INTELLIGENT MONITORING OF A PNEUMATIC ROBOT LEG SYSTEM BY NEURAL NETWORKS THAT CAN AUTOMATICALLY ADAPT

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Abstract

This paper describes the selection of key parameters to charactersise a pneumatic robot system and the use of a neural network to classify changes to each key parameter. As systems can be characterized by parameters that can be monitored over time, once initialised with random experimental data then changes to the network reflect changes in each key parameter and therefore changes to the monitored system. A decision tree is then used to diagnose problems by analysing the results for the monitored parameters.

Introduction

Actuators in industrial systems [Münzer (2000)] and walking robot systems [Luk *et al* (2004)] sometimes provide large forces and where a strong mechanical load is used then life expectancy reduces, especially for some components such as motors, valves, pumps and gears. Zavarehi (1997) proposed some general monitoring techniques that could be used but although their approaches are efficient, their techniques often need additional equipment.

Signatures created from key parameter data can represent the status of a system. This data can be provided by direct measurement of key parameters, for example vibration, noise, pressure and temperature. A parametric model may be created using on-line identification techniques [Sjöberg berg (1996)] although the estimation of the key parameters may be difficult because of non-linearity and complexities and unknowns. Models need to be precise if the monitoring and diagnosis of a complex system is to be achieved. This can be achieved by careful observation of key parameters and then analysis using an on-line parametric identification model. If a fault began to appear then these parameters would deviate over time.

To achieve this the key parameters that characterize a system need to be selected and then values extracted from the raw data for each parameter. This raw data can be used in a neural network to provide the input for a decision tree. Lurette and Lecoeuche (2001) initially described a system to detect change using a neural network classifier and later the network was adapted to have the ability to learn and detect changes. This adapted system was described in Lurette and Lecoeuche (2003).

Bishop (1995), Looney (1997) and Gupta *et al* (2002) used neural networks to classify natural data. Neural networks have also been used in fault diagnosis using pattern recognition Haynes *et al* (1994) or residual generation decision. Crowther *et al* (1998) described the application of neural networks to fault diagnosis. Experimental faults can be diagnosed using neural networks trained both on simulation data and on trial-and-test data.

Data can be labelled in a representation space by describing shapes [Gupta *et al* (2000), Gomm and Yu (2000), Mak and Kung (2000)] so that unsupervised learning can take place and auto-adaptation can be introduced [Mao and Jain (1996)]. Neural networks have used unsupervised learning and auto-adaptation but few can adapt their architecture by creating neurons or adapting their model. The architecture discussed in this paper is based on rules for unsupervised learning and an auto-adaptive structure.

The method is based on the CDL auto-adaptive network described by Eltoft and Rui DeFigueiredo (1998) and used by Lurette and Lecoeuche (2003). The network consisted of a classical three-layered feed-forward network that uses learning rules for the creation of new neurons.

The artificial neural network

The number of key parameters to be monitored dictates the number of neurons in the input layer. The hidden layer is completely connected to the input layer and the output of each neuron of the hidden layer defines a degree of membership.

$$\mu(P_j, X_i) = \exp\left(- \frac{(\mathrm{d}(P_j, X_i))^2}{2\alpha_{P_j}} \right).$$

{Reproduced from Lurette and Lecoeuche (2003)}

Where P_j is a normalization factor and the distance is chosen as the Mahalanobis distance so that position in the representation space and normalization factor P_j defines each output state. The output layer consists of as many neurons as detected states. The connection weights between the hidden layer and the output layer characterize the relation between states.

The output of each neuron of the output layer defines a degree of membership. The general architecture of the network resembles a classical RBF neural network, but the architecture described in this paper uses unsupervised learning rules to give the network an auto-adaptive structure. Not only are connection weights adapted but also the size of the hidden layer and the size of the output layer are varied. Additionally, the normalization factor P_j is adapted using techniques described by Mak and Kung (2000) who introduced an equivalent coefficient as a smoothing parameter so that Pj ensures a membership degree greater than some maximum. This method was used by Lurette and Lecoeuche (2003).

Once all input vectors had been defined then a set of classified examples could be defined. If an ambiguity was detected then it was resolved by merging the different ambiguous states into a single state. Eliminating neurons defining ambiguous states left a unique neuron as the result of the merged states and this modified the output layer.

States containing less assigned examples than some thresholds were eliminated and corresponding examples marked as "unclassified". Lurette and Lecoeuche used a second threshold to avoid small states that were not significant due to having few associated examples butthis was not used in the system described in this paper.

Target System

An articulated robot leg powered by pneumatic cylinders was selected as a target system. This is described in Luk *et al* (2003). Pneumatic actuation is particularly suitable for climbing robots due to its high force to weight ratio and inherent compliance.

The robot leg was an endoskeletal structure; an internal frame was used to provide the required strength and stiffness for locomotion as well as locations for the joints, whilst the external actuators act as the prime mover. The advantage of using this structure is that it is more practical for fabrication and maintenance. A group of legs could be organised as a spider-like structure. A pneumatic robot leg is shown in figure 1.

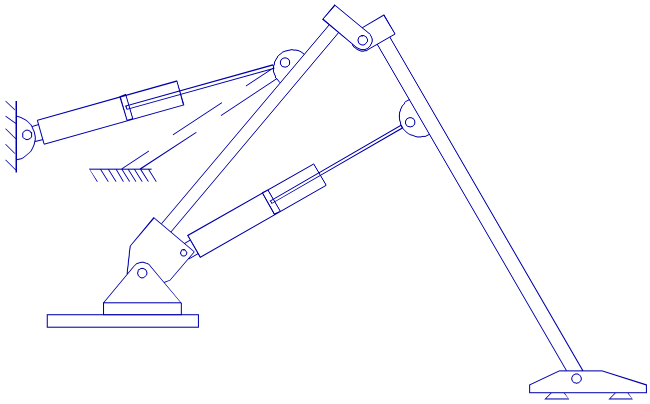

Figure 1: Pneumatic robot leg

The robot leg had three degrees of freedom and a vacuum gripper foot for climbing vertical surfaces.

A group of leg mechanisms makes a pneumatic robot with the ability to negotiate and climb over obstacles. It also has the advantage of keeping a body close to the surface which increases the stability of the robot. An open three bar linkage mechanical structure was used to provide all three degrees of movement of each leg. The anchorage points of the hip and abductor cylinders, and the hip joint are widely separated to reduce stresses on the chassis.

The gripper foot is attached to the leg by a ball joint, this provides the gripper foot with the flexibility required to align itself with uneven surfaces. These gripper feet and the base suckers are driven by compressed-air ejector pump and can provide a pull-off force corresponding to 80% atmospheric pressure.

Pneumatic System

Each root leg is controlled by an on-board dedicated microcontroller board. These controller boards provide position, force and compliant control modes. An additional board is used to provide sensor information. A supervisory computer at the user end provides the human-machine interface, path planning and functions necessary for co-ordinated motion. A master-slave configuration via a serial link is used to network the supervisory computer and all the leg controllers as shown in figure 2.

Each pneumatic cylinder is controlled by three electrically controlled valves as shown in figure 3. Pulse Width Modulation method is used to drive the cylinder.

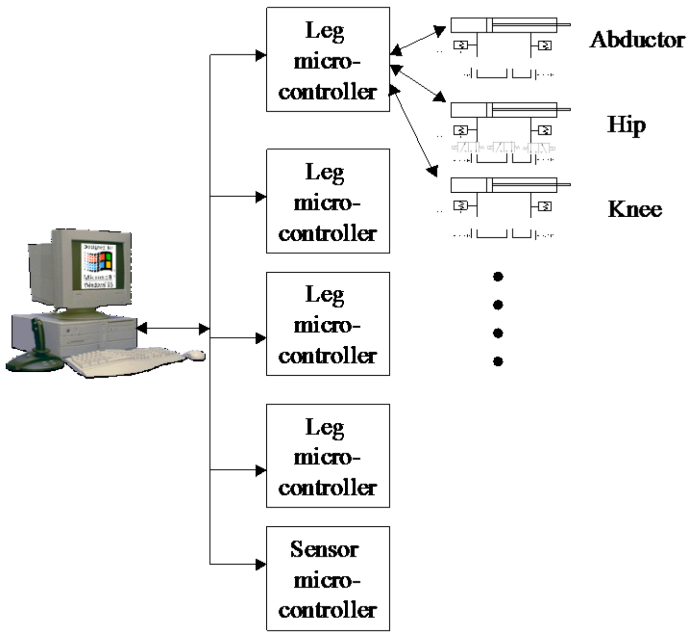

Figure 2. Control System

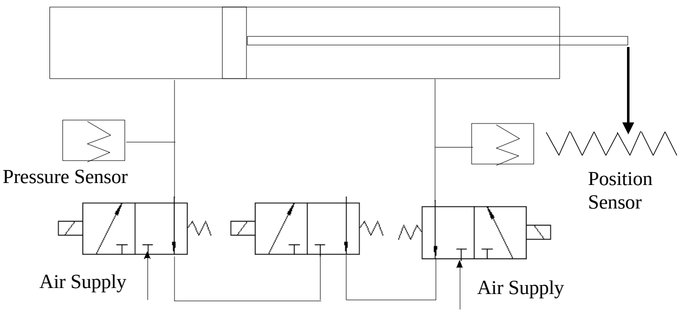

Figure 3: Valve arrangement for cylinder control

Using the network to monitor a pneumatic system

The network was designed to detect changes of specific key parameters that characterize a system and then to recognize the type of change. The system needed to be observed over time and a measure of system health applied. To be independent of the data the data-signal was normalised and normalization coefficients were fixed during training. The neural network was then used to associate each vector to a state that described a particular type of change. The neural network was initialised during a learning stage with a set of data from observation of the system, including faults and the onset of faults. Once learning was completed then a copy of this initial trained network was used for each monitored parameter. A decision tree was then used to associate different results to establish a diagnosis [Lurette and Lecoeuche (2003)]. The ability of the network to learn and detect different kinds of change had been evaluated by Lecoeuche using the "Synthetic Control Chart Time Series" database [Pham and Chan (1998)].

A conventional piston compressor was controlled to ensure a pre-defined air pressure and an accumulator was used as energy storage to compensate the response time of the pump and to reduce pressure oscillations.

The sensors shown in figure 3 were monitor via the sensor micto-controller in figure 2. The ANN learnt from normal operation of a pneumatic robot leg and from synthetic data fed to the micro controller. A second database corresponded to experimental data about the changes to the key parameters. The auto-adaptation took account of new kinds of change during on-line functioning so that each network grew from a unique learned network dedicated to a key parameter. For example known states were adapted if the parameter data were more or less noisy. The boundary of each state was defined by a membership degree. Data for on-line adaptation were extracted in the same manner as those used for detection.

This work is similar to the work on a hydraulic system described by Lurette and Lecoeuche (2003). They were also concerned with piston position. In their work an axial piston pump was mechanically controlled to ensure a pre-defined service pressure in a hydraulic circuit and an accumulator was used as storage of hydraulic energy to compensate the response time of the pump and to reduce pressure oscillations. Possible faults and drifts in this system included the abrasion of mechanical components of the servo-valve, the oil pollution, degradation of the quality of functioning of the accumulator, or the breaking of a piston. They concentrated on the hydraulic accumulator and the pump because of the potential cost of these faults. A pump and accumulator are described in Lurette and Lecoeuche (2003).

Results

The position and air sensors and the pressure from the compressor were monitored and deviations outside of normal operation were detected.

Conclusion

In this paper, some developments in intelligent monitoring of industrial systems by automatically adapting neural networks have been described. These systems can monitor systems in real time in order to detect changes and recognise faults and the onset of faults. Auto-adaptation of the architecture can improve performance and the learning rules can automatically create new states. It is possible to detect some changes and therefore faults.

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