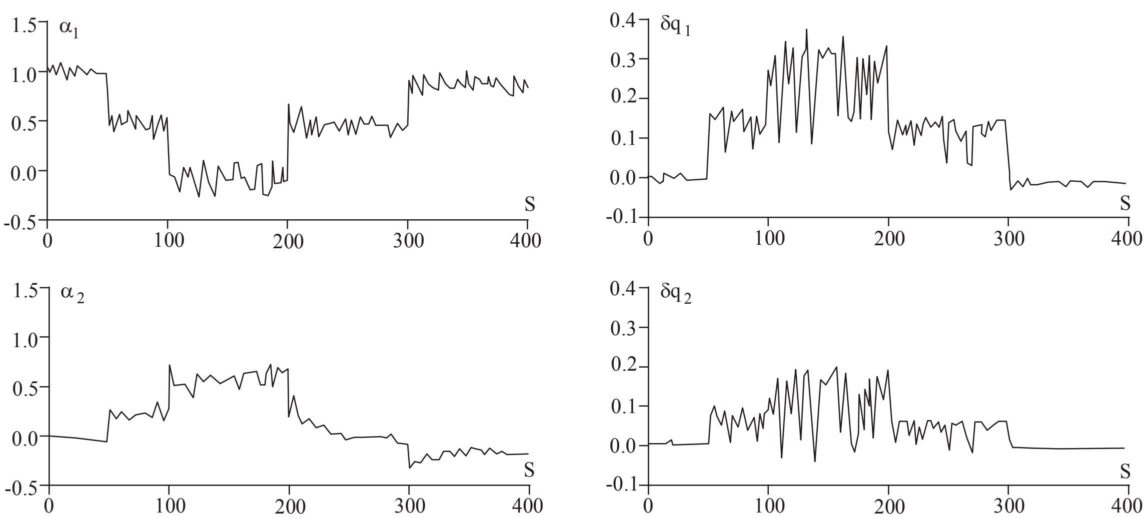
SIMULATION RESULTS

The simulation study of the proposed system is carried out using the model of PUMA-560 robot, with the gear ratio of 30. The controller was designed for two of the joints, shoulder and elbow. Assuming uncertainty of the payload and graspring center-point, parameterization of the robot model is accomplished with a ϕ vector of four components with m: payload mass and L; Position of center of mass of load in x coordinate of the link fixed system. Now, asset of N = 4 NNs is used to produce the feed-forward control signal. Each NN has 6 inputs, two hidden layers of 50 and 25 neurons and one output layer. The learning method for training each NN consists of two phases. In a first learning phase, the general learning structure, second phase is feed-forward error learning structure is used. It is clearly explain the following Fig. 3a and b. The simulation results are shown in Fig. 4. In Fig. 4a shows



(a) (b)

Fig. 3: (a) Generalized learning structure, (b) feedback error learning structure



(a) (b)

Fig. 4: (a) Evolution of motion errors in adaptive control, (b) evolution of motion errors in non-adaptive control

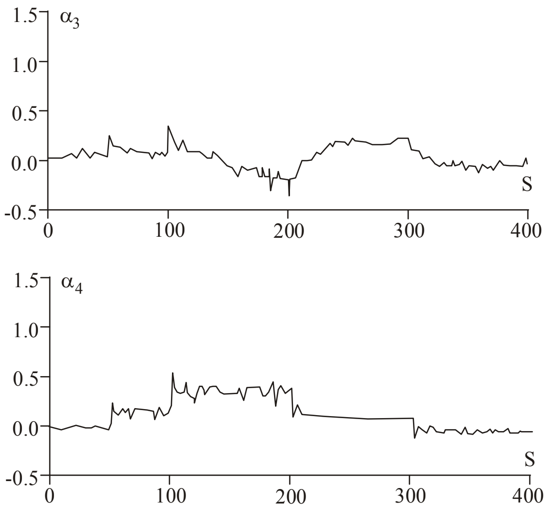


Fig. 5: Evolution of parameter estimation

the evolution of motion errors in adaptive control and Fig. 4b shows the evolution of motion errors in Non-adaptive control. Figure 5 shows the evolution of parameter selection.

CONCLUSION

In this study a neural network based hybrid adaptive controller for robot manipulators are proposed. The controller uses a fuzzy logic based support vector machine and back propagation based artificial neural network. Each of network has two stages learning stages and detection stages. The proposed scheme produces a feed forward signal which adapts to changes in the payload and other operating parameters. According to the simulation results the proposed system easier to manipulate and have a better performance after failure on one of its joints, also notable characteristics for the application of fault tolerance, which protest the reach-ability, operates easily without mechanically braking its functionality and performs better without new architectural configuration after recovery. To show the feasibility and performance of the proposed control scheme, it has been tested of the model of a PUMA-560 robot, with a gear ratio of 30.

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