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FUNDAMENTAL STUDY OF INTELLIGENT MULTI-FUNCTIONAL INSTRUMENTATION AND ITS SIGNAL PROCESSING ABILITIES

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Abstracts An intelligent system which is an integration of multi-functional instrumentation(MFI) and a neural network is discussed. According to some experiments of temperature and wind velocity it is clear that this system can learn the data structure of two parameters above. So it makes good performances for estimations of non-sample data.

Keywords multi-functional instrumentation(MFI), intelligent system, neural network, signal processing, estimation

1. INTRODUCTION

All systems, not only industrial systems but also biological ones, are consist of at least sensing(input), processing, and controlling(output) parts. So there seems to exist three types of intelligence. Multi-functional instrumentation(MFI)[1] which spends great efforts on signal processing is one of examples of the intelligent sensing part. It can detect some information simultaneously and discriminate them by suitable information processing. Fuzzy and neural networks are those of the intelligent processing part. In particular the later one, a neural network, is a model of biological brains consisting of nonlinear operating units called neurons. It possesses plasticity so it can extract underlying rules from several data pairs. In this article an intelligent instrumental system named intelligent MFI [2][3] which combined MFI with a neural network is discussed.

By the way there are no reports concerning about the intelligent controlling part except tasks of biological motor control in the field of neurocomputing.

2. INTELLIGENT MFI

As showing in Fig.1, MFI consists of two parts. One is a sensing part and the other is a signal processing one. Details of each part are described as below.

2. 1 Sensing Part

In general instrumentation techniques are based on various kinds of physical phenomena. One of them is an interaction between materials or status of them. Let $\alpha^{[i]}(i = 1, 2, 3, \cdots, n)$ be some physical parameters such as temperature, humidity and V be an output signal of a sensor device, then its input-output relationship ϕ denoted as follows,

$$V = \phi(\alpha^{[1]}, \alpha^{[2]}, \alpha^{[3]}, \cdots, \alpha^{[n]}). \tag{1}$$

In this case, if $\alpha^{[1]}$ is the most dominant parameter and $\alpha^{[i]}(i = 2, 3, \cdots, n)$ are negligible, an approximation of eq(1) becomes

$$\tilde{V} = \tilde{\phi}(\alpha^{[1]}). \tag{2}$$

Therefore if the inverse function of $\tilde{\phi}$ is known, the estimated value of the parameter $\alpha^{[1]}$ can be derived from

$$\widetilde{\alpha^{[1]}} = \tilde{\psi}(\tilde{V}) = \tilde{\phi}^{-1}(\tilde{V}). \tag{3}$$

Now consider that scalar operations are replaced by vector operations. Then eqs(2) & (3) become as follows,

$$\tilde{\boldsymbol{V}} = \tilde{\boldsymbol{\Phi}}(\boldsymbol{\alpha}), \tag{4}$$

$$\tilde{\boldsymbol{\alpha}} = \tilde{\boldsymbol{\Psi}}(\tilde{\boldsymbol{V}}) = \tilde{\boldsymbol{\Phi}}^{-1}(\tilde{\boldsymbol{V}}). \tag{5}$$

Assume that all vectors in these equations consist of n elements, it is said that "If n different kinds of sensors are available, n different physical parameters can be estimated simultaneously." This is a basic idea of MFI and it is an only extended version of the conventional uni-functional instrumentation(UFI) technique.

2. 2 Signal Processing Part

The most important and difficult thing of MFI is how to decide a procedure of signal processing. That is equivalent to how to get an outline of a nonlinear transform function $\tilde{\Psi}$. Assume that $n = 2$ in *2. 1*, a part of eq(5) becomes

$$\widetilde{\alpha^{[1]}} = \widetilde{\psi_{11}}(\widetilde{V^{[1]}}, \widetilde{V^{[2]}}). \tag{6}$$

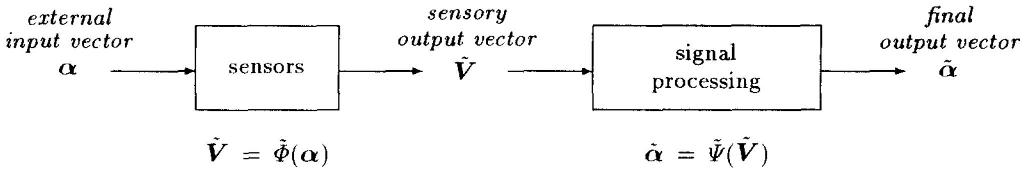


Fig. 1. Schematic diagram of multi-functional instrumentation (MFI)

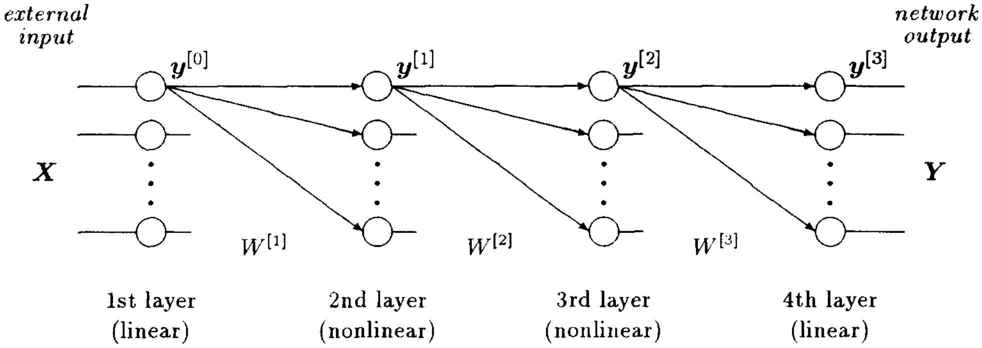


Fig. 3. Four-layer perceptron (4LP)

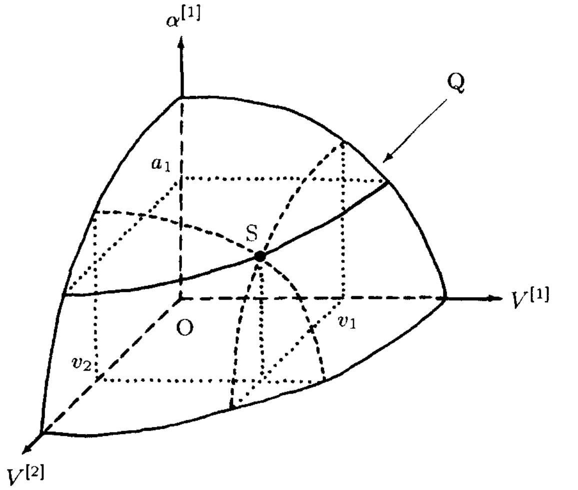


Fig. 2. An example of the outline of $\tilde{\Psi}$

The solution of this equation where $(V^{[1]}, V^{[2]}) = (v_1, v_2)$ is the point S on the three-dimensional curved surface Q over the input space $(V^{[1]}, V^{[2]})$ shown in Fig.2. Using least mean square is one of the most popular techniques to solve this kind of problem. But in this article adaptivity which a neural network possesses is utilized. A neural network is a model of biological brains and its major features are parallel distributed processing and adaptivity. A multi-layer perceptron(MLP)[4] is one of the most famous networks and it is often used in various kinds of tasks. Fig.3 shows an example of MLP. Let $\boldsymbol{X}$ and $\boldsymbol{Y}$ be an input and an output vectors respectively, the dynamics of this four-layer perceptron(4LP) is defined as follows,

$$\boldsymbol{y}^{[0]} = \boldsymbol{X}, \tag{7}$$

$$\boldsymbol{y}^{[1]} = f_1\left(W^{[1]} \cdot \boldsymbol{y}^{[0]}\right), \tag{8}$$

$$\boldsymbol{y}^{[2]} = f_2\left(W^{[2]} \cdot \boldsymbol{y}^{[1]}\right), \tag{9}$$

$$\boldsymbol{Y} = \boldsymbol{y}^{[3]} = f_3\left(W^{[3]} \cdot \boldsymbol{y}^{[2]}\right), \tag{10}$$

where

$$f_1(\boldsymbol{x}) = f_2(\boldsymbol{x}) = \frac{1}{1+\exp(-\boldsymbol{x})}, \tag{11}$$

$$f_3(\boldsymbol{x}) = \boldsymbol{x}. \tag{12}$$

It is clear that the effective nonlinear transformations are performed only the second and the third layers. If this network is regarded as a black box, its input-output function $\mathcal{F}$ is denoted as follows,

$$\boldsymbol{Y} = \mathcal{F}(\boldsymbol{X}). \tag{13}$$

The black box deals with continuous signals so the input and the output spaces are interpolated respectively throughout the training phase. Moreover a mapping between the two spaces are developed topologically.

3. EXPERIMENTS

3.1 Estimation of Temperature and Wind Velocity

We can feel temperature and wind velocity by some thermal sensory receptors distributing the outer skin. So a thermistor, one of thermal sensors, can detect these information. It is said that a thermistor changes its resistance

TABLE 1. Parameters of pre- and post-processing

parameter	X_{low}	X_{high}
$R_{25}[\Omega]$	1100	1800
$R_{50}[\Omega]$	700	1300
$T[^\circ\text{C}]$	20.0	40.0
$V[\text{m/sec}]$	0	5.0

TABLE 2. Estimated values of untraining data

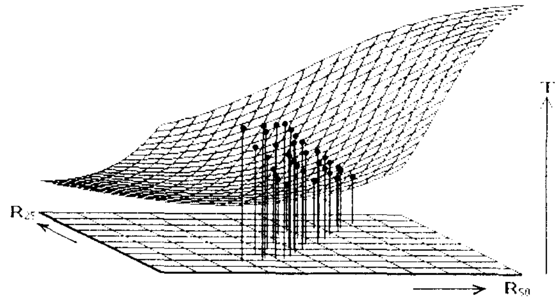
	DATA-1	DATA-2
$R_{25}[\Omega]$	1317.1	1330.1
$R_{50}[\Omega]$	956.2	985.3
$T[^\circ\text{C}]$	33.4	33.5
$V[\text{m/sec}]$	2.5	3.5
$T_{\text{NN}}[^\circ\text{C}]$	33.42	33.70
$V_{\text{NN}}[\text{m/sec}]$	2.58	3.64
$T_{\text{LMS}}[^\circ\text{C}]$	33.47	33.65
$V_{\text{LMS}}[\text{m/sec}]$	2.46	3.73

widely depending on temperature with a negative correlation coefficient. And depending on its supplied current, too. Therefore different supplied current makes a thermistor different characteristic.

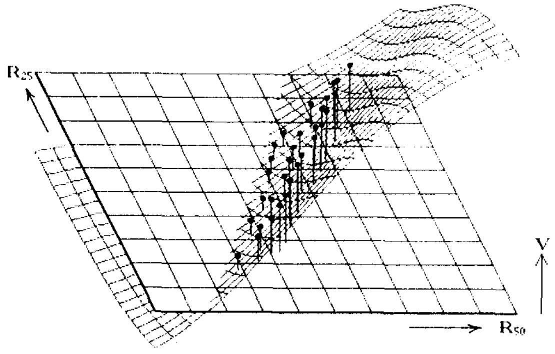
This time two thermistors are used and let each supplied current be 2.5mA and 5.0mA. The combination of two output resistances (R_{25}, R_{50}) contains naturally information of temperature T and wind velocity V. And because the range of analog neurons is (0, 1.0), the linear transformation

$$X_{\text{new}} = \frac{X_{\text{old}} - X_{\text{low}}}{X_{\text{high}} - X_{\text{low}}} \tag{14}$$

are performed. Each parameter is shown in TABLE 1. Then these compressed signals are applied to 4LP, each layer consists of two, nine, nine, two neurons except bias neurons, and this network learns the relation between (R_{25}, R_{50}) and (T, V) by error back-propagation method [5]. Its initial states are determined by ten different small random noises distributed [-1.0, 1.0]. After learning of 30,000 iterations with learning rate $\eta = 0.01$, some evaluations of untraining dates are performed (see TABLE 2). In this table the suffix of "NN" means estimated value of the proposed method using 4LP and that of "LMS" means one of the conventional methods using least mean square. It is clear that there are no significant difference between the two methods.



(a) $T = \mathcal{F}_T(R_{25}, R_{50})$



(b) $V = \mathcal{F}_V(R_{25}, R_{50})$

Fig. 4. Outline of transform function made by 4LP

resistance (R_{25}, R_{50})

$\longrightarrow$ temperature T / wind velocity V

3. 2 Signal Processing for the Better Estimation

The outline of transform function $\tilde{\Psi}$ made by 4LP are shown in Fig.4. Its surface is changing smoothly so that it is compatible with less perturbation of physical parameters. These results seem to suggest that 4LP can learn the data structure between temperature T and wind velocity V from several sample data. It is nothing else but this data structure, an interaction between T and V, is the inverse dynamics of the sensing part. So this is the major reason why 4LP gets good score of estimations compared with least mean square.

Fig.5 is an example of weighting values, binding coefficients between two neurons, of 4LP after learning. White and black boxes mean excitatory(positive) and inhibitory(negative) connections respectively and their size indicates magnitude of the connections.

Based on this figure some evaluations concerning about which pathways are more dominant during signal processing

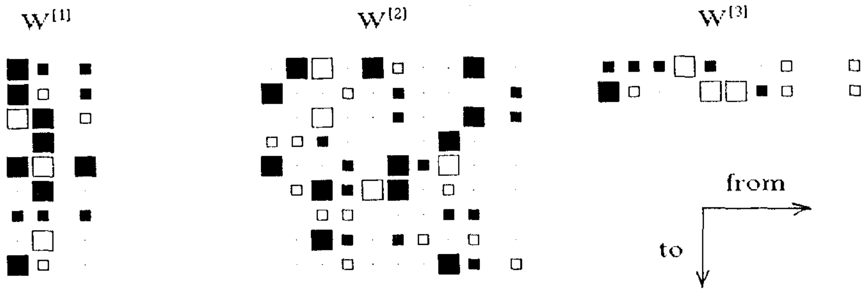


Fig. 5. Weighting values of 4LP after learning

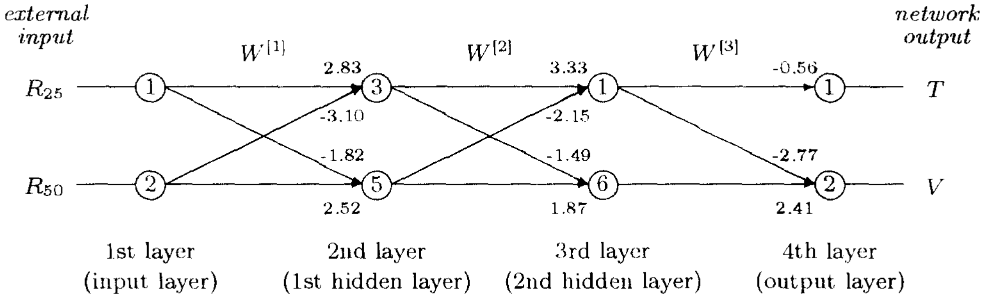


Fig. 6. Dominant pathways of 4LP after learning

are made. And its rough sketch is shown in Fig.6. It can be said that the information of wind velocity V is derived from the difference of the two resistances R_{25} and R_{50}. This result can be explained by some our experiences as follows. Assume that two cases, A:(T_a, V_a) and B:(T_b, V_b),

perhaps we feel cooler case-A than case-B when $V_a > V_b$ nevertheless $T_a = T_b$. Same phenomenon may occur in these sensors i.e., the more the supplied current of thermistors, the stronger the effects of wind velocity.

4. DISCUSSION

The proposed intelligent system is useful as an instrumentation technique. It is only an extended version of the traditional method but it may be possible to say that "A group of less accurate sensors is more accurate than an accurate sensor." This is the same idea as range fractionation theory[6] which is an explanation of biological sensory organ's high sensitivity. At this point of view this system becomes a model of biological sensory system consists of peripheral sensory organs and central nervous systems.

5. CONCLUSION

In this article an intelligent system for MFI and its signal processing abilities are discussed. Then it is clear that this system is useful and its signal processing part, a neural network, achieved good estimations compared with the traditional method because it can learn the inverse dynamics of the sensing part.

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