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An Approach to Linguistic Instruction Based Learning and Its Application to Helicopter Flight Control

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ABSTRACT

In this paper, we notice the fact that a human learning process is characterized by a process under a natural language environment, and discuss an approach of learning based on indirect linguistic instructions. An instruction is interpreted through some meaning elements and each trend. Fuzzy evaluation rule are constructed for the searched meaning elements of the given instruction, and the performance of a system to be learned is improved by the evaluation rules. In this paper, we propose a framework of learning based on indirect linguistic instruction based learning using fuzzy theory: FULLINS(FUzzy-Learning based on Linguistic INStruction). The validity of FULLINS is shown by applying it to helicopter flight control.

Key-words: *Machine Learning, Indirect Linguistic Instruction, Meaning Element, Fuzzy Controller, Fuzzy Evaluation Rule, Helicopter Flight Control*

1 Introduction

Human learning based on natural language is superior to any other kind of learning. A human learning process is essentially characterized by the fact that we learn under a natural language environment.

Learning by instructions has been studied in Machine Learning M.D. Rychener[1]. A basic framework of learning has been proposed, but a direct instruction with many constraints is used as a linguistic instruction. It is difficult for a supervisor to give an instruction, because he has to give an instruction based on the precise structure and components of rules to perform a given goal of an objective system.

In this paper, we discuss a way of learning to improve the performance of a system by supervisor's indirect instructions. An indirect instruction is not given in specific format, and the contents of the instruction are concerned with the macroscopic states or the quality of a system performance. Hence, an indirect instruction has macro, connotative, and imprecise properties. We propose a method that a system interprets multi-dimensionly a given instruction using meaning elements. Meaning elements are something like expressing the context of situation where the meaning of an indirect instruction is interpreted. After interpreting, a fuzzy evaluation rule for the system performance is constructed. Then the system performance is improved by the fuzzy evaluation rules which modify the system elements.

We have suggested a method of learning for fuzzy control based on linguistic instructions[2-5]. In this paper, we suggest a framework of learning based on linguistic instructions FUzzy-Learning based on Linguistic INStruction(FULLINS). The validity of FULLINS is shown by applying it to helicopter flight control problem.

2 FULLINS

We build a learning system called FULLINS, where the performance of an objective system is improved by a supervisor's indirect linguistic instructions[3-5]. FULLINS consists of six functional components: Task Performance, Dialogue, Explanation, Background Knowledge, Interpretation of Instructions, and Self-Regulating component.

Task Performance Component

This component performs tasks achieving a given goal. It consists of a basic performance knowledge module and a kinematics module.

The performance knowledge module plays the role of the FULLINS kernel. This module contains performance knowledge of basic tasks acquired from an expert's experience and knowledge of a learning object. The kinematics module simulates the dynamics of an objective system. In case of helicopter flight control problem, the helicopter simulator corresponds to this module.

Dialogue Component

The dialogue component is an interface between the system and the supervisor so that the instructions given by the supervisor can be interpreted by the meaning elements and their trends. The meaning element are words and phrases to interpret a supervisor's instructions. Trends of meaning elements are defined for an element m_1 as follows: $\Delta m_1(+)$ means that m_1 contributes to a meaning element of an instruction with trend(+). $\Delta m_1(0)$ means that m_1 does not act on a meaning element of an instruction. $\Delta m_1(-)$ means that m_1 contributes to a meaning element of an instruction with trend(−).

A supervisor's indirect instruction consists of three parts: Linguistic Hedges(LH), Atomic Words(AW) and Auxiliary Phrases(AP). The input type is as follows: $L_i = [AP][LH_i][AW]$.

If a linguistic instruction is given, this module is activated to understand the meaning of the instruction through dialogue with a supervisor. The system asks the supervisor whether his intention does or does not involve each element and its Meaning elements Set for Dialogue(MSD) trend. The sentences for asking a supervisor about each element of MSD are prepared in the dialogue module.

Explanation Component

This component, which explains the procedure that a system performs given tasks, helps the supervisor to evaluate the performance of a system. The task performing procedure is explained by an image on a computer screen and restricted natural language. The details of explanation are the enabled knowledge(rules) to perform given tasks and graphics about critical state variables.

Background Knowledge Component

Two kinds of background knowledge are required in FULLINS. The first one is background knowledge for Constructing Evaluation Rules(CER). CER consists of two knowledge memories, Evaluation Rule-Membership Function Memory(ERMFM) and Evaluation Rule-Constructing-Procedural Knowledge Memory(ERCPKM). ERMFM consists of the membership functions for all the meaning elements and their trends. The second one is background knowledge for Self-Regulating by Evaluation value(SRE). SRE is the background knowledge required to modify the basic performance knowledge given some constraints and characteristics of an objective system.

Interpretation Component

In this component, a supervisor's linguistic instruction is interpreted by a combination of meaning elements and their trends. Meaning elements are searched through dialogue between system and supervisor, and then MSD and the Linguistic Instructions Knowledge Base(LIKB) are used. LIKB consists of two memory modules: Atomic Words Memory(AWM) module and Linguistic Hedges Memory(LHM) module. AWM is a module in which some atomic words are memorized. If an instruction is given, dialogue takes place on whether each element of MSD is or isn't a meaning element of the instruction's AW. The searched meaning element for the instruction is memorized in AWM, and is also used as a meaning element without searching when other instructions with the same AW are entered. Some linguistic hedges are memorized with each weight in LHM: [(non,0), (slightly,0.2), (rather,0.4), (more,0.6), (pretty,0.8), (very,1.0)]. LH entered together with AWM is matched with each linguistic hedge prepared in LHM, then the weight allocated on the hedge is selected. The meaning of the instruction is restricted by the LH: the consequent parts of the evaluation rule constructed by the searched meaning elements are modified by the weight of LH. An interpretation of linguistic instruction is represented as follows: L_i = [Drive(AP_1)] [more(LH_i)] [fast(AW_i)] [than the previous performance(AP_2)]; $L_i = (LH_i)(\Delta m_1(+))$.

The evaluation rule is constructed by a combination of the meaning element and its trend using CER. If meaning elements and their trends are searched, the membership functions of the premise part for evaluation rule are selected from ERFM according to each meaning element: the membership functions are [small], [med], [big]. Three membership functions of the consequent part corresponding to the premise part are selected from ERFM according to an element and its trend: the membership functions are singleton type. ERCPKM is the procedure knowledge to select a membership function according to each element and its trend [(+)] or [(−)]. The meaning of linguistic instruction is actually restricted by modifying the consequent part of the evaluation rule by the given weight for LH_i.

Self-Regulating Component

In this component, the performance knowledge is improved by the evaluation rules constructed from the meaning elements by which the instructions are interpreted. If there are some constraints and characteristics in the system, good performance cannot be obtained by merely modifying the basic knowledge by adding, proportionally, the evaluated value. SRE is required to modify successfully the basic performance knowledge. Fig.1 shows the framework of FULLINS.

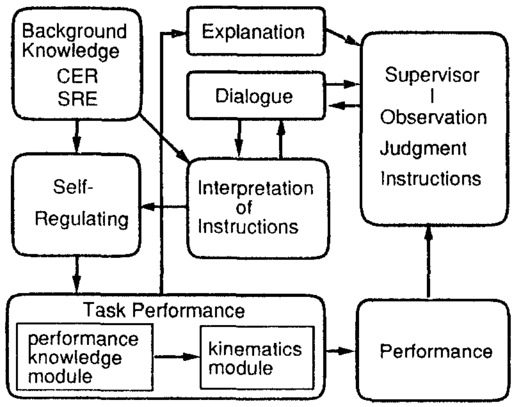

Fig.1 Framework of FULLINS

3 Example

We apply FULLINS to two helicopter flight control problems: Objective Line Following Flight System(OLFFS) and Figure EIght Flight System(FEIFS). We use the helicopter flight simulator developed by Kawasaki Heavy Industries Co. The helicopter motion is calculated using a non-linear dynamics equation and a parameter table. This simulator is operated in on a Silicon Graphics IRIS workstation, and the simulation is performed by linking the fuzzy control module to it[5][6]. Fig.2 shows the fuzzy control module.

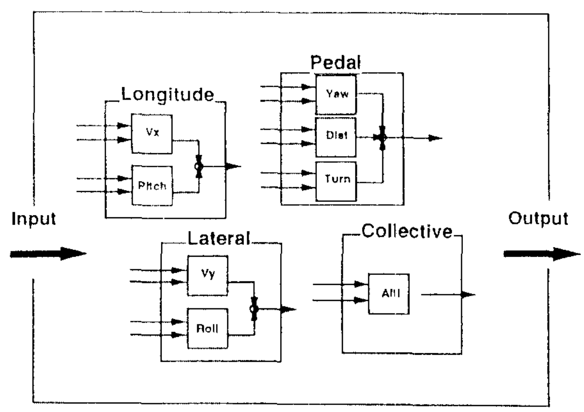

Fig.2 Flight Control Module

The module consists of four control modes: Longitude, Lateral, Pedal and Collective control mode, and each control mode consists of sub-control modes. In the Pedal control mode, only the Yaw and Dist control sub-modes are activated for performing the tasks in OLFFS, while only the Turn control sub-mode is necessary for FEIFS. The Dist control sub-mode is one to control a helicopter's approaching to a given objective line. The Turn control sub-mode is one to control the pedal and only the Yaw sub-mode is activated for the other flight modes. All of the sub-modes contain nine fuzzy rules-three partitions of two variables for the consequent part.

3.1 OLFFS

The flight plan consists of three patterns of flight: the first one is hovering in an initial position for twenty seconds and the second one, line following up to four lines-three points, and the last one, hovering in the first position for thirty seconds. The objects of learning in OLFFS are three kinds of basic performance knowledge: DSFL, ROLL, C-DIST. DSFL is the distance between each objective point and the position of the helicopter beginning to turn that point. ROLL is the roll angle to turn the objective points. C-DIST is the parameters of the consequent part of the Dist sub-mode rule.

Task Performance

The kinematics module is the helicopter simulator on a IRIS workstation. The basic performance knowledge is the initial DSFL value and the fuzzy rules of the four control modes.

Dialogue, Explanation, Background Knowledge

Dialogue comes from the sentences prepared for each meaning element and its negative trend, to ask whether a supervisor's instruction does or does not include given meaning elements. The system gives, through the Explanation Component, the supervisor the information about the change of fourteen input variables and four output variables from initial status to the end of each learning cycle. The relation among these variables is displayed as graphs on the IRIS screen. The system also displays, on the screen, the constructed evaluation rule and the modified values of three learning objects implemented by the evaluation rule. SRE consists of two kinds of background knowledge, SRE for Consequent part of Dist sub-mode(CD-SRE) and SRE for adapting the Roll modifying value according to each objective point(RO-SRE).

Interpretation, Self-Regulating

The meaning element set of OLFFS consists of four elements: arriving time(m_1), line following inclination(m_2), overshoot(m_3), starting time of the stable flight path(m_4). The arriving time is the time arriving to the next line, beginning to turn at an objective point. The line following inclination is the relative angle between the direction of an objective line and the direction of the locus of the flight path. The overshoot is one past the objective line. The starting time of the stable flight path is the starting time of the stable portion of the flight path over each objective line with an error less than 10m. The three basic performance knowledge, DSFL, ROLL, and C-DIST, are modified by the evaluation rule constructed by the meaning element for the supervisor's instructions. The performance knowledge is repetitively modified by SRE over one learning cycle until the supervisor is satisfied with the learned performance.

Results of Simulation

Two kinds of simulation are performed: under no-wind and under various wind directions with random wind velocity in the range 7.5-12.5(m/sec). Fig.3 shows the result of simulation under no-wind. The good performance after the 3rd learning is obtained through the supervisor's instruction: [follow objective lines][non][quickly].

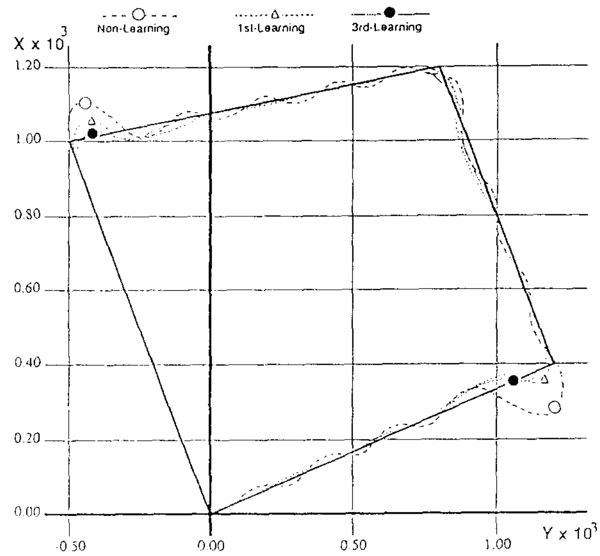

Fig.3 Simulation under No-wind

Fig.4 shows the result of simulation under wind direction 0^o. The good performance after the 4th learning is obtained through the supervisor's instruction: [Turn at the objective points and follow objective lines][non][quickly].

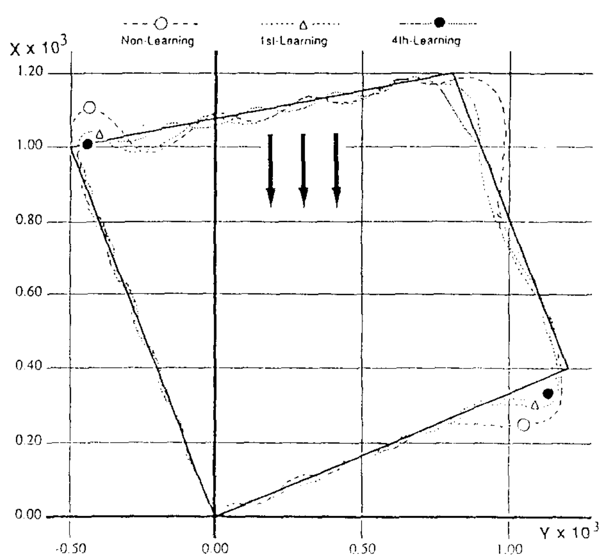

Fig.4 Simulation under Wind Direction 0^o

3.2 FEIFS

The objects of learning are three kinds of basic performance knowledge: LBANK, RBANK, DSFP. LBANK is the roll angle of left turning and the diameter of the left turning circle depends on LBANK. RBANK is the roll angle of right turning. DSFP is this is the distance between the objective point P_1 and the position to begin the line following to the second objective point P_2 after turning rightward.

Task Performance

The basic performance knowledge is the initial DSFP and the fuzzy rules of the four control modes. In the Pedal control mode, only the Turn sub-mode is selected.

Dialogue, Explanation, Background Knowledge

Dialogue takes place by the sentences prepared for the three meaning elements and their negative trends. The system explains to the supervisor about the information from all the state variables, output variables, and evaluation rules, in just as OLFFS problem. ERFM and ERCPKM are prepared for the three meaning elements as background knowledge CER, however SRE is not used.

Interpretation, Self-Regulating

In FEIFS, the supervisor's instructions are interpreted by three meaning elements. The meaning elements are the diameter of left-turning circle, the diameter of right-turning circle, and the overshoot in flight path beyond to the objective point P_2.

Three basic performance knowledge LBANK, RBANK, and DSFP are modified through the evaluation rule constructed by the meaning element for a supervisor's instructions. The performance knowledge is repetitively modified over one cycle until the supervisor is satisfied with the learned performance.

Result of Simulation

In Fig.5, the supervisor gives an instruction L_1 for the performance before learning that the right-turning circle is smaller than the left-turning circle: L_1 = [Turn rightward][non][largely]. After the 3rd learning, the right turning circle becomes to be approximately equal to the right turning circle.

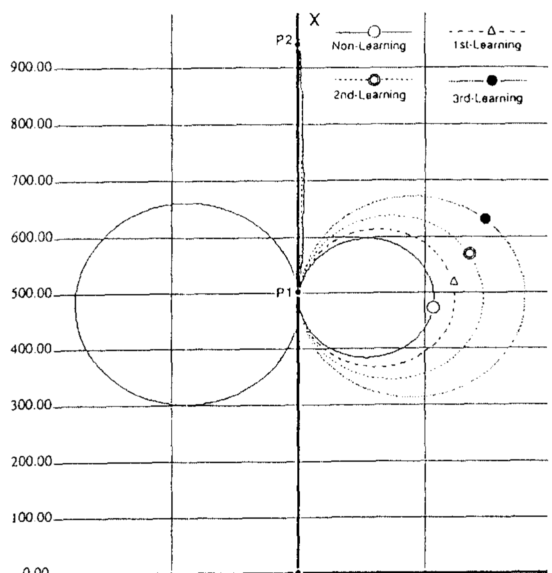

Fig.5 Simulation for Figure Eight Flight Control

4 Conclusion

We discussed an approach of learning based on a supervisor's indirect linguistic instructions. In this paper, we proposed a framework of learning based on linguistic instructions using fuzzy theory(FULLINS). The indirect instruction was multiplely interpreted by meaning elements and their three trends, positive, negative, and zero. The performance of a learning object was improved by the fuzzy evaluation rule constructed for each meaning element. The validity of FULLINS was shown by applying it to two flight control examples of helicopter.

FULLINS may also be applied to man-machine systems and intelligent robot control problems. The framework of FULLINS will be improved in the future through the interpretation of instructions based on context of situation and the rule generation based on instructions.

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