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Robotic Manipulators Fault Diagnosis by Multilayer Perceptrons

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Abstract: *In this paper a novel the artificial neural networks are used for both residual generation and residual analysis for fault diagnosis of robust manipulators. A Multilayer Perception (MLP) is employed to reproduce the dynamics of the robotic manipulator. Its outputs are compared with actual position and velocity measurements, generating the so-called residual vector. The residuals, when properly analyzed, provide an indication of the status of the robot (normal or faulty operation). The ANN architecture employed in the residual analysis is also a multilayer perception (MLP) or a radial basis function network (RBFN) which uses the residuals of position and velocity to perform fault identification. Simulations employing a SCARA robotic manipulator are showed demonstrating that the system can detect and isolate correctly faults that can occur during the performance of its task. We opted in our study on fault diagnosis for a dual neural classification. Thus, the architecture of the proposed approach is based on two types of classifiers: Firstly a classifier consisting only of one neural network (MLP or RBF) followed by a comparison of the results of detection and localization. Secondly a classifier consisting of two neural networks (RBF and MLP) and is followed by a final decision system*

Keywords: *Robust manipulators, fault diagnosis, Multilayer perceptions.*

1. INTRODUCTION

A system can be fault tolerant if it is reconfigurable, case which FDI is essential. A number of studies have been dedicated to the assessment and analysis [1-2] of robot reliability. Other studies related to enhancing a robot's tolerance to failure include work on layered failure tolerance control, failure tolerance by trajectory planning kinematic failure recovery and manipulators specifically designed for fault tolerance. Being able to identify the extent of fault-tolerance in a system would be a useful analysis tool for the designer [3-4]. In recent years neural networks have been applied to variety of problems in the areas of pattern recognition, signal processing, image processing, process identification, etc. Fault diagnosis and isolation methods are usually based on the residual generation and analysis concept [5-6]. A mathematical model is used to reproduce the dynamic behavior of the fault-free system; the deviation of the output predicted by the model from actual output measurements forms the so-called residuals, which, when properly analyzed, provides valuable information about failures. In this paper, two artificial neural networks are employed to identify and isolate the faults. A learning architecture, approximation of dynamic behavior of robot manipulator, is used to generate the residual vector, by comparing with actual measured values. The ANN outputs are compared with the measured system outputs and, thus, generate the residual vector. In this paper, two ANN are utilized: a multilayer perception (MLP) is employed to reproduce the manipulator dynamic behavior and a second MLP or a radial basis function network (RBFN) is used to classify the residual vector. The ANN used in this paper is describe in section 2. The robotic manipulator system is described in section 3 together with some methods for FDI in this system. the multilayer perception (MLP), trained with the classical back-propagation algorithm, is employed to reproduce the manipulator dynamic behavior and the radial basis function network (RBFN), initialized with the classical Kohonen self-organizing map [7], is used to classify the residual vector. The second proposed approach with two neural networks classifier (MLP and RBF), followed by a decision system is described in section 4.Manipulator simulation results using two ANN training procedures are given in section 5 and, finally, the conclusions are in section 6.

2. ARTIFICIAL NEURAL NETWORKS

In this paper, an MLP with back-propagation algorithm is used to reproduce the behavior of nonlinear dynamical systems and a second MLP is used to residual classification. For a p- dimensional input vector and a q-dimensional output vector, the MLP input/output relationship defines a mapping from a p-dimensional Euclidean space to a q-dimensional Euclidean output space. Using only one hidden layer, presenting in the n-th sample (where n = 1, 2,...,n_p), the input vector $X(n)=[X_1(n)\ X_2(n)\ \dots\ Xp(n)]^T$, the activation of the output neuron k (where k = 1, 2,..., q) is:

$$O_k(n)=\varphi_k[\sum_{j=0}^{m} W_{jk}(n)\varphi_j[\sum_{i=0}^{p} W_{ji}(n)X_i(n)]]$$

where m is the number of neurons in the hidden layer, is the weight between the j-th neuron of the hidden layer and the k-th neuron of the output layer, is the weight between the i-th neuron of the input layer and the j-th neuron of the hidden layer, *jk* is the non linear activation function of the output layer and k*j* is the nonlinear activation function of the hidden layer. In this article, the weights of the MLP are trained by the well known back-propagation algorithm.

The RBFN employed in this article has three layers. There are no weights linking the first and the hidden layers. The hidden layer has neurons with radial activation functions. Each neuron *j* in the hidden layer (called radial unit *j*) is responsible for the creation of a receptive field in the *p*-dimensional input space. The receptive field of each radial unit is centered in a *d*imensional vector μ*j*, called radial unit center. Therefore, the radial unit *j* activates according to the vector distance between the input vector and the radial unit center. There are weights between the hidden and the output layers, and the activation in the last layer is linear. Presenting in the *n*-th sample the input vector X(n) = [X1(n) X2(n) … Xp(n)]T, the activation of the *k*-th output neuron (*k* = 1, 2,..., *q*) is given by μj

$$O_k(n)= \sum_{j=0}^{m} W_{jk}(n)\ h_j\ (n)$$

Where *m* is the number of radial units, w*kj* is the weight between the *j*-th radial unit and the *k*-th output neuron, and *hj* is the activation of the *j*-th radial unit. In this work, the Cauchy radial function is employed as activation function in the radial units:

$$h_j\ (n) = 1/1 + \left\| R^{-1}(X(n) - \mu_j) \right\|^2$$

Where *R* is a diagonal matrix formed by the individual parameters that define the receptive field size in each dimension of the input space.

3. DUAL NEURAL CLASSIFICATION

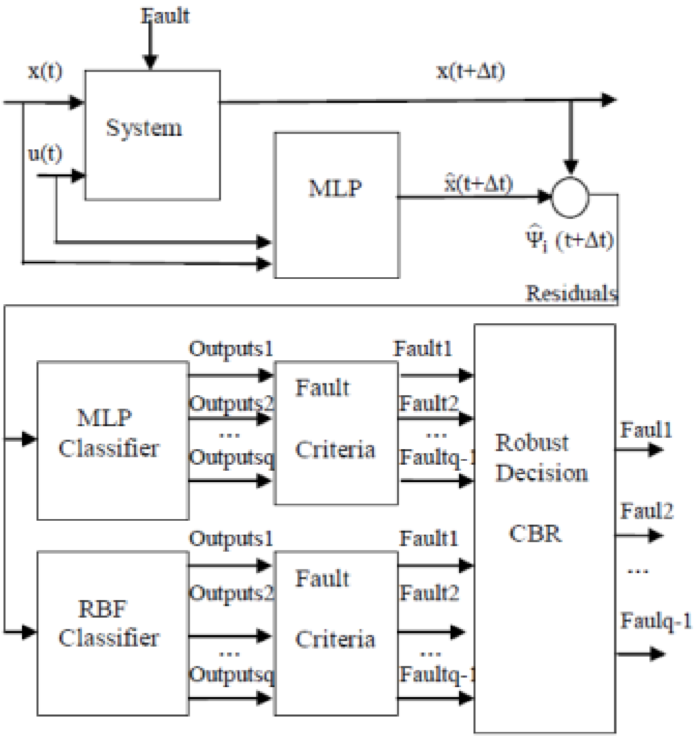

Fig1. *Dual classification with robust decision.*

The second proposed approach consists of two neural networks (MLP and RBF), followed by a decision system (Figure 2). There are several methods for decision making (Analogy, Fuzzy Logic, statistical treatment, etc.). We opted for the analogy approach. This method is more natural and nearest to the human reasoning. The principle of this method is to draw the decisions taken in the past in similar situations to solve new problems. The technique of this method is the reasoning from cases (examples) or" Case-Based Reasoning (CBR)." This technique is based on the assumption that the decisions and the resolution of a problem is the access to information stored in previous experiments to further exploitation.

Indeed, opting for multiple classification , one of the usual solutions is to choose the classification model giving the best result. In our work, we used both the redundancy and complementarily of classification models used.

4. Simulation and Results

To simulate the occurrence of free-swinging joint faults, we set the torque applied at a joint to zero. In first time, the residual analysis for fault isolation purposes is performed with an MLP utilizing the velocity residuals. The figures 3, 4 and 5 shows the residual, position and velocity of the joint 2 with a free-swinging joint faults occurring at t = 4s.

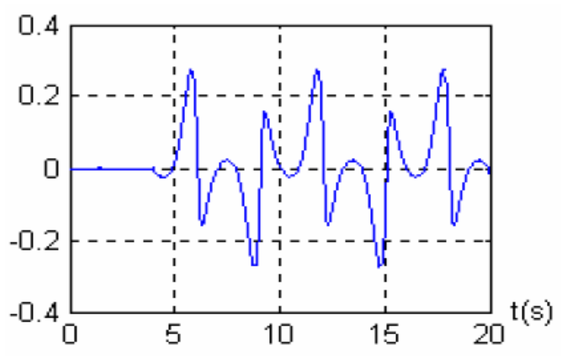

Fig2. *Residual with a free-swinging joint faults in joint 2 at t=4 s*

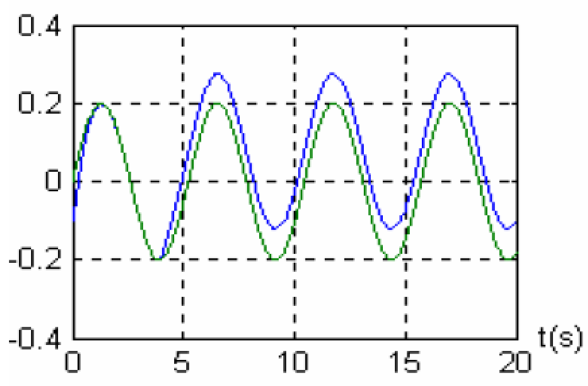

Fig3. *Normalized position and respective MLP output in a trajectory with fault in joint 2 at t=4 s.*

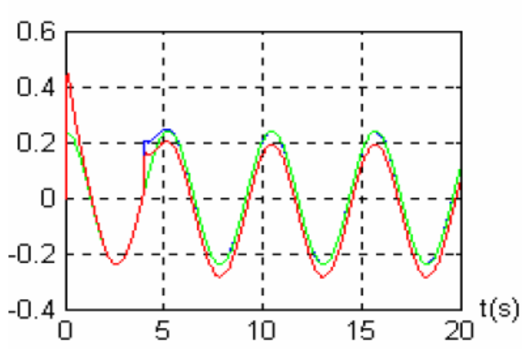

Fig4. Normalized velocity and respective MLP output in a trajectory with fault in joint 2 at t=4 s.

5. CONCLUSIONS

The Fault Diagnosis System proposed here presents good results when it is applied to a three-link SCARA robot. With an extensive simulation study results, we were able to conclude that ANNs are a powerful means for Fault Diagnosis System tasks, robustly performing both residual generation and residual analysis.

Research work developed in this paper deals with decision support systems for fault diagnosis and decision-making based on Artificial Intelligence using hybrid techniques, and soft computing implying neural networks and Case-Based Reasoning (CBR).

Further work on this is to extend the Fault Diagnosis System scheme to robotic manipulators with a larger number of degrees of freedom. Other different types of faults can be detected and isolated using other methods: Fault detection and isolation of robotic manipulator via fuzzy logic, neuro-fuzzy control, hybrid system and expert system [8-12]. The work presented here can be expanded to include post failure control of the robotic manipulator in a hybrid system framework.

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