

於虛擬環境中之人性化人機介面技術開發及其於機器臂操控之應用
(III)---有加強式學習能力之模糊口語控制介面技術開發及其於機器臂操
控之應用(III)

A Reinforcement Fuzzy Vocal Learning Control System and its Application on Telerobot Operation

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中文摘要

本年度研究中提出一個四層的「適應性模糊語言句解析神經網路 (Adaptive Fuzzy Language Acquisition Network)」系統。我們簡稱為「AFLAN」。AFLAN有三個重要的特質：第一，使用者不受任何語言的限制，也不需要文法上的或者是句子組織學上的結構。第二，代表言辭上的模糊修飾程度是經由適應性的學習而得來的。第三，此網路具有即時操作時線上學習的能力。我們探討兩種學習形式，一為非線上學習主要是使用在學習用的資料是已知的環境下，我們利用「相互資料指導性學習 (mutual information supervised learning)」法則來學習語意上的動作，此外還利用「模糊倒傳遞學習 (fuzzy back-propagation learning)」法則來學習言辭上模糊修飾的程度。另一為線上學習，主要是使用於在做即時操作時而所使用的資料是在不確知的環境下。在線上學習的學習法則方面我們將之歸類為兩組，除了上述在非線上學習所提到的兩種學習法則外，我們更利用「相互資料加強式學習 (mutual information reinforcement learning)」法則來學習語意上的動作及「模糊加強式學習 (fuzzy reinforcement learning)」法則來學習言辭上模糊修飾的程度；而這兩組學習法則的不同點主要是在評判式訊號 (critical signal) 的來源不同，前組的訊號是由指導者 (supervisor) 所提供的 (監督式學習)；而後組的加強式訊號是由使用者直接提供 (加強式學習)，而這組學習方式使得線上學習更為即時。

1. INTRODUCTION :

It is hard to reach the ultimate goal --- unrestricted free communication between man and machine in a changing and uncertain world [1]. Many researches want to develop a theory which can predict the set of grammatical sentences in a language from a finite number of observations [2]-[5]. In [6,7], the

systems learn the mapping from sentences to symbolic representations. In 1989 and 1991, Miikkulainen and Dyer [8] use a modular network to learn to paraphrase script-based stories. In 1990, St. John and McClelland [9] also used modular connectionist networks to learn the mapping from input sentences to an output event description. For the purpose of performing at a desired level, those systems require great constrained input --- a severely restricted vocabulary or a rigid syntax. In contrast, a different approach was proposed by Gorin et al. [10,11], where the system's understanding of an input message was evaluated on the basis of whether the system responded in an expected and appropriate way over a wide range of scripts.

We establish a fuzzy neural network, called Adaptive Fuzzy Command Acquisition Network (AFCAN). It consists of four layers, and can be regarded as a cascaded network comprising two subnetworks, the CCNO (Crisp Connectionist Architecture with Numerical Output) net and the FCLO (Fuzzy Connectionist Architecture with Linguistic Output) net. The former is a two-layered network with crisp mutual information weights, and the latter is a three-layered network with fuzzy weights. The input to the AFCAN is unrestricted text in fuzzy language, and the output of the AFCAN is the user's desired semantic action and the associated fuzzy linguistic information. More clearly, the CCNO processes the user's input command to acquire the desired semantic action, and the FCLO maps a crisp input to a desired fuzzy linguistic output presented in the form of α -level sets [12]. The proposed AFCAN can be applied in a voice control system as shown in Fig. 1.

2. ADAPTIVE FUZZY COMMAND ACQUISITION NETWORK

In this section, we shall propose a network for our acquisition system whose input is unrestricted text of fuzzy commands and output is one of a finite

set of semantic fuzzy actions. This network is called adaptive fuzzy command acquisition network (AFCAN).

A. Basic structure of the AFCAN

Fig. 2 shows the proposed network structure of the AFCAN, which has a total of four layers.

• Layer 1-Detector Layer:

The nodes in this layer are divided into two groups; word detector nodes and phrase detector nodes. The inputs to the phrase detector node, $V_m V_n$ are the outputs of the word detector nodes V_m and V_n . For this reason, the input sentences have to pass the word detector nodes first, and then pass through the phrase detector nodes.

(1)Word detector nodes: The function of each word detector node is to detect the presence of a vocabulary word V_m in the input sentence S , and produce an output between 0 and 1. In this paper, words are counted only once, no matter how often they appear. The word detector nodes execute some function that can detect the presence of a word in the sentence. The simplest function is a matching function that produces the output 1 if a particular word is observed; otherwise produces the output 0. A more sophisticated function is one that produces an output equal to the probability that the word V_m is in the sentence.

(2)Phrase detector nodes: The function of each phrase detector node is to detect the presence of a vocabulary phrase $V_m V_n$ in the sentence S , and produce an output between 0 and 1. The simplest case is for noise-free input, in which the output is 1 if phrase $V_m V_n$ is observed; otherwise, the output is 0.

Input (S)=an unrestricted sentence (1)

$$\text{Output } (y_{m1}, y_{m2}, \dots, y_{mn}) = \begin{cases} 1, & \text{if the word } (V_m) \text{ or phrase } \\ & V_m V_n \text{ is observed} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

• Layer 2-MI-Value Layer:

The input of each node in this layer is a numerical number coming from the output of in layer one multiplied by the weight, assuming that the semantic action in layer four is recognized. That is, the input to a layer-two node is $y_{m1}^1 (y_{m1}^1) \times W_{m1k0}$. Each node in this layer only transmits input numerical number to the next layer directly. Hence we have

$$y_i^2 = y_{m1}^1 (or y_{mn}^1) \times W_{nk0}^{14} \quad (3)$$

where $1 \leq m, n \leq M, n \leq M, 1 \leq k0 \leq K$, and K is the number of nodes in this layer.

• Layer 3-Hidden Layer:

As described previously, layers two, three and four of the AFCAN constitute the FCL0 network that can map numerical input values to fuzzy output numbers. The input values fed into each node in this layer are the weighted output values of layer two, which are numerical numbers. In order to produce fuzzy outputs, there should exist fuzzy weights between layer two and layer three, so each node in this layer is fully connected to the nodes in layer two through fuzzy weights. More precisely, we have

$$\text{Output: } Y_j^3 = f(Net_j^3), j = 1, 2, \dots, N_h \quad (4)$$

$$Net_j^3 = \sum_{i=1}^{M+2} W_{ji}^{23} y_i^2 (+) \theta_j^3 \quad (5)$$

where Y_j^3 is computed by using the extension principle [13], “(+)” represents the addition of fuzzy numbers [13],[14], $f(x)$ is the sigmoid function, N_h is the number of hidden nodes.

• Layer 4-Semantic Layer.

The input values fed into each node in this layer have two sources, one is from layer one and the other from layer three. The outputs of layer one are combined by each of the semantic nodes in this layer to produce output activations a_k for a semantic action ck as follows:

$$a_k = \sum_{m=1}^M y_{m1}^1 W_{m1k}^{14} + \sum_{m=1}^M \sum_{n=1}^M y_{mn}^1 W_{(mn)k}^{14} + W_k \quad (6)$$

The outputs of layer three are fed into each node in this layer too, and each layer-four node is fully connected to the nodes in layer three through fuzzy weights. The fuzzy output of each layer-four node is described by

$$\text{Fuzzy Output: } Y_k^4 = f(Net_k^4), k = 1, 2, \dots, K \quad (7)$$

$$Net_k^4 = \sum_{j=1}^{N_h} W_{kj}^{34} Y_j^3 (+) \theta_k^4 \quad (8)$$

where Y_k^4 is computed by using the extension principle [13], “(+)” represents the addition of fuzzy numbers [13],[14], $f(x)$ is the sigmoid function, K is the number of nodes in layer four.

B. Learning of the AFCAN

In the AFCAN, we perform off-line learning to build an initial network and then use on-line learning to rebuild or tune a trained AFCAN according to the critics from the user/environment when the AFCAN is in use. The mutual information (MI) supervised learning and fuzzy backpropagation (FBP) learning are employed for the off-line learning of the AFCAN. For off-line learning, we need to prepare a set of training data for supervised learning. At first, we use

the MI supervised learning, which is a well-known statistical method of measuring association, to obtain connection weights between the detector layer (layer one) and the semantic action layer (layer four) in the CCNO of the AFCAN (see Fig. 3.). When the MI supervised learning is completed, the FBP learning, which can be viewed as an extension of the backpropagation learning algorithm to the case of fuzzy data, is applied to the FCLO of the AFCAN (see Fig. 4.).

3. SUPERVISED AND UNSUPERVISED LEARNING

We will use a supervised learning scheme for the proposed AFCAN. This scheme is suitable to the situations where pairs of input-output training data are available. For each training datum, the input is an unrestricted sentence and the outputs are a numerical number and a fuzzy number. The AFCAN learning includes two parts, off-line learning and on-line learning. In off-line learning the training phase is finished before doing the performance phase, but in the on-line learning, the training proceeds during the course of performing task. For these two kinds of learning, four learning algorithms are developed and employed, (1) Mutual Information (MI) supervised learning, (2) Fuzzy Backpropagation (FBP) learning, (3) MI reinforcement learning, and (4) Fuzzy reinforcement learning. Learning algorithms (1) and (3) are used in the CCNO to adjust its crisp MI weights, and algorithms (2) and (4) are used in the FCLO to adjust its fuzzy weights. Learning algorithms (1) and (2) are used for off-line learning to build an initial network for real performance. These two learning algorithms are also used in the supervised mode of on-line learning, and algorithms (3) and (4) are used in the reinforcement mode of on-line learning. The on-line learning is to rebuild or tune an off-line trained AFCAN according to the critics from the user/environment.

4. AN ILLUSTRATION EXAMPLE-FUZZY COMMAND ACQUISITION OF A VOICE CONTROL SYSTEM

In this section, we shall establish a system based on the proposed AFCAN that can acquire fuzzy commands given by users in voice or typed input form. The system can acquire only one semantic action at a time, so if it acquires several semantic actions at the same time, it will list them along with their uncertainty factors, and the user should do a judgement (maybe a positive answer or negative answer) from the listed actions. The actions and associated linguistic information (fuzzy predicates) that this system can acquire are listed in Table 1. After a command is acquired, the system will show the selected action and linguistic information in the form alpha-level sets. We can make use of such

output information to do the fuzzy control task directly.

Initially, we set up the detector nodes in layer one of the AFCAN according to the given reference words and put random weights in the FCLO. The initial AFCAN has 41 word detector nodes (layer one), 1640 phrase detector nodes (layer one), 1681 MI value nodes (layer two), 10 hidden nodes (layer three), and 8 semantic node (layer four). The 41 reference words for the word detector nodes are listed in Table 2. We also design a word filter containing 36 words such as "the," "is," "are," "you," "mine," "hers," etc. We train the system using the off-line learning scheme on some input-output training pairs <sentence, fuzzy \ action>, where the fuzzy action is represented by an action number (1-8) and a \alpha-level set ($\alpha = 0.2, 0.4, 0.6, 0.8, 1.0$). When the system is set up and in use, the on-line learning scheme is performed all the time. We next do some simulations to illustrate the power and specialist of the command acquisition system. We illustrate four cases in the following.

The first case is shown in Fig. 5, which is a screen copy of the system interface. According to Fig. 5(a), the system acquires the command correctly without further iteration after the user gives the command. Hence the user replies "yes" as the next input to accept the selected action of the system. After the system recognizes the user's desired action, it then continues to acquire the linguistic information as shown in Fig. 5(b). The user then makes a critic on the shown membership function, where we use "1" to stand for positive critic, "-1" for negative critic, and "0" for good critic (i.e., agree the system's output) (Fig. 5(c)). In the current case, the linguistic information matches the user's desire, so he/she chooses the "0" input.

The second case is shown in Fig. 6(a), illustrates that the system cannot catch the user's intention exactly, so it shows all the promising actions that it acquires. After the user gives another command containing clarifying information, the system reduces its initial uncertainty and appropriately recognize the command. This case shows the power of the system's on-line learning ability using the MI reinforcement learning algorithm. As shown in Fig. 6(b), the system can acquire the user's meaning correctly after it receives the second command via on-line learning. Another example belonging to this case is shown in the following.

```
Machine : May I help you? Please enter your
          command!
User    : Seize the pinwheel very tightly
          opposing wind and let it whirl very
          fast.
Machine : Do you want [action 2] or [action 3]?
User    : I mean to hold the pinwheel very
```

tightly when opposing the wind!
Machine : Do you want [action 2]?
User : You can answer (y/n) y
Machine : Your command is [action 2].

The third case is shown in Fig. 7. We aim at the on-line learning of the acquired linguistic information. After the action is acquired correctly, the system will show the membership function of the acquired linguistic information. The user then has three kinds of critic signals for use to express his/her judgement on the acquired linguistic information: positive (1), negative(-1) and good (0). In the current case, the user feel the linguistic information in Fig. 11(b) is "too slow", so he/she gives a negative critic (-1) (see Fig. 7(c)). At this time, the system will perform on-line learning according to the user's critic (Fig. 7(d)). If the user change the mind and has different thinking on the linguistic information, he/she can again continue to give critics to the system. It is noted that the user can give the critics any time during the fuzzy reinforcement learning, since we perform multistep prediction in the fuzzy predictor of the RAFCAN.

The fourth case is shown in Fig. 8. In the above cases, all the input commands can be acquired to some extend, since the input words and phrases have existed in the initial detector nodes. In the fourth case, we shall illustrate that the system can learn new words (phrases) and their semantic associations from interactive command inputs. From Fig. 8(a), we observe that the command "Go ahead very fast" is not understood by system, because the words "go" and "ahead" are not included in the reference words originally (see Table 2). Hence the system replies with "The system cannot recognize" and ask for the user to enter the command in other expression. When the user gives the second command "I mean to go forward very fast," the system understands this command, and response with "Do you want [action 5]." Since action 5 is the user's desired action, the user presses the "y" key. When the above process is finished, the system will add new detector nodes. Before doing this, the new words should pass the word filter to dismiss some usual-use words (e.g., he, she, and). After adds new detector nodes, the system learns the weights (MI weights and fuzzy weights) of the new network. When the re-learning process is finished, we give the original command to test the effect of the processes of new word adding and weight re-learning. Fig. 8(b) shows that the system after learning can acquire correctly the command "Go ahead very fast." Fig. 8(c) shows the acquired linguistic information of this command.

5. CONCLUSION

The fuzzy command acquisition network,

AFCAN, which consists of command acquisition and fuzzy information acquisition is proposed. Unlike the general language acquisition systems, the proposed system has the following characteristics. (1) The system is built as a neural network trained by users' given data, so the system equips the ability to tune its

parameters and structure to match the application environment. (2) The system has the ability to acquire fuzzy command, which is a nature language comprising the desired actions and fuzzy linguistic information. (3) The input sentences (commands) of this system are unrestricted, but the kinds of output semantic actions are quite restricted. Hence the proposed AFCAN is suitable for constrained-action tasks. That is, one can ask the machine to perform one of a small number of actions, but is allowed total freedom in making such requests. (4) The proposed system needs not any acoustic, prosodic, syntactic and grammatical structure. It is the network (connectionist) structure that enables it to decode the intended information from a natural language message, and this structure makes the system be able to perform more human-like command acquisition and learning. (5) The system can acquire fuzzy command during the course of performing task.

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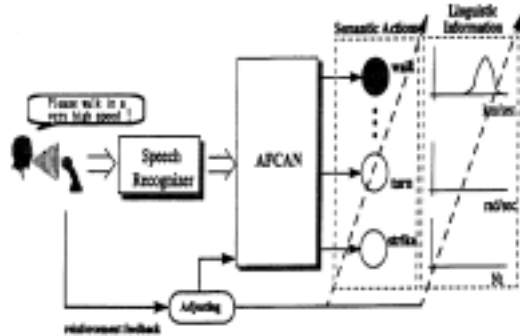


Fig. 1. The use of the proposed AFCAN in a voice control system.

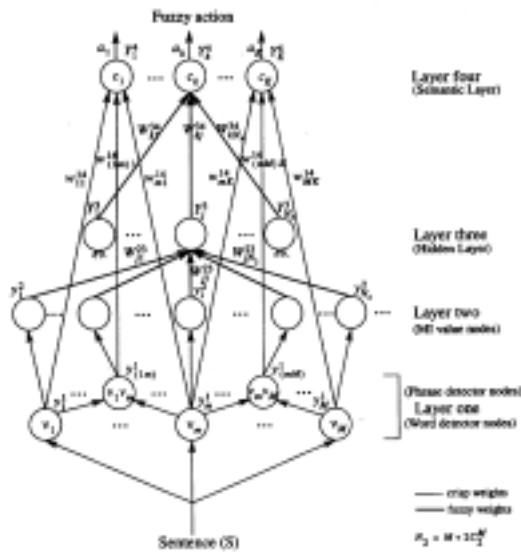


Fig. 2. Network structure of the AFCAN.

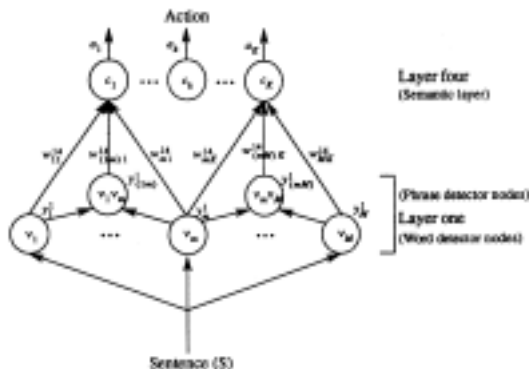


Fig. 3. Network structure of the CCNO.

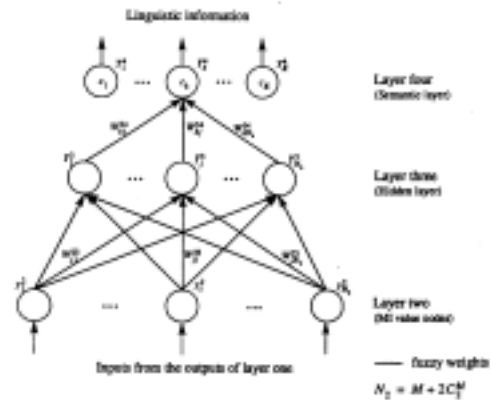
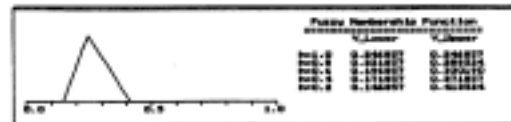


Fig. 4. Network structure of the FCLO.

```
Machine: > Hey I help you ? Please enter your command!
USER :> Move forward at a low velocity !
Machine: > Do you want location S1
USER :> Yes can answer (gray)
Machine: > Your command is location S1
```

(a)



(b)

```
Machine: > Your critic for the linguistic information :
If you want to give position critic, press (+)
If you want to give negative critic, press (-)
If you want to give good critic, press (R)

Waiting for your critic input ..... > R
```

(c)

Fig. 5. Screen copy of the voice control system-the first case.

```

Machine: May I help you ? Please enter your command!
USER : It's your turn to seize the leap line.
Machine: Do you want facton 21 or facton 31
USER : You have to seize the line !
Machine: Do you want facton 21
USER : (y/n)
Machine: Your command is facton 21

```

(a)

```

Machine: May I help you ? Please enter your command!
USER : It is your turn to seize the line.
Machine: Do you want facton 21
USER : You can answer (y/n)
Machine: Your command is facton 21

```

(b)

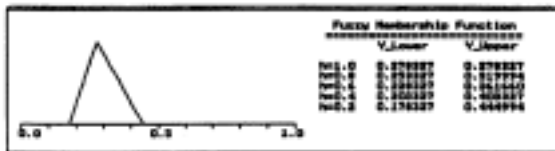
Fig. 6. Screen copy of the voice control-the second case.

```

Machine: May I help you ? Please enter your command!
USER : Please move in the forward direction and be slow.
Machine: Do you want facton 51
USER : You can answer (y/n)
Machine: Your command is facton 51

```

(a)



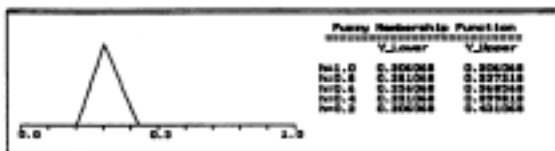
(b)

```

Machine: Your critic for the linguistic information :
If you want to give positive critic, press < 1 >
If you want to give negative critic, press < -1 >
If you want to give good critic, press < 0 >
Waiting for your critic input ..... => -1

```

(c)



(d)

Fig. 7. Screen copy of the voice control system-the third case.

```

Machine: May I help you ? Please enter your command!
USER : Go ahead very fast !
Machine: The system cannot recognize !!
Machine: Please input your command in another expression!
USER : I want that you should move forward very fast !
Machine: Do you want facton 51
USER : (y/n)
Machine: Your command is facton 51

```

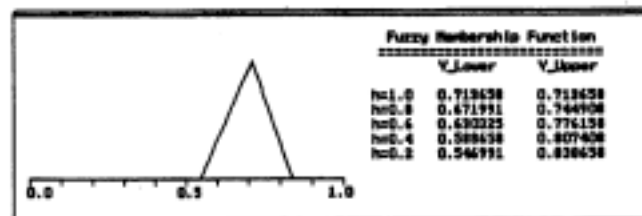
(a)

```

Machine: May I help you ? Please enter your command!
USER : Hey! Go ahead -- very fast!
Machine: Do you want facton 51
USER : You can answer (y/n)
Machine: Your command is facton 51

```

(b)



(c)

Fig. 8. Screen copy of the voice control system-the fourth case.

THE ACTIONS AND FUZZY TERMS USED IN THE ILLUSTRATED VOICE CONTROL SYSTEM

Action No.	1	2	3	4	5
Action	fall, kneap, strike, etc.	hold, catch, seize, etc.	turn, whirl, rotate, etc.	leap, jump, bound, etc.	move forward, shift forward, pass forward, etc.
Fuzzy term	very heavy, highly heavy, slightly heavy, heavy	very tight, tight, loose, very loose	very fast, fast, slow, very slow	very high, high, low, very low	very fast, fast, slow, very slow
	6	7	8		
	move backward, shift backward, pass backward, etc.	move right, shift right, pass right, etc.	move left, shift left, pass left, etc.		
	very fast, fast, slow, very slow	very fast, fast, slow, very slow	very fast, fast, slow, very slow		

Table 1. The actions and fuzzy terms used in the illustrated voice control system.

THE REFERENCE WORDS FOR THE WORD DETECTOR NODES IN THE ILLUSTRATED VOICE CONTROL SYSTEM

node 1	node 2	node 3	node 4	node 5	node 6	node 7	node 8
fail	heavy	light	knap	hit	strike	knock	hold
node 9	node 10	node 11	node 12	node 13	node 14	node 15	node 16
catch	gab	grasp	seize	tight	lux	loose	turn
node 17	node 18	node 19	node 20	node 21	node 22	node 23	node 24
whirl	rotate	whirl	speed	low	high	fast	slow
node 25	node 26	node 27	node 28	node 29	node 30	node 31	node 32
leap	jump	hop	skip	bound	transfer	pass	move
node 33	node 34	node 35	node 36	node 37	node 38	node 39	node 40
ambulate	shift	forward	backward	right	left	very	highly
node 41							
slightly							

Table 2. The actions and fuzzy terms used in the illustrated voice control system.