Intelligent Control.
Telemanipulation and Microtelemanipulation

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Abstract: This paper surveys the research work in the areas of intelligent control, telemanipulation and microtelemanipulation at Tampere University of Technology. Neural networks are applied in static and dynamic fault diagnosis, and control. In fuzzy control the main research has been in the area of tuning. This includes tuning of multivariable fuzzy controllers and autotuning of fuzzy controllers. In telemanipulation the design of controllers for force reflection is discussed. A mini-telemanipulator has been implemented.
Keywords: Artificial neural networks; fuzzy control; fault diagnosis; paper machine; real-time control;telemanipulation; microtelemanipulation.

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In 1971 he joined the Department of Electrical Engineering of the University of Toronto, Ontario, Canada as a Visiting Assistant Professor, and served there as an Assistant Professor from 1972 to 1975. From 1975 to 1979 he was an Associate Professor in Applied Mathematics , and from 1979 to 1984 in Control Engineering at Tampere University of Technology, Tampere , Finland. From 1984 to 1995 he was Professor in Automation Technology. In 1986 he was the Chairman of the Department of Electrical Engineering. Since 1995 he has been Professor in Automation Technology at Helsinki University of Technology. His research interests are adaptive and learning control, mechatronics and computer control of processes. He has authored about two hundred publications in these areas. Dr. Koivo is a member of the Editorial Board of Journal of Adaptive Control and Signal Processing, Journal of Intelligent and Fuzzy Systems and Intelligent Automation and Soft Computing. He is also an Associate Editor of IEEE Transactions on Robotics and Automation. He is a Fellow of the Finnish Academy of Technical Sciences. He is the Finnish representative in the Council of European Union Control Association.

1. Introduction

Research work at Tampere University of Technology is surveyed. The paper first discusses intelligent control, which is divided into static fault detection with an application to paper machine web breaks, dynamic fault diagnosis, real-time neural network control and fuzzy control. Neural network results in the literature are mostly based on simulation and applications have been few. Here practical side of neural networks use is emphasized. Finally telemanipulation and microtelemanipulation are briefly discussed.

2. Static Fault Detection

The use of ANNs in automation, especially in fault diagnosis and control, becomes more and more common (Miller et al, 1990; White and Sofge, 1992). Conventional fault detection and diagnosis uses static and dynamic models of the process (Willsky, 1976; Himmelblau 1978; Isermann, 1984; Frank, 1990). In real industrial processes it is often very troublesome to obtain fairly accurate models for reliable fault detection and diagnosis.

Rule-based expert systems have been investigated intensively for fault detection and diagnosis problem (Patton et al, 1989). Fault diagnosis using rule-based expert systems needs an extensive database of rules and the accuracy of diagnosis depends on the rules. Also the updating of the rules and the uniqueness of the knowledge are problems when large industrial plants are concerned.

The research applying neural networks in fault diagnosis has been very active in the last six years. Inputs of the neural networks have been both binary (McDuff and Simpson, 1990) and continuous (Watanabe et al, 1989; Kramer and Leonard, 1990; Sorsa et al, 1991).

The classification of process data can be carried out with the information about different classes. Then we know that certain measurement patterns correspond to normal operation and other measurement patterns correspond to faulty operations. The training of neural networks using this kind of information is called *supervised.* Perceptron and radial basis function networks are typical examples of supervised trained network architectures. If a neural network classifies the data autonomously, the training is *unsupervised.* Kohonen feature maps are examples of networks exhibiting this property. Especially in industrial applications it is not always straightforward what causes the fault (Sorsa et al, 1992). Then a natural approach is to use unsupervised networks.

The simulations with the data of the test process have shown (Sorsa et al, 1991, Sorsa and Koivo, 1993) that the multilayer perceptron network can classify the measurements very reliably. The radial basis function neural network is not as easy to use as the perceptron networks but the knowledge about measurement data and classes can be employed in training radial basis function networks. The most critical phase in training is the search for the centres of the Gaussian functions and if this is done successfully the performance of the network is usually very good.

The Kohonen feature map, which is trained unsupervised, is not always able to classify even the training data correctly. However, its ability of classifying the measurement data autonomously is very interesting and useful, particularly when real industrial processes are considered (Sorsa et al, 1992).

3. Paper Machine Web Breaks

Although there have been many promising simulation examples about neural networks in fault diagnosis in the literature, real applications are still quite rare. Here the capabilities of neural networks to detect breaks in a paper machine are reported. Typically, a break costs about $ 10.000 /hour, so any headway made is economically significant.

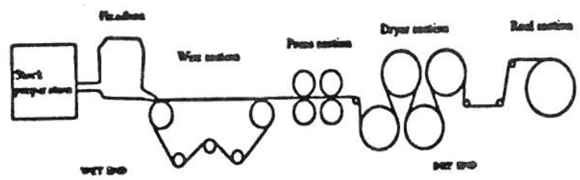


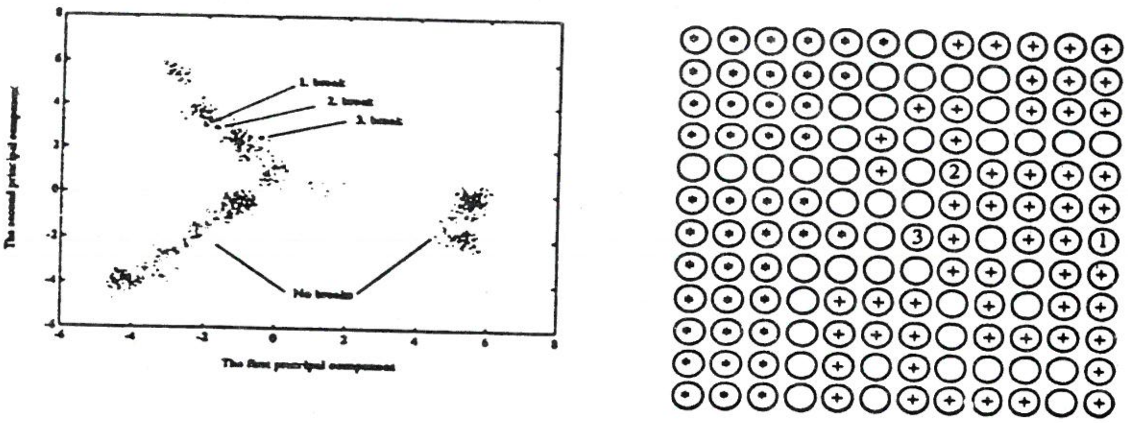
Figure1. Simplified Schema of a Paper Machine

A paper machine consists of wet end and dry end (Figure 1). The width of a modern paper machine can be 9 meters and speed of 1200 meters/min is not unusual. Typically, a modern paper machine can produce about 20 tons paper per hour. Breaks occur as a result of a high load and a low strength of a web. Typical sources of web load variations can be poorly tuned tension systems or out-of-round rolls. Web strength variations can be a consequence of fluctuations in stock manufacturing process. A break takes place when a transient high load coincides with a weak spot on a web.

The breaks of a production paper machine in Finland have been investigated (Sorsa et al, 1992). The aim has been to search for features that increase the risk of a break and should therefore be avoided. The machine has quite normal break statistics, having about 20 breaks per week. The continuous measurements of the process variables that could have something to do with the breaks, have been selected in consultation with the paper machine staff.

Figure 2a presents some paper machine measurement values by the first and the second principal components. The original measurement space is 35-dimensional and the points in Figure 2a present the projected measurement values.

The data in Figure 2a are composed of three different running periods of roughly the same length (10 hours). During these periods the paper



(a) (b)

Figure 2. Three Different Periods of Paper Machine Measurements Presented by the First and the Second Principal Components (left) and A Kohonen Self-organizing Map (right), when the Basis Weight is the Same $37g/m^2$. Each Measurement Vector is Originally 35- dimensional

machine was producing the paper of basis weight $37g/m^2$. In two cases, there were no breaks, but during the third run there were three breaks. Figure 2a shows how the normal runs produced clusters in the area of clock 3 (run 1), and clock 7 (run 2). The cluster in the position of clock 11 is sensitive to breaks (run 3). The break points are indicated with little circles.

Next, Kohonen self-organizing feature maps are used to cluster the paper machine measurements. Figure 2b shows a feature map for the same data that were used in the principal component analysis in Figure 2a. The feature map is composed of 144 elements and the elements are fully connected to the inputs. The input layer is left out. The training data are classified unsupervised and the labels shown in Figure 2b are written after the training.

In Figure 2b the data concerning the situations where no breaks occurred (the first and the second clusters in Figure 2b) are classified into the elements denoted by asterisk (*). The data concerning the break sensitive situations (the third cluster in Figure 2b) are classified into the elements denoted by cross (+). The mapping elements indicated by numbers (1, 2, 3) are activated by the measurement patterns where the breaks occurred but also by some other patterns of the third running period (the third cluster).

It is very difficult, if not impossible, to classify every break but the best suggestion is to classify operation runs and operating points according to break frequencies. The approach has been to examine methods in order to help operators notice different operating points and running styles.

4. Fault Diagnosis of Dynamic Systems

One problem with the static classification methods is that the dynamic behaviour of the process is not taken into account. There are two main approaches to using models in fault detection and diagnosis, namely parameter estimation and state estimation approaches (Isermann, 1984). The parameter estimation approach requires exact knowledge about the process model and the values of the real physical parameters must be known quite accurately. In practice, this knowledge may be difficult to acquire. The state estimation methods of fault detection and diagnosis employ observers to generate state estimates. Then the residuals are calculated and the decision of a fault is made with the aid of the residuals. Usually models are supposed to be linear. Some results for nonlinear models are also presented (Frank, 1992) but the studies have considered only certain classes of nonlinear systems.

In the traditional model-based fault diagnosis, the idea of a model bank or an observer bank is very familiar (Isermann, 1984; Patton et al, 1989; Frank, 1992). In a similar way, when appropriate process data are available, the bank of neural network models can be generated in the nonlinear case. The bank contains both the model for normal operating process and the models for the fault situations. Every possible fault must be known beforehand in order to make accurate diagnosis. When the model bank is complete, the next step is to design the decision making procedure, which selects the best matching model. The most common method is a Bayes classifier.

Neural networks provide a very useful tool for nonlinear system modelling. When neural networks are used to model the behaviour of a practical system, the most appropriate model structure is the discrete-time nonlinear model (Chen et al, 1990), which in multivariable stochastic case can be presented as follows

$$y(t)=f\left(y(t-1),\ldots,y\left(t-n_y\right),u(t-1),\ldots,u\left(t-n_u\right)\ldots,\right. \qquad (1)$$

$$\left.\ldots,e(t-1),\ldots,e\left(t-n_e\right)\right)+e(t)$$

where *y*, *u* and *e* are the output, input and noise vectors with the maximum lags of n_y, n_u and n_e respectively and *f* is a vector-valued nonlinear function, which in this case is implemented with neural networks.

Instead of the general multivariable model structure, a separate neural network model for every measurement is constructed. In this way several small neural network models are made and the decision of the dimensions (the delays and the number of terms) is easier to make than in the case of one large neural network model. Therefore the following model structure is used

$$y_i(t)=f_i\left(y(t-1),\ldots,y\left(t-n_y\right),u(t-1),\ldots,\left(t-n_y\right)\right), \qquad (2)$$

$i = 1,2,\ldots$

where the functions f_i are implemented with the radial basis function neural networks.

In Suontausta et al (1993) the idea for dynamic fault detection is proposed.

The proposed diagnosis method is studied with the simulations of the jacked reactor presented in Figure 3. In the continuously stirred tank reactor a first order irreversible, exothermic reaction $A \rightarrow B$ takes place. The heat of the reaction is

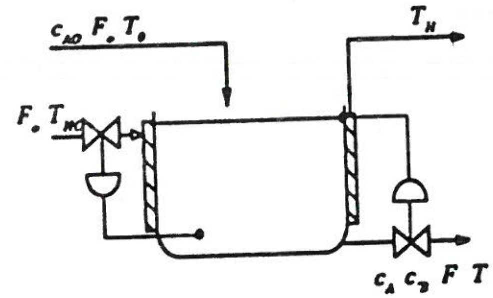


Figure 3. Example Process

removed with the cooling jacket which is really a heat exchanger around the reactor. The system has two control loops with discrete PI controllers.

In fault diagnosis simulations four fault situations are studied. In the first fault situation the input flow rate to the tank is too high, 10% over the normal flow rate, and in the second fault it is too low, 10% under the normal flow rate. In faults three and four, the input concentration of A is 5% too high or low, respectively. A model has been constructed for the normal operation and for every fault situation. Each model consists of four single-output radial basis function networks - one network per one measured process variable. The parameters of the radial basis function networks have been estimated off-line with the orthogonal least squares algorithm.

The test example of the constructed diagnosis system is presented in Figure 4, which shows the situation where the process works normally at first and then fault number two (input flow rate too low) occurs at the time 2500 minutes. There have been several operating-point changes during the simulation. The outputs of the radial basis function network models are shown by dashed lines (--) and the process measurements by solid lines (-). The Bayes classifier indicates quite rapid and reliable fault diagnosis. In Figure 5 a slow fault, fault number three (input concentration A too high) occurs at 4167 minutes. The operation point changes rapidly and the model estimates of the normal situation have significant error after the fault. Model estimates of fault no.3, on the other hand, pick up the situation, but slowly, because of reactor dynamics. This can be clearly seen in the Bayes classifier.

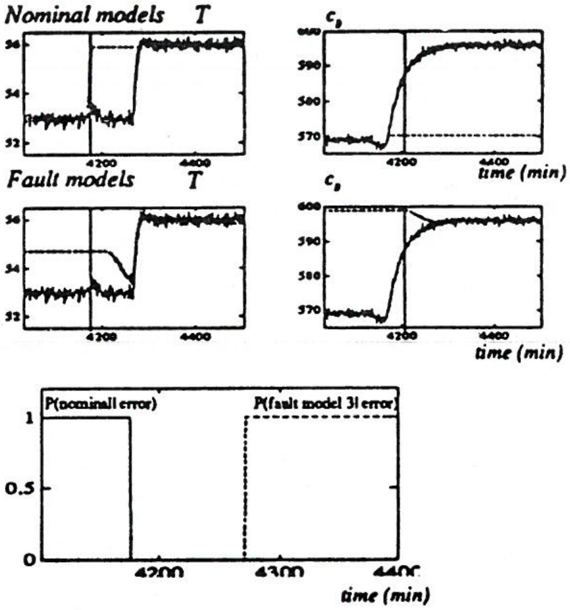


Figure 4. Fault no.2 occurs at 2500 minutes. Above the nominal model (temperature and concentration C_B) following at first normal operation, but at 2500 creating significant error. In the middle, the corresponding fault model first does not follow the output, but after the fault, tracks the output very well. Below, the behaviour of the Bayes classifier as a function of time

The simulation studies of the jacked reactor show that the proposed method works reliably with nonlinear processes even when the ranges of several operating points are considered.

5. Real-time Neural Network Control

Much of the current research effort in the control literature is focussed on developing nonlinear control methods which give good performance in the presence of disturbances and unmodelled or time-varying dynamics. At the same time, many papers indicate that neural networks have a lot of attractive properties required in nonlinear time-series modelling and in nonlinear control (Bhat and McAvoy, 1990;Koivisto, 1990; Narendra and Parthasarathy, 1990; Psichogios and Ungar, 1991). In this context, nonlinear

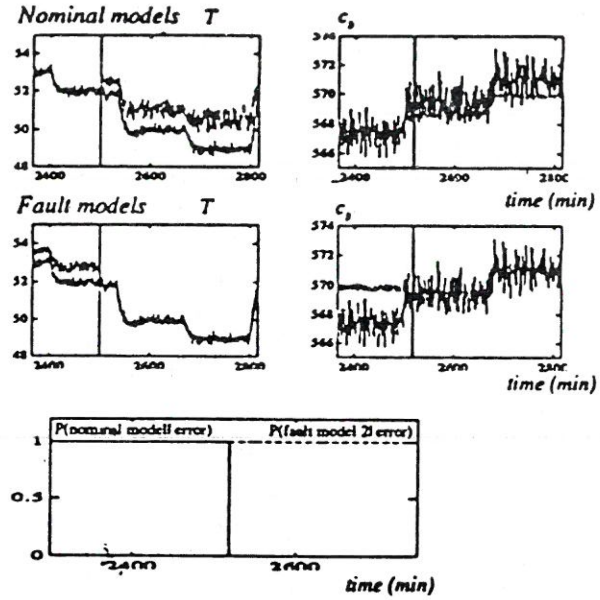


Figure 5. Fault no.3 occurs at 4167 minutes. Above the nominal model, in the middle, the corresponding fault model and below, the Bayes classifier as a function of time

internal model control (IMC), realized by neural networks, provides a flexible and practical tool to treat nonlinear control problems.

The linear IMC has been studied extensively in the literature (Morari and Zafiriou, 1989). The main principle of the IMC is that for an open loop stable process one can find a perfect controller by inverting the "minimum phase" part of the process model. In (Hunt and Sbarbaro, 1991, Koivisto et al, 1992) it is shown that neural networks can also be applied straightforwardly in the IMC framework. Here the IMC strategy discussed in (Economou et al, 1986) for time-discrete, nonlinear single-input single-output (SISO) systems, is applied to the control of a laboratory heating process. Unlike existing nonlinear control design techniques that incorporate IMC concepts, the new design method relaxes the assumption about the stability of the system inverse (Hunt and Sbarbaro, 1991) by using an optimal controller within the IMC architecture and parameter projection to ensure the stability of the controller.

The development of a general nonlinear extension of IMC poses serious difficulties due to the inherent complexity of nonlinear systems. For instance, the linear process model can be factorized so that the part containing all the time delays and unstable zeroes is separated and left uninverted. Consequently, the controller is stable and realizable with a suitably chosen IMC filter. Unfortunately, the IMC factorization has no general nonlinear analogy. Thus previous results based on (Economou et al, 1986) have been restricted to refer only open-loop stable nonlinear systems with stable inverse, that is, the assumption about the existence of the model inverse must be made. This can be relaxed.

Assume that a deterministic discrete-time nonlinear model of the process is available. This model can be any physical process model or an experimental one. In the case of an experimental model, the model should have the d-step ahead predictor form

$$\hat{y}(t+d)=f\left(\varphi(t)\right) \tag{3}$$

$$\varphi(t)=\left[\hat{y}(t+d-1),\ldots,\hat{y}\left(t+d-n_a\right),u(t),\ldots,u\left(t-n_b+1\right)\right]$$

Here φ is the data vector, $\hat{y}(t+d)$ is the d-step ahead prediction of the measurement, u is the input of the process and f is a differentiable function. The predictor (11) is a nonlinear extension of linear d-step ahead output error predictor (Ljung and Söderström, 1983) and is named a nonlinear output error (NOE) predictor. In this paper, the function f is realized with a multilayer perceptron network. The identification of the neural network NOE predictor with recursive prediction error method (RPEM) is presented in Koivisto et al (1992).

The problems related to the model-inverse-based IMC design can partially be avoided by designing the nonlinear controller

$$\hat{y}(t+d)=f\left(\varphi(t)\right)$$

$$\varphi(t)=\left[y^*(t+d-1),\ldots,y^*\left(t+d-m_c\right),\hat{y}(t+d-1),\ldots,\right. \tag{4}$$

$$\left.\ldots,\hat{y}\left(t+d-m_a\right),u(t),\ldots,u\left(t-m_b+1\right)\right]$$

where f is the data vector, q is the parameter vector of the controller, $y^*(t)$ is the setpoint and h is a differentiable function, which minimizes a quadratic cost function (Economou et al, 1986).

The controller can be effectively realized with a multilayer perceptron network, which represents a special form of parametric function (3). In this case, the structure of the parametric nonlinearity is fixed and the parameters, i.e. the weights of the multilayer perceptron network, are obtained by minimizing the cost function.

5.1. Real-Time Experiments

The neural network IMC controller described in the previous sections, is tested in real-time experiments with a laboratory scaled heating process (Figure 6a). The water flows from the domestic water network into an uninsulated 0.4 litre tank through a multidelay pipe and is heated by a resistor. The aim of the control is to drive the temperature of the outlet flow to the desired value. The process has four important characteristics for control design: 1) The time-delay is 15 seconds and the dominating time constant is about 30 seconds. 2) The dynamics is sensitive to the flow changes. 3) Noise is a function of the temperature and the inlet flow. 4) The process has extremely slow modes due to the lack of insulation.

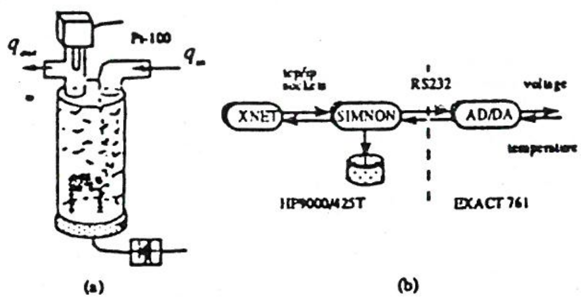


Figure 6 (a) Schema of the Heating Process and (b) Software Configuration.

The software of the control workstation HP9000/425T, Figure 6b, consists of the commercial process simulator, Simnon (1991), communicating through tcp/ip sockets with the Planet/XNet neural network software (Miyata, 1990), which provides a flexible software tool for neural network computation. Here Simnon is used to store the measurement data to a file and to communicate with the unit controller. The control signal itself is computed in XNet. Both software packages are modified by adding necessary procedures to tcp/ip communication and RS 232 serial bus protocol. The combination of Simnon and XNet provides a flexible and practical research tool for real-time experiments and simulation studies when the Simnon is used to solve differential or difference equations of the simulated process.

The NOE model structure with $na=nb=2$ and $d=5$, and the controller structure with $ma=mb=1$ and $mc=2$ are used. The model network consists of two hidden layers with five hyperbolic tangent nodes and an one-output node with linear activation function. The controller has the same network structure, except that the hidden layers have ten nodes and the activation function of the output node is hyperbolic tangent.

The NOE predictor is fitted in 3000 iterations to the input- output data collected by driving the process through the whole operation range from 10 to 50^0 C. After the model identification the controller (4) is designed by minimizing a cost function using a similar setpoint sequence as in modelling. Moreover, the pole of the controller is limited to [0.8, 1.0] by projecting the parameters of the controller into the stable region. This not only ensures the stability of the controller but also considerably reduces the possible oscillations of the control signal. After 2000 iterations, the parameters were fixed and the prediction error feedback with the filter was added to the feedback path.

Six weeks after the model identification the performance of the control system is tested in real-time experiments. This results in significant modelling error. The behaviour of the control system and the controller/model loop are shown in Figure 7. The setpoint responses show that in spite of the mismatch between the process and the model, the overshoot is very small and the response is fast and robust.

6. Fuzzy Control

In fuzzy control the major contributions have been in the area of tuning. This is a very important area in fuzzy control. New methods for tuning of multivariable fuzzy logic controller have been developed (Makkonen and Koivo, 1995a; Viljamaa and Koivo, 1995). A new, relay autotuning method for scalar fuzzy PID controllers is reported in Makkonen and Koivo (1995 b).

Fuzzy control has been applied to a very difficult servoproblem, which includes all practical nonlinearities like friction, backlash and saturation (Makkonen and Koivo, 1995 a). The developed servo model is a good test problem for different control methods. Conventional approaches do not work very well and are difficult to tune. Here robustness properties of fuzzy control are clearly demonstrated. Fuzzy and self-organizing control has been tested e.g. on an industrial robot (Franssila and Koivo, 1992).

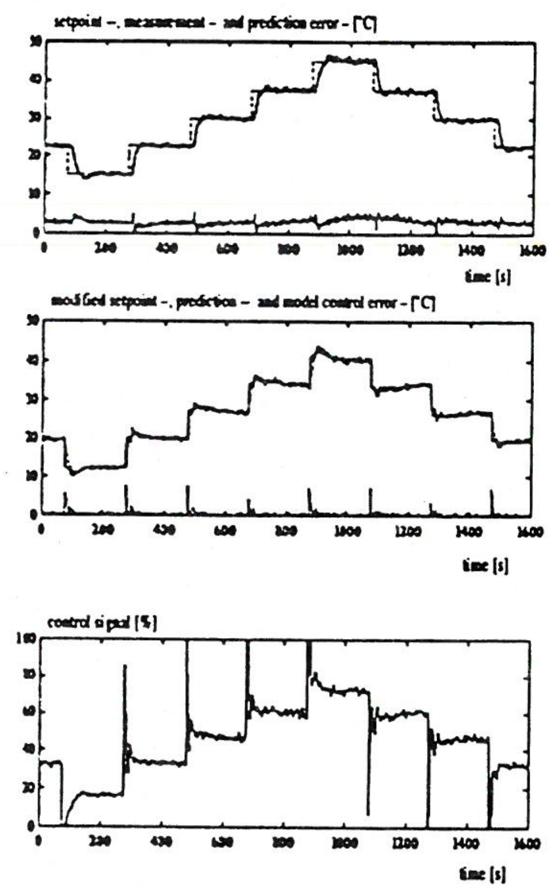


Figure 7. The behaviour of the control system and the controller/model loop. The setpoint, the measurement, and the prediction error are presented above. The middle picture shows the modified setpoint, the prediction, and the

7. Telemanipulation

Telemanipulators are widely used in many hazardous environments - e.g. in high radiation, undersea or space environments. They offer better flexibility compared with conventional manipulators due to their man-in-the-loop property. Interaction between human and manipulator also induces many difficulties in control schemas (Hogan, 1989).

Servo-master-slave teleoperation system usually consists of three subsystems: master, slave and communication system. Master and slave are not usually connected, but connection is artificial through the communication system. The communication system includes the control systems for master and slave, transmission of measurement and control signals, and information system that delivers information (e.g. vision and sound) about the environment of the slave to the master side, where the operator is. In addition to the actual teleoperation system, both operator and the object to be manipulated belong to the total system under study.

Good force reflection or tactility is of utmost importance when manipulating objects by the telemanipulator. It enables precise and safe operation and hence increases the use of telemanipulator. Many control strategies suggested in the literature for master-slave control, are based on the modelling of the system using basic principles (e.g. Bobgan and Kazerooni, 1991; Furuta et al 1987; Lee and Lee, 1992). At Tampere University of Technology a procedure for quick design and tuning of controllers was developed based on on-site measurements (Rauhala and Koivo, 1994). The approach is different, since no physical or parametric models of the system are needed, but the tuning of controllers is based on the frequency response analysis. Therefore the scheme is easily implemented for different kinds of manipulators.

8. Microtelemanipulation

Electronics has developed very fast in recent decades. The sizes of microchips have been reduced from centimeters to micrometers and very high component densities have been achieved. In the future, the microelectromechanical systems are expected to develop in the same way. Consequently, microsystems are expected to have prominent impact on technological development. Manipulators capable of operating with an accuracy of micrometers can be applied to the assembly of microelectromechanical systems, the test and assembly operations of microchips, microsurgery and biotechnological operations. Micromanipulators can be, depending on the application, either micro-sized or normal-sized. All of them can handle micro-sized objects and are called micromanipulators in the literature. At Tampere University of Technology an one degree of freedom test bench for control experiments has been implemented (Kallio and Koivo, 1995 a and b). The master-slave type of manipulator moves minute objects having size of few millimeters. A voice-coil actuator drives the slave, which is controlled using an one degree of freedom lever. The end effector of the slave - a thin aluminium link - is mounted on the voice-coil motor detached from a 3.5" hard disk drive of a PC as shown in Figure 8.

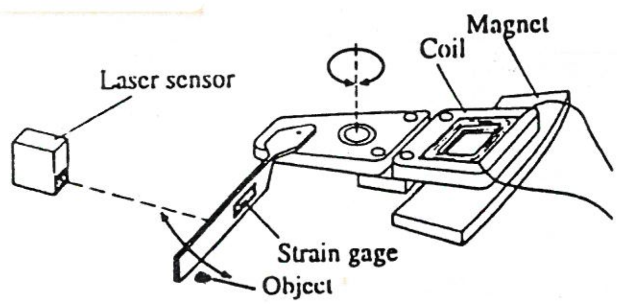


Figure 8. An Overview of the Mini-telemanipulator

When the slave comes into contact with an object the force exerted on the slave is magnified and reflected to the master. The force is sensed by strain gages and a laser sensor measures the positions of the link. A bilateral control method which has been used in the normal-size telemanipulator is used also for the minitelemanipulator.

A joint project with Mechanical Engineering Laboratory of MITI, Tsukuba, Japan, is also in progress. Here a Stewart-type micromanipulator has been designed and implemented. Extension of its workspace and control design has been reported in Ojala et al (1994). The next phase in the project is to apply micromanipulation to biological cell manipulation.

9. Conclusion

A brief summary of the research activities of Control Engineering Laboratory in the areas of intelligent control, telemanipulation and microtelemanipulation, has been produced.

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