ON PROCESSING AN INPUT IMAGE IN FUZZY AND NEURAL CONTROLLERS

J. Chojcan, E. Czogala, G. Tyma

Slesian Technical University,
Department of Automatic Control, Electronics and Computer Sciences
Akademicka 16, 44-101 Gliwice, Poland

Abstract - In this paper we discuss processing an input image related to a knowledge base in fuzzy and neural controllers. A deeper analysis of such an input image may lead to the improvement and completeness of a knowledge base for both types of controllers. Several examples of the input images aproppriate for various controllers are presented and analyzed here. The application of fuzzy control to the purification of air in closed areas is also exemplified in this paper.

Keywords: fuzzy control, neural networks, input image.

1. INTRODUCTORY REMARKS

Numerous applications of the fuzzy logic controller to the control of various ill-defined complex processes have been reported since Mamdani's first paper was published in 1974 (cf. [8,9]).
In many real processes control relies heavily upon human experience. Skilled human operators can control such processes quite successfully without any quantitative models. The control strategy of the human operator is mainly based on linguistic qualitative knowledge of the behaviour of an ill-defined process.
Fuzzy controllers (FL) and neural fuzzy controllers (fuzzy controllers employing neural nets) for short called here neural controllers (NC), synthesized from a collection of qualitative "rules of thumb", are applicable to the control of the processes (plants) that are mathematically difficult to understand and describe [11,13].

This paper consists of seven sections: the first one presents introductory remarks, next, selected design aspects of the fuzzy controllers are presented, the third section describes two structures of neural nets employed in neural fuzzy controllers, the fourth one presents the notion of an input image and the main stages of its processing are listed. The fifth section provides examples of input images. The application of a fuzzy control system to the purification of air employing one of the presented input images is shown in the sixth section, while the last one presents the most important concluding remarks.

2. SELECTED DESIGN ASPECTS OF FUZZY CONTROLLERS

In this section we will recall a rule-based approach to an approximate reasoning process based on the compositional rule of inference [13], which forms a basis of the fuzzy controller. The knowledge base of a fuzzy controller includes the specification of the collection of control rules consisting of linguistic statements that link the controller inputs with outputs, respectively. This knowledge can be delivered by a human expert (e.g. operator of an industrial complex process). Such knowledge, expressed by a finite number ($r=1,2,..,n$) of the heuristic rules of the MISO type (two inputs single output), may be written in the form:

$$R^{(r)} : \textbf{if } x \textbf{ is } E_i^{(r)} \textbf{ and } y \textbf{ is } DE_j^{(r)} \textbf{ then } u \textbf{ is } U_k^{(r)} \tag{1}$$

where $E_i^{(r)}$, $DE_j^{(r)}$ denote values of linguistic variables x,y representing error and change in error (conditions) defined in the universes of discourse **X**, **Y**, and $U_k^{(r)}$ stands for the value of linguistic variable u of action (conclusion) in the universe of discourse **U**.

If we employ a knowledge base of MISO system, the compositional rule of inference may be written symbolically as:

$$U' = (DE',E')\circ R \tag{2}$$

The global relation R now aggregating MISO system rules will be expressed as:

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

where an implicit sentence connective "also" denotes any t- or s-norm or averages [6,8]. Symbol ○ stands for the compositional rule of inference operators.

An output of the fuzzy logic controller (MISO), which has a knowledge base containing a finite number of rules connected by means of the implicit rule connective "also" interpreted as a union (**max** operator), takes the following form:

$$U'=(DE',E') \circ \bigcup_r \left(E_i^{(r)}\times DE_j^{(r)}\rightarrow U_k^{(r)}\right) = \bigcup_r U'^{(r)} \tag{4}$$

where × stands in this case for the explicit sentence connective "and".

Applying **sup-min** operations to the compositional rule of inference, the membership function of the output fuzzy set may by expressed as follows:

$$U'(u) = \sup_{x,y} \min[\min(DE'(y),E'(x)), \max_r (E_i^{(r)}\times DE_j^{(r)}\rightarrow U_k^{(r)})(x,y,u)] \tag{5}$$

If we take fuzzy sets E', DE' as singletons (measurements), i.e. $E'(x) = \delta_{x,x0}$ and $DE'(y) = \delta_{y,y0}$ where

$$\delta_{z,z0} = \begin{cases} 1 & \text{for } z = z_0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

the membership function of the output may be simplified:

$$U'(u) = \max_r [(E_i^{(r)}\times DE_j^{(r)} \rightarrow U_k^{(r)})(x_0,y_0,u)] \tag{7}$$

Now let us consider the rule connective "also" as an intersection. In this case the inequality mentioned above takes the following form:

$$\begin{aligned} \underline{U}_\cap &= (DE',E')\circ[\bigcap_r (E_i^{(r)}\times DE_j^{(r)}\rightarrow U_k^{(r)})] \\ &\le \bigcap_r (DE',E')\circ(E_i^{(r)}\times DE_j^{(r)}\rightarrow U_k^{(r)}) \\ &= \bigcap_r U'^{(r)} = \overline{U}'_\cap \end{aligned} \tag{8}$$

By means of the membership function the inequality may be rewritten as follows:

$$\begin{aligned} \underline{U}'_\cap(u) &= \sup_{x,y} \min[\min(DE'(y),E'(x)), \min_r (E_i^{(r)}\times DE_j^{(r)} \rightarrow U_k^{(r)})(x,y,u)] \le \\ & \min_r \sup_{x,y} \min[\min(DE'(y),E'(x)), (E_i^{(r)}\times DE_j^{(r)} \rightarrow U_k^{(r)})(x,y,u)] = \overline{U}'_\cap(u) \end{aligned} \tag{9}$$

Considering fuzzy sets E', DE' as singletons (in this case $U'_\cap(u) = \underline{U}'_\cap(u) = U'_\cap(u)$) we get a simple formula:

$$U'_\cap(u) = \min_r [(E_i^{(r)}\times DE_j^{(r)} \rightarrow U_k^{(r)})(x_0,y_0,u)] \tag{10}$$

Assuming the explicit sentence connective "and" as product **(prod)** and

sup-prod for the compositional rule of inference we obtain formulas analogical to those given above.

Taking into account the fact that none of the operators **max** or **min** are sufficiently "good" as a rule connective "also", we may try to compensate one of them for another one [6]. The convex linear combination may be used:

$$(1-p)(x *_t y)+p(x *_s y) \quad (11)$$

where ($*_t$ denotes t-norm and $*_s$ s-norm respectively).

Such a combination can be written for the controller output in the form:

$$U_C'(u) = (1-p)\,U_{*_t}'(u)+p\,U_{*_s}'(u) \quad (12)$$

Taking intersection and union for $*_t$ and $*_s$, we obtain:

$$U_C'(u) = (1-p)\,U_{\cap}'(u)+p\,U'(u) \quad (13)$$

Let us notice that for parameter value $p = 0.5$ we get an arithmetic average that is proportional to the sum (plus) interpreted as the rule connective "also". Of course, for parameter value $p = 0$ we obtain a maximal compensation of **max** operator by **min** operator [6].

Applying the defuzzification operator denoted *DEFUZZ* to both sides of the last equality we get the following expression:

$$DEFUZZ\,[U_C'(u)] = DEFUZZ\,[(1-p)\cdot U_{\cap}'(u)+p\cdot U'(u)] \quad (14)$$

Choosing the defuzzification operator as a center of gravity (*COG*) we get:

$$COG\,[U_C'(u)] = COG\,[(1-p)\cdot U_{\cap}'(u)+p\cdot U'(u)] \quad (15)$$

or

$$u_C = (1-p)\cdot u_{\cap}+p\cdot u \quad (16)$$

where $u_{\cap}$ and u stand for centers of gravity of intersection and union respectively.

3. NEURAL CONTROLLERS (NEURAL FUZZY CONTROLLERS)

The description of two structures of a neural controller (here considered to be a neural fuzzy controller) will be provided below. Generally speaking, a neural controller uses a neural network for information storage and processing. It also employs input-output interfaces that transform the information from the controller's environment into a form which is acceptable for the network and vice versa. The controllers mentioned here employ multilayer perceptrons [7] for information storage and processing. These relatively well-known networks allow supervised learning and generalization [2,3,4].

The training process is performed off-line and uses quantitative measurements expressed by triples (*Error*, *Change in Error*, *Control Action*) obtained during the observation (sampling) of the process controlled by a human operator. It should be mentioned here that neural nets may also be initially trained using information obtained from the control rules (qualitative knowledge) [7]. As a learning scheme, the widely used backpropagation algorithm can be applied [12].

After training, the network can be used to control the process. This is accomplished by feeding process data (error and change in error) via the input interface to the input layer of the network which then recalls the appropriate action. Afterwards the response of the network is translated into the actual control value by the output interface.

Considering the discretization of the universes of discourse for error - **X**, change in error - **Y**, and control action - **U**, we can now construct two versions of the neural fuzzy controller. Both use a multilayer perceptron for information storage and processing. The structure of the network's input layer is considered to be linear for the 'vector' version and rectangular for the 'matrix' version (see Fig. 1). The structure of the hidden and output layers is always linear.

4. PROCESSING THE INPUT IMAGE IN FUZZY CONTROLLERS

Now let us consider the Cartesian product of the knowledge base rule, i.e. $E_i^{(r)} \times DE_j^{(r)} \subseteq \mathbf{X} \times \mathbf{Y}$, the projection of which on the x-y plane represents an element of the input image (an input pattern) of the knowledge base.

The whole input image consisting of input patterns which are the above mentioned Cartesian products:

$$II^{(r)} = E_i^{(r)} \times DE_j^{(r)} \tag{17}$$

obtained from all rules may be written in the form:

$$II = \bigcup_r II^{(r)} \tag{18}$$

Using an alfa-cut of corresponding sets we get

$$II = \bigcup_\alpha \bigcup_r \alpha II_\alpha^{(r)} \tag{19}$$

The formula written above can be expressed by means of the membership function

$$II(x,y) = \sup_\alpha \max_r \alpha II_\alpha^{(r)}(x,y) \tag{20}$$

where

$$II_\alpha^{(r)}(x,y) = \left(E_i^{(r)}(x) *_t DE_j^{(r)}(y)\right)_\alpha \tag{21}$$

and $*_t$ denotes a respective t-norm (e.g. min) [6,8].

It also means that all input patterns projected on the *x-y* plane create an input image. In other words, the input image is made up of overlapping input patterns obtained by means of respective rules of a knowledge base. As a result the input image constitutes a basis for processing in fuzzy controllers.

After each input pattern has been formed separately in the implication rule, we can differentiate three stages of processing the input image.

Firstly, the rules are combined by means of the implicit rule connective "also" (at this point the input image can be created).

Secondly, the input image is processed by means of the compositional rule of inference on condition that input information is provided.

Thirdly, a defuzzification procedure is employed to obtain the respective control value.

The idea of the input image has numerous advantages. It enables us to test the completeness and correctness of the knowledge base. Such an input image can be obtained e.g. by means of an ordinary fuzzy partition of the input space. In this case the number of rules increases exponentially with the number of inputs. Another way of obtaining an input image is the application of fuzzy clustering (fuzzy c-means) [11].

5. EXAMPLES OF INPUT IMAGES

Let us introduce some important input images which can be processed in fuzzy controllers as well as in neural fuzzy controllers. They fall into two groups.

The first group contains input images (1D, 2D, 3D respectively) theoretically designed for conventional controllers P(I), PI(PD), PID, but based on knowledge bases, not on mathematical formulas [5,10] (Figs. 2, 3, 4). The second group contains two input images. The first 2D-input image concerns the nine-rule knowledge base for a fuzzy logic controller of the PI(PD) type (Fig. 5). The second one (Fig. 6) has been recorded with an industrial video camera and processed by means of a computer. It reflects a real nine-rule knowledge base of a fuzzy controller applied to the control of an industrial (steel industry) process. The last input image is particularly appropriate for the automatic edition of input files used for training neural nets.

6. NUMERICAL EXAMPLE

Now we will present the simulation results of fuzzy control (Fig. 7) of the process of the purification of air in closed areas through processing the input image (shown in Fig. 5) in a fuzzy controller.

Let us introduce a mathematical model of an air-ventilated closed area with the emission of dangerous gasses, which will be used here for simulation purposes. For the sake of simplicity we have made the following assumptions:

- the flow is considered to be incompressible and one-dimensional,
- the volume rate of noxious gas sources $Q_g=Q_g(t)$ and the volume rate of the delivered fresh air fulfil the inequality $Q_g << Q(t)$,
- in the closed area, the volume of which is V, noxious gasses mix with the air forming a uniform gas-air mixture which has concentration $C=C(t)$,
- the transport of gas by diffusion is neglected.

Because volume V of the air-ventilated room is constant and outflow equals inflow (volume rate Q_g is much lower than volume rate Q of fresh air), the rate of the accumulation of gas in the closed area can be described by the following differential equation:

$$V \cdot dC(t)/dt + Q(t) \cdot C(t) = Q_g(t) \qquad (22)$$

As it was mentioned above, this equation can be used to describe the process of reducing the concentration of dangerous gasses accumulated in closed areas. The danger can be averted by diluting these substances and by carrying them away.

Now we will present the simulation results of controlling the purification process which have been obtained by means of processing the input image in PI-type fuzzy controller. The volume rate of the gas emitted into the aired room has been treated as a random function (simulated by means of a generator of random numbers uniformly distributed in the interval [0,2])

The following parameters of the model were taken into account in the computing process:

- the volume of the closed room equals $V = 2000$ m^3,

- the dimensionless control value was taken as Q/Q_0, where $Q_0 = 720$ m^3/min

- initial conditions were set: $C(0) = 1\%$, $Q(0) = Q_0$

- the set point value within the first 5 min was assumed to be 0.75% and then it was lowered to the level of 0.5%.

Total simulation time amounts to 10 min. The concentration of gas (X1), control value (Dr) and control error (Err) as functions of time are shown in Fig. 8. Again, it should be pointed out that the curves of the picture are the results of processing the input image depicted in Fig. 5. Applications of neural controllers are described e.g. in [1].

7. CONCLUDING REMARKS

In this paper several aspects of processing the input image of the knowledge base in fuzzy and neural controllers have been mentioned. The presented concept of an input image appears to be suitable for testing the correctness and completeness of knowledge bases for the described types of controllers. The results of the control of the processes described above by means of fuzzy controllers seem to be satisfactory. As an objective for future research, the partition of the input and output spaces should be selected more carefully .

8. REFERENCES

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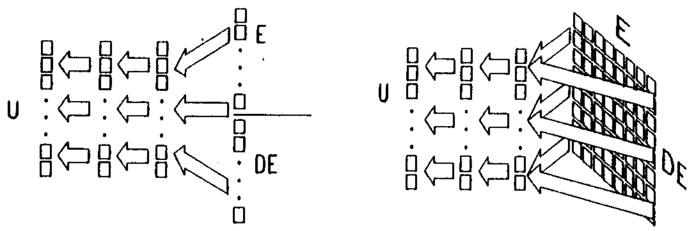

Fig. 1. Two structures of neural nets with 'vector' and 'matrix' input layers.

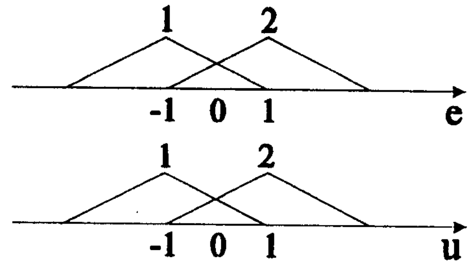

Fig. 2. 1D input image for conventional controllers P(I).

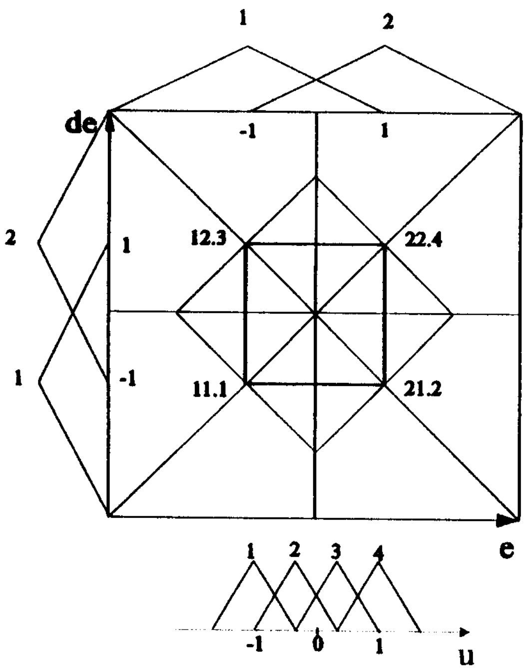

Fig. 3. 2D input image for conventional controllers PI(PD).

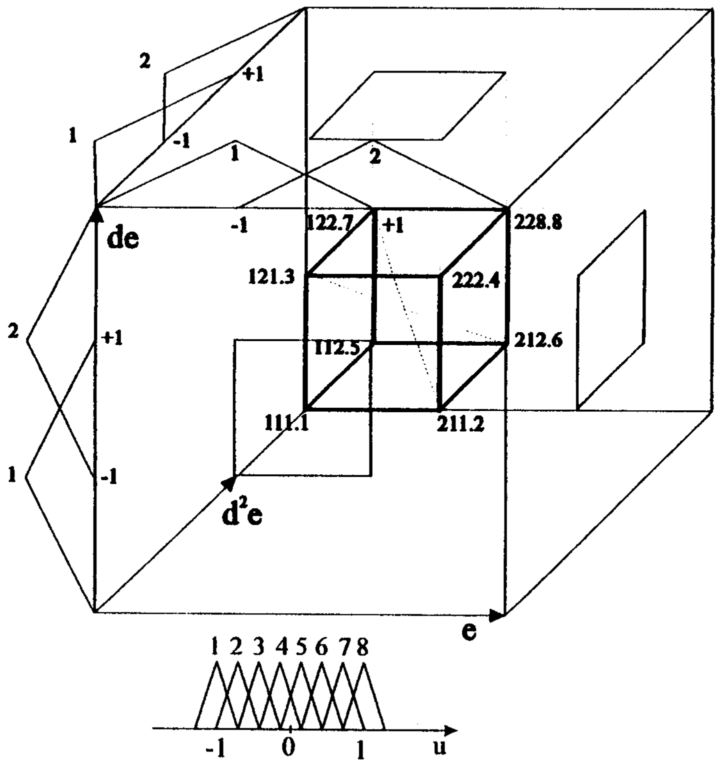

Fig. 4. 3D input image for conventional controller PID.

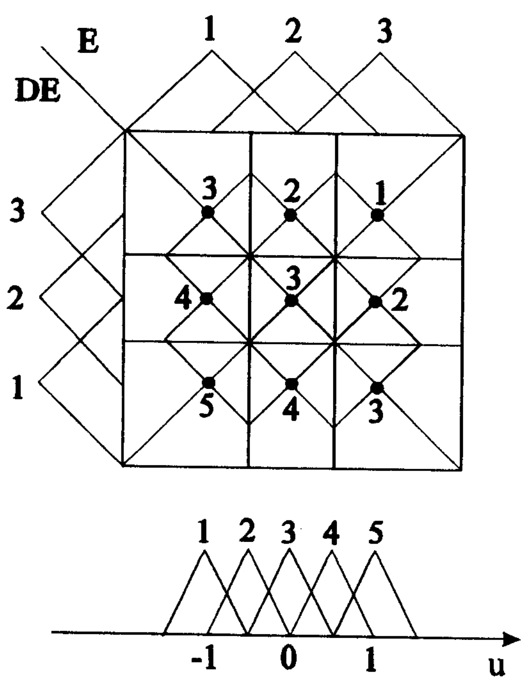

Fig. 5. 2D input image for fuzzy controller of PI(PD) type.

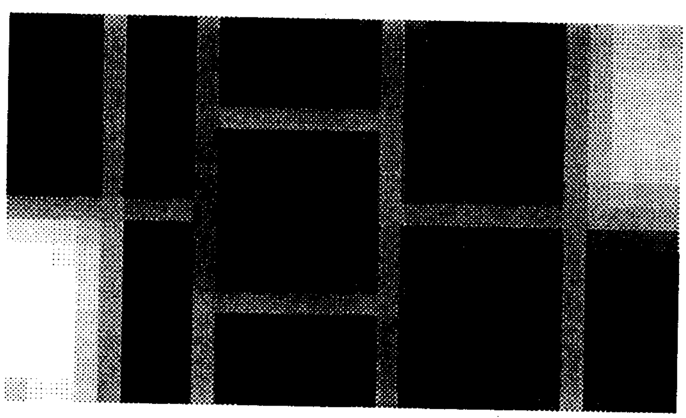

Fig. 6. 2D input image employed in the fuzzy controller applied to control an industrial process.

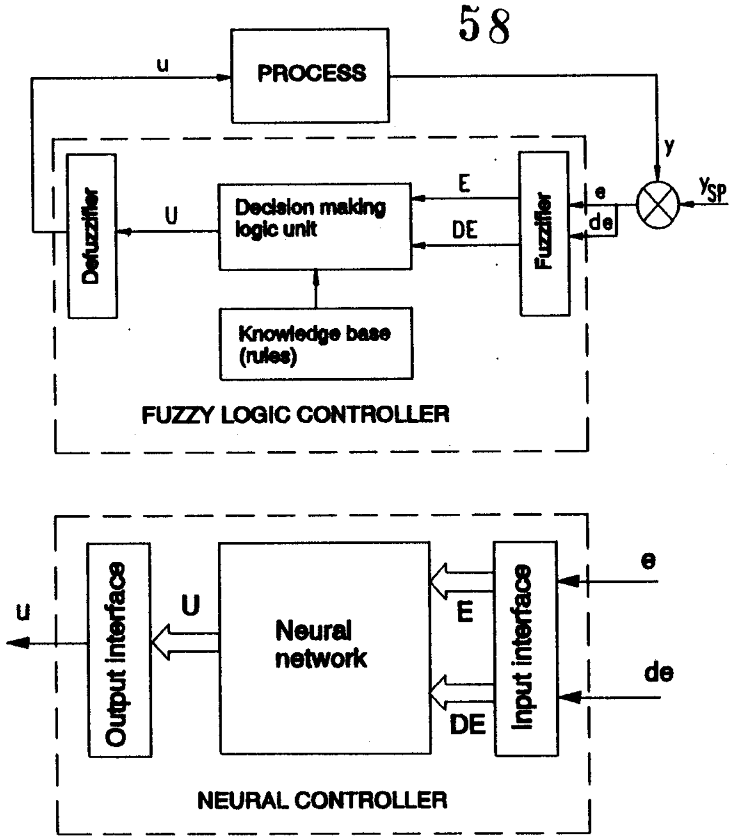

Fig. 7. A block diagram of control system using fuzzy or neural controllers.

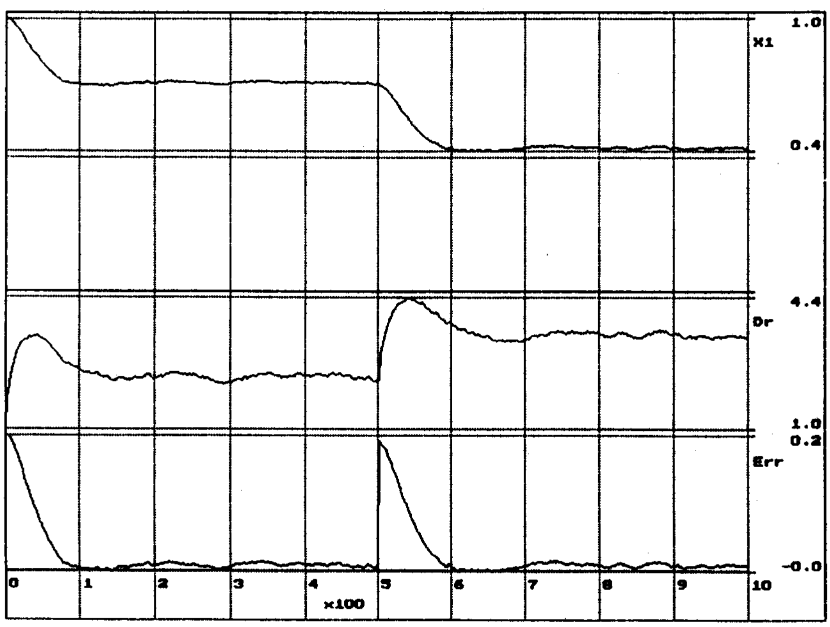

Fig. 8. Simulation results of fuzzy control.