A NEURAL NETWORK AIDED APPROACH TO DIAGNOSTICS OF COMPLEX SYSTEMS USING UNCERTAIN INFORMATION

by

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ABSTRACT

The idea of a diagnostic system of complex technical devices based on uncertain linguistic information is presented in this paper. The symptoms and faults in a diagnostic process are treated as the imprecise concepts described by fuzzy sets. The fuzzy logic and neural network based approach to the solution of two main tasks of diagnostics of complex systems is applied here. A numerical example illustrates considerations presented in this paper.

Keywords: diagnostics, complex system, uncertain information, neural network.

1. INTRODUCTORY REMARKS

In numerous complex systems, the relationships between the symptoms of abnormal system behaviour and its possible faults, are not clear enough and contain a great amount of uncertainty. Thus, diagnostic processes of such systems deal with various kinds of information. Some of these have a precise (accurate) character whereas others are of an uncertain character. Based on the kinds of information mentioned above, the following main tasks of the diagnostics of complex systems [2] (e.g. electronic-mechanical devices) are analyzed, viz.;

- how to obtain a relation (describing the relationship between symptoms and faults) which will be used to determine the set of faults when the respective set of symptoms is known;
- how to estimate the possible symptoms when the faults are known.

Considering the first task, we assume that the relation can be formed on the basis of a collection of production rules [3,4,5] (obtained for example experimentally).

The second task (an inverse problem) is the problem of finding the possible symptoms which may occur when the faults are known. One way to get any solution of this problem is to construct the opposite rules to the aforesaid and then to build an opposite relation.

Using the respective processing tools (e.g. neural networks, expert system shells) in order to utilize linguistic information, a computer-aided preventing software system can be constructed, especially suitable for initial diagnostics of complex devices. Such a system may form the first stage of hierarchical diagnosis using imprecise but valuable information.

The paper is divided into four sections. The main idea of diagnostic system of complex devices based on uncertain linguistic information is presented in section 2. The direct and inverse tasks of diagnostics of complex systems are briefly highlighted here as well. A numerical example extensively illustrating the considerations of this paper is presented in section 3. Section 4 contains some concluding remarks.

2. RELATIONSHIPS BETWEEN SYMPTOMS AND FAULTS DIRECT AND INVERSE TASKS OF DIAGNOSTICS

In order to describe symptoms of abnormal work and faults of any complex system (for instance the aforesaid electronic-mechanical device) by means of the qualitative linguistic information, we will use the concept of fuzzy set [5]. The use of fuzzy sets provides a basis of a systematic way for the manipulation of uncertain (vague or imprecise) concepts which may also characterize symptoms and faults in diagnostic processes. For our purposes the important concepts are: a linguistic variable (characterizing a symptom or a fault), a fuzzy implication describing a relationship between symptoms and faults and a compositional rule of inference used for approximate reasoning.

In the first task of diagnostics of a complex system, we are looking for a relationship between symptoms of abnormal behaviour of such a system and its possible faults.

Let as assume that a particular relationship between imprecise symptoms and faults can be expressed by a rule (for instance gained by experience):

$$R_r: \quad \text{If } A \text{ is } A_i^{(r)} \text{ and } B \text{ is } B_j^{(r)} \text{ and } \ldots \text{and } C \text{ is } C_p^{(r)}$$
$$\text{then } U \text{ is } U_k^{(r)} \text{ and } V \text{ is } V_l^{(r)} \text{ and } \ldots \text{ and } W \text{ is } W_q^{(r)} \tag{1}$$

where $A_i^{(r)}, B_j^{(r)}, \ldots, C_p^{(r)}$ denote linguistic values of the condition variables representing symptoms defined in the following universes of discourse: X, Y,..., Z and $U_k^{(r)}, V_l^{(r)}, \ldots, W_q^{(r)}$ stand for linguistic values of the conclusion variables representing faults defined in universes of discourse U,V,...,W respectively. Such a rule corresponds to a relation which may be represented by a fuzzy implication [5].

The approximate reasoning is performed by means of compositional rule of inference which may be written in the form:

$$(U', V', \ldots, W') = (A', B', \ldots, C') \circ R \tag{2}$$

R represents the global relation aggregating all rules and may be expressed as

$$R = \text{also}_r\ (R_r) \tag{3}$$

where the sentence connective "also" may denote any t- or s-norms [3,5] (e.g. usually min or max operators).

A symbol $\circ$ stands for the compositional rule of inference operation (e.g. sup-min, sup-bounded product etc.). $(A', B', \ldots, C')$ denotes input symptoms and $(U', V', \ldots, W')$ stands for output faults.

The equality (2) called fuzzy relational equation connects faults with symptoms in a more general way than functional relationship $y = f(x)$.

The inverse task of diagnostics of complex systems is formulated as follows [2]:

- how to estimate the possible symptoms when the faults are known.

Thus, we are concerned with finding possible symptoms that may occur when some of the faults are observed. It should be mentioned that there is no unique approach to the solution of the inverse diagnostic problem. One way of obtaining a solution of this problem is to construct the opposite fuzzy relation defined as

$$R^{-1} = \text{also}_r\ (R_r^{-1}) \tag{4}$$

where R_r^{-1} represents a following rule:

$$\begin{aligned} R_r^{-1}: \quad & \text{If } U \text{ is } U_i^{(r)} \text{ and } V \text{ is } V_j^{(r)} \text{ and } \ldots \text{and } W \text{ is } W_p^{(r)} \\ & \text{then } A \text{ is } A_k^{(r)} \text{ and } B \text{ is } B_l^{(r)} \text{ and } \ldots \text{ and } C \text{ is } C_q^{(r)} \end{aligned} \tag{5}$$

where $U_i^{(r)}, V_j^{(r)}, \ldots, W_p^{(r)}$ denote linguistic values of the condition variables representing faults defined in the universes of discourse: $U, V, \ldots, W$ and $A_k^{(r)}, B_l^{(r)}, \ldots, C_q^{(r)}$ stand for linguistic values of the conclusion variables representing symptoms defined in universes of discourse $X, Y, \ldots, Z$ respectively.

The approximate reasoning is also performed by means of compositional rule of inference which may be written here in the form:

$$(A', B', \ldots, C') = (U', V', \ldots, W') \circ R^{-1} \tag{6}$$

where R^{-1} represents a kind of inverse relation to R.

Assuming that our previous considerations remain valid we may end this section.

3. NUMERICAL EXAMPLE

As an illustration of the above presented considerations, let us make a thorough analysis of the first task of diagnostics of a subsystem being a part of a complex device. Let us assume that the considered part consists of three blocks.

Let X be the space of elements in which all linguistic values of symptoms are constructed. Assume that X consists of 17 elements (X = {0.1, 0.15, 0.2, 0.25, ..., 0.9}) in which three imprecise levels of noise are distinguished. We will represent these levels by similar triangular fuzzy sets that have the following interpretation

- the modal value describes the most likely value of the parameter representing the noise level;
- the spread reflects the precision of this parameter.

Suppose that these three sets represent three linguistic values: high, higher, very high and their membership functions are described by the formula [cf. Fig.1]

$$X_i(x) = \begin{cases} 1 - \dfrac{(0.2i+0.1-x)}{0.2} & \textit{for } 0.2i-0.1 \le x \le 0.2i+0.3 \\ 0 & \textit{otherwise} \end{cases} \qquad (7)$$

Now, let us assume for simplicity that the space of faults also consists of 17 elements (i.e. Y = {0.1, 0.15, 0.2, 0.25, ..., 0.9}). Furthermore, let us distinguish three imprecise faults represented by similar fuzzy sets as the symptoms. Interpretation of these imprecise faults is as follows

- potentially, the fault is in the first block but could be in the second, however, definitely not in the first;
- potentially, the fault is in the second block but could be in the first and third;
- potentially, the fault is in the third block but could be in the second and definitely not in the first.

Let us also assume for simplicity that the three rules only are describing the global relation, i.e.

$$R = also_i \; (X_i \rightarrow Y_i) \tag{8}$$

We will analyze two cases

i) X' is one of X_i, say X_1

ii) X' is exactly half way between X_1 and X_2 i.e. it can be described by the formula

$$X'(x) = \begin{cases} 1 - \dfrac{|0.4-x|}{0.2} & for\ 0.2 \le x \le 0.6 \\ 0 & otherwise \end{cases} \tag{9}$$

This case is also a critical one for diagnostic systems.

Taking minimum as a sentence connective, Lukasiewicz's implication and sup-bounded product ($a \odot b \equiv \max(0, a+b-1)$) composition, we get the following results for the faults.

i) For $X' = X_1$ we get $Y' = Y_1$ (Fig. 1). The first block should be at fault but the second block should also be examined.

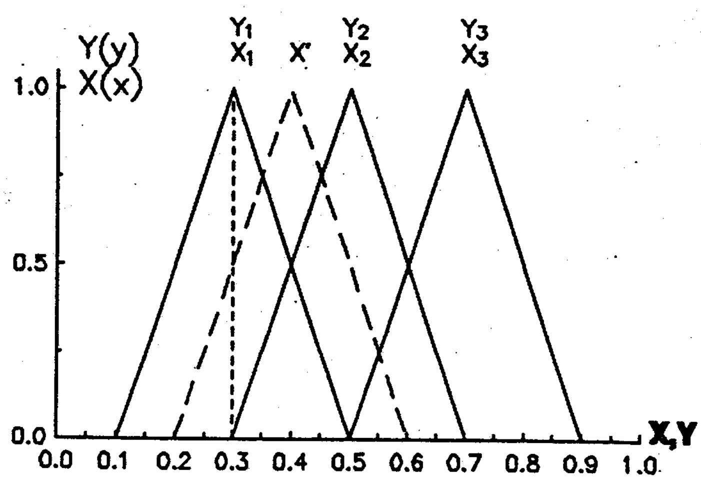

Fig. 1 The membership functions of fuzzy sets describing symptoms and faults

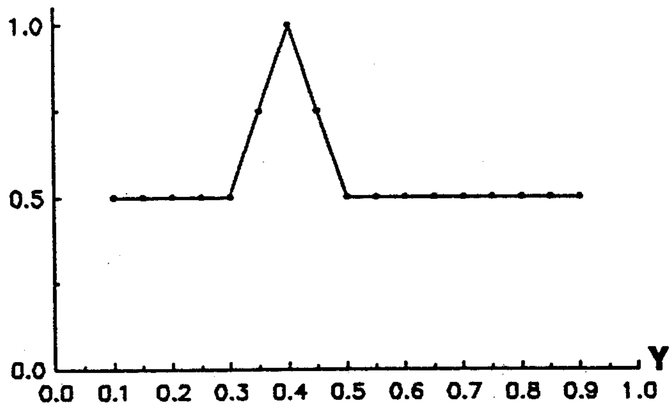

Fig. 2 The membership function of the fault for the critical case

ii) For X' being a half way between X_1 and X_2 we get a fuzzy set Y' illustrated in Fig. 2. Both, the first and the second block could be at fault but the third one could also be at fault.

Using the same 17-levels discretization analogical computation have been carried out using three layers (on hidden layer) feed-forward back propagated neural network of configuration (17-17-17) (Fig. 3).

Learning process of such a network by means of pattern coming only from the collection of three rules took 1500 rounds with learning coefficient 0.9 and fixed momentum term 0.6. The initial weights of the net were chosen randomly with a uniform distribution between plus 0.1 and minus 0.1.

Recalling the net for the pattern of case i), we get the answer which is desired (trained pattern).

For the case ii), we get more specific answer then using compositional rule of inference (Fig. 3). It can be interpreted that only the first or second block could be at fault.

All results concerning neural networks were obtained by means of the NeuralWorks Professional II/Plus network simulation package [6].

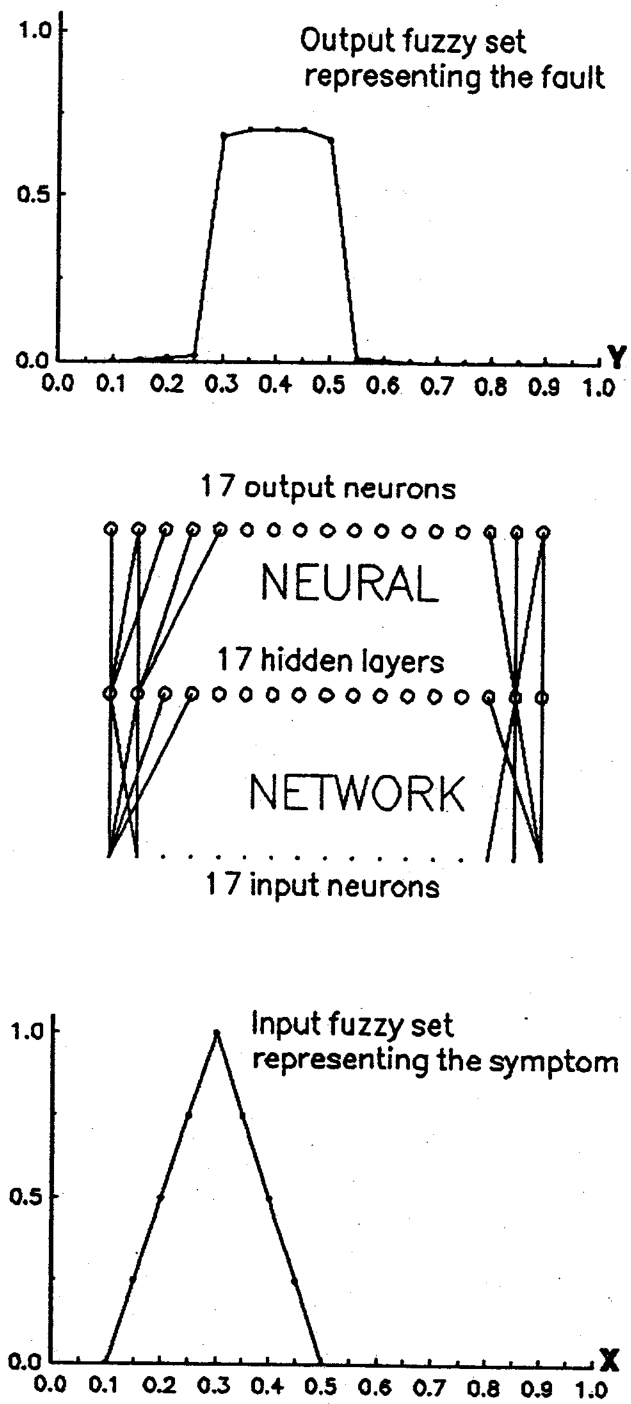

Fig. 3 The application of neural network for computing the fault in the critical case

4. CONCLUDING REMARKS

In practice many faults of complex systems are prevented by a suitable activity of the human operator.

Application of fuzzy logic methods in diagnostic of systems may be useful in hierarchical diagnosis which consists at least of two levels :

- level of diagnostics where the faults of every block of device may be computed by using the ideas presented above;
- level of detailed diagnostics where every element of the block is examined.

The presented considerations and tools (like a suitable fuzzy expert system shells (e.g. [3]) or neural networks [6]) enable to build an automatic preventing system based on a very general kind of information viz. inexact knowledge.

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