Rough Control: A Perspective

Toshinori Munakata
Computer and Information Science Department
Cleveland State University
Cleveland, OH 44115
munakata@cis.csuohio.edu

§ Introduction

The term "rough control" refers to applications of the rough set theory to control problems. The objective of this article is to show that there are compelling reasons to pursue rough control and to explore a preliminary survey for its potentials of truly practical applications.

The field of rough sets is relatively new and has remained unknown to most of the computing community. There appears, however, to be a growing interest among many researchers recently. Most research works in the field of rough sets so far have been in "symbolic" approaches such as data and decision analysis, databases, knowledge based systems and machine learning. Also, more emphasis appears to have been placed on theoretical aspects rather than everyday commercial and industrial applications. No one can over-emphasize the importance of the theoretical foundation of any field; without sound foundation, this field would be a castle on sand. On the other hand, one would doubt the true value of any theory if it does not offer any practical applications. For a field to prosper, we need balanced successes on both theory and applications.

There has been some research on applications of rough control [1-6]. However, their number and application domains have been relatively few. This fact has been confirmed by my recent contacts with experts in rough sets at the RSSC'94 [7]. Also, my search in a national literature database has yielded a relatively small number of publications. Furthermore, some of the works in rough control are published in form of technical reports, which are not very visible to the world computing community. To promote rough control, quality articles should be published in more widely circulated international journals. Also, after a preliminary version of this article was presented at the ACM CSC'95 in March 1995, a Rough Control Group was initiated and I have been named as the first Chair. The major objective of the group is to pursue research and development of rough control and coordinate such efforts. Currently about 60 researchers worldwide are in the group.

Whether rough control will succeed is yet to be seen, but there are several reasons for which at least one should pursue its potentials. For the past couple of years, I have been serving as the Guest Editor of two special issues for commercial and industrial AI for the Communications of the ACM [8, 9]. In the second issue, an article for rough sets by Zdzislaw Pawlak, et.al. will appear [10]. This should introduce the theory to a wide spectrum of audience worldwide. In these two issues, I have assembled some of the foremost minds in AI to author and/or review about 23 articles. Through this extensive experience, I have observed practical and not-so-practical application domains within AI. The following Table 1 is a summary of my speculation regarding ratings on potentials of successful everyday applications of rough set theory [11].

Table 1. A Future Perspective on Successful Industrial Applications of Rough Sets.
(On scale of 0 to 10, where 0 least and 10 most)

Application Area	Success Expectation
Use of common sense	0
Machine learning	3
Expert systems	5
Control	7
Hybrid with other existing systems (e.g., fuzzy systems)	8

Control has been the most successful application domain for recently evolved AI areas, such as fuzzy sets and chaos theory [12, 13]. Control is also one of the most practical application domains for neural networks [14]. It would be too naive to assume that these success stories in fuzzy sets, chaos, and neural networks will also be repeated for rough sets. However, observing these successful applications, control definitely deserves attention. There are several reasons to further support this claim: for example, there are some similarities between fuzzy and rough sets. Simply stated, control is a mapping problem from inputs to outputs. When compared with symbolic AI, the effectiveness of control is often easier to prove than, say, symbolic expert systems. If a machine can operate 5%, or even 1%, more efficiently than before, we do not need to elaborate words to explain its validity.

§ The Control Problem

"Control" in this article refers to control of the various physical, chemical, or other numeric characteristics, such as temperature, electric current, flow of liquid/gas, motion of machines, various business and financial quantities (e.g., flow of cash, inventory control), etc. A control system can be abstracted as a box for which inputs are flowing into it, and outputs are emerging from it. Parameters can be included as parts of inputs or within the box, i.e., the control system.

For example, consider a system that controls room temperature by a heat source. The inputs may be the current room temperature and a parameter representing a target temperature. The output can be the amount of the heat source to be applied. The control problem in general is to determine the numeric values of the outputs for given values of the inputs. That is, the problem is to develop a formula or algorithm for mapping from the inputs to the outputs.

Although the statement of the control problem is straightforward, achieving good control is not necessarily a simple matter for several reasons. For example, bad control can be time consuming or inefficient, it may unnecessarily fluctuate before reaching the target, or even worse, it may become unstable. A good algorithm will be relatively simple yet it performs efficient and stable control. For easy problems, a simple mathematical formulation may be sufficient. When problems get harder, traditional control techniques such as PID (proportional, integral, and differential) may not work well. This is the type of problems where fuzzy control has been successful, and where our major target domain is centered for rough control as well.

§ The Case of Fuzzy Control

Although fuzzy and rough sets are different, there are some similarities. Fuzzy control has already been successful in many applications, thus a reasonable approach exploring rough control would be to examine in what types of application domains and how or why fuzzy control has been successful.

Typical situations where fuzzy control are particularly successful are difficult cases where traditional control methods do not work well. For example, the control rules may be so complex that mathematical formulation is either impossible, or even if it is possible, it is too complicated or costly for practical applications. For such situations, fuzzy approaches allow us to represent descriptive or qualitative expressions such as "slow" or "moderately fast." These expressions are much closer in spirit of human thinking and natural language, and are easily incorporated with symbolic statements in form of fuzzy logic. Fuzzy systems are also suitable for uncertain or approximate reasoning. For example, the input and parameter values of a system may involve fuzziness, inaccuracy, or incompleteness. Similarly, the control rules that derive output values may also be incomplete or inaccurate. Fuzzy logic allows decision making with estimated values under incomplete information.

In the following, we will illustrate the basic ingredients of fuzzy control by a simple example. (For more on basics, see Tutorial of [12]; for more extensive coverage see [15].)

Given two input values, E = (the difference between the current temperature and the target temperature) and dE = (the time derivative of the difference), we are to determine output value, W = (the amount of heat or cooling source). We select *fuzzy variables*, such as, NB = Negative Big, NS = Negative Small, ZO= Zero, PS = Positive Small, and PB = Positive Big. Membership functions for the fuzzy variables, as functions of input and output values, are then defined (typically as a set of triangles or trapezoids in a graph representation). For example, the membership function value or degree of variable PS is 1 and other variables, NB, NS, and so on, are 0, when E = 0.5. Generally, other membership functions can be defined and selections can affect the control performance. Fuzzy if-then rules that derive W from E and dE in terms of the fuzzy variables are given as the following table. For simplicity, assume the empty entries do not occur.

		dE				
		NB	NS	ZO	PS	PB
	NB			PB		
	NS			PS		
E	ZO	PB	PS	ZO	NS	NB
	PS			NS		
	PB			NB		

This table represents nine rules corresponding to the nine entries in the table. For example, "if E = ZO and dE = NB, then W = PB" may be called Rule 1. The remaining four entries in the same horizontal line of the table may be called Rules 2, 3, 4 and 5. The remaining four entries in the vertical line may be called Rules 6, 7, 8 and 9.

Now with all the predetermined information, we can compute W for given values of E and dE. Suppose that E = 0.75 and dE = 0. From the membership function defined earlier, E can be PB with degree = 0.5 and PS with degree = 0.5, dE is ZO with degree = 1.0. Hence, in the if-then table, two rules are applicable, Rules 8 and 9. Using each of these two rules we compute a membership function for W as follows, where $\wedge$ takes the minimum of the operand membership functions. The weight (firing strength) of each rule is determined as:

$$\alpha_8 = \mathrm{m_{PB}(E)} \wedge \mathrm{m_{ZO}(dE)} = 0.5 \wedge 1.0 = 0.5$$

$$\alpha_9 = \mathrm{m_{PS}(E)} \wedge \mathrm{m_{ZO}(dE)} = 0.5 \wedge 1.0 = 0.5$$

Then the membership function associated with each rule is determined as:

$$\mathrm{m_8(W)} = \alpha_8 \wedge \mathrm{m_{NB}(W)} = 0.5 \wedge \mathrm{m_{NB}(W)}$$

$$\mathrm{m_9(W)} = \alpha_9 \wedge \mathrm{m_{NS}(W)} = 0.5 \wedge \mathrm{m_{NS}(W)}$$

The membership function for W, m(W), is obtained as the max of the above two intermediate membership functions, $\mathrm{m_8(W)}$ and $\mathrm{m_9(W)}$. This m(W) gives the fuzzy version of the solution for W, but we need a specific single value $\mathrm{W_0}$ as a system output to perform control. For this purpose, we compute the center of gravity of m(W) as $\mathrm{W_0}$, which is called a difuzzification procedure.

§ Rough Control Taxonomy

To develop various potential types of rough control in an organized fashion, classification of such types would be helpful. Generally there are different ways of classification and the following is just one possibility. In the course of developing actual applications, a newer and more appropriate classification may emerge in the future.

I. Pure (rather than hybrid) Rough Control

1. Under an assumption of existing control rules, output values are determined for imprecise or incomplete input and parameter values and/or rules.
2. Deriving feasible control rules when the input-output relations are vague.

II. Hybrid systems

1. Rough + fuzzy systems.
2. Fuzzy + rough systems.
3. Rough + neural network systems.
4. Neural network + rough systems.
5. Rough + other systems (e.g., PID, chaos).

§ **Principles of Rough Control**

I. Pure (rather than hybrid) Rough Control

1. Under an assumption of existing control rules, output values are determined for imprecise or incomplete input and parameter values and/or rules. The basic concept here is to explore the most typical feature of rough set theory. Inputs and parameters correspond to condition attributes in standard rough set theory; outputs are decision or action attributes.

   Typically, values of decision attributes in rough sets, i.e., outputs in rough control, are given in descriptive expression such as "slow." For control problems, we need to derive numeric values. Possible methods include the following.

   Methods of deriving numeric output values:

   (1) Making the control rules fine enough to produce numeric values.
   (2) Use of rough measures (e.g., dependency), possibly in conjunction with a simple arithmetic formula.
   (3) As an extension of (2), a technique similar to defuzzification process discussed above for fuzzy control may be employed. The idea is to find "the center of gravity" or weighted mean of several possible output values. For example, "rough variables" in place of fuzzy variables may be defined. Their weights (firing strengths) may be evaluated based on their dependencies.

   This type of rough control has high potentials when we look at proven successes of fuzzy control, the key elements contributed to those successes, and the similarities of the key elements in fuzzy and rough control. As stated earlier, the key elements for fuzzy control successes are the use of descriptive expressions and uncertain reasoning. Rough control also has these characteristics.

2. In this approach, we derive feasible control rules when the input-output relations are vague. The basic principle again, is to tailor a typical application of rough sets for discovering relationships in data to particularly fit control problems. Inputs and parameters correspond to condition attributes in standard rough set theory as before, and outputs are decision or action attributes. A set of existing control rules, whether it is described by human experts

or developed for PID or fuzzy control, may be incomplete, imprecise, or contain redundancy. By employing rough set theory, nonessential rules may be identified then deleted, or less important rules may be downgraded in priority or weighted by smaller factors.

II. Hybrid systems

This category is also one of the most promising for practical applications. The fundamental concept is to complement each other's weakness, thus creating new approaches to solve problems. For example, fuzzy control has many established application cases while rough control has relatively few. Integrating rough control with successful fuzzy control cases could be relatively easy for accomplishing real world practicality of rough control. Fuzzy sets allow partial membership to deal with gradual changes or uncertainties, while rough sets allow multiple memberships to deal with indiscernibility. A fuzzy-rough hybrid system may allow multiple-partial membership (e.g., multiple membership where each can be partial) to deal with both indiscernibility and uncertainty. In rough + fuzzy systems, for example, the macroscopic, possibly symbolic, output is determined by rough control while fine tuning is carried out by fuzzy control. In fuzzy + rough systems, the roles will be reverse. Or, rough control lacks capabilities of pattern recognition or memory. A hybrid system of rough control and neural networks may work well for certain applications.

§ **Case Study**

In the previous two sections, potentials of rough control are stated in an abstract manner. In order to relate these statements to real world applications, we will consider a fictitious control example. We note that although we use one specific hypothetical example for easy understanding, the basic idea can be applied to many other types of control problems.

Imagine we want to perform delicate room temperature control for a sophisticated experiment, perhaps for biomedical or solid state physics. In this scenario, we need fine temperature control: the allowable temperature deviation range is, say, within $\pm 0.02\ ^\circ C$ of the target temperature throughout the room. Furthermore, the homogeneity of the temperature distribution is required, i.e., the temperature difference between any two points of one meter distance must be less than, say, $0.01\ ^\circ C$. The difficulty of temperature control is compounded because of the various boundary conditions. For example, the current level of robotics is not good enough to make robots perform the experiment. That is, human technicians must be in the room, which themselves are complicated heat sources.

Solving the problem theoretically, for example, by the Navier-Stokes' equation for air flow, associated with thermodynamic equations for heat conduction, convection, and radiation, under such complicated boundary conditions is out of question. A practical approach is to develop empirical formula for control from experimental data for temperature distributions and various heat/cooling sources. Rough control may be used in various stages of such development.

The major component of the inputs (attributes) is the measured temperatures throughout the room. Since the temperatures have to be measured three dimensionally, many sensors will be required at least initially. Other factors, such as the human body heat source, can be added as a part of the inputs. These inputs can be denoted as s1, s2, ... The outputs can be heat/cooling sources, which can be denoted as, t1, t2, ... The problem here is to deal with incomplete and imprecise data. Even if we use many sensors, there are still many points in the room where the true temperatures are never measured. Also, in addition to the sensor reliability problem, local temperature fluctuations due to various causes such as convection, radiation, and small turbulence, will make measurements inaccurate.

An input-output mapping table may look as follows:

An input-output mapping table

(Input)	s1	s2	s3 ...	(Output)	t1	t2 ...
		...				
	+.03	+.01	-.04 ...		-.6	+.2 ...
	+.03	+.01	-.03 ...		-.6	+.3 ...
		...				

Such a table can be constructed initially in various ways. For example, if there are any existing methods to approximate the mapping, they can be used. Or, experiments can be conducted by human experts, possibly involving trial-and-errors.

Since maintaining many temperature sensors is expensive, lesser sensors are desirable. During the first stage, rough control may be used to reduce the number of sensors required to achieve the required control. For example, suppose that contributions of Sensors No. 4, 7, and 23, to the outputs are found to be insignificant, then they may be deleted. Similarly, some of output elements may be found insignificant and thus deleted. Or, rough control may suggest other possible ways for achieving the same results.

After the initial construction of the input-output mapping table, the system becomes operational. However, the operations probably require much fine tuning. For example, there will be a certain limit to the number of the table entries because of the space and efficiency. In other words, all the possible combinations of input-output values may not be included in the table. Also, the data are incomplete and inaccurate. Rough control may be used for fine tuning of such a circumstance. For example, the closest table entries are used as "zeroth approximation." Rough control then finds "superposing corrections" to the zeroth approximation. Rough control may compute the corrections by first determining the input-to-output dependencies, then taking "the center of gravity" as in case of defuzzification. Generally, the use of traditional method for zeroth approximation and rough control for fine tuning may be conservative but probably safer than relying the total control on a new technology.

The above illustrates a basic idea of rough control. Many other variations and extensions for employing rough control would be possible, depending on the types of applications.

§ Conclusions

This article has presented a preliminary study on rough control potentials. The topics are arranged in a top-down approach starting from a global overview of the subject to somewhat detailed specifications of rough control.

Once rough control is proved to be feasible, its implication can be enormous. As stated earlier, it can be applied to control various physical, chemical, or other numeric characteristics, such as temperature, electric current, flow of liquid/gas, motion of machines, various business and financial quantities, etc. This means that controlling these characteristics in turn can be applied to many areas involving various engineering, scientific and management problems. Again, a list of successful application areas of fuzzy control [9] would be a good reference source to consider potential application areas for rough control. The list may include: transportation, consumer electronics, robotics, computers, communications, agriculture, medicine, management, finance, and education.

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