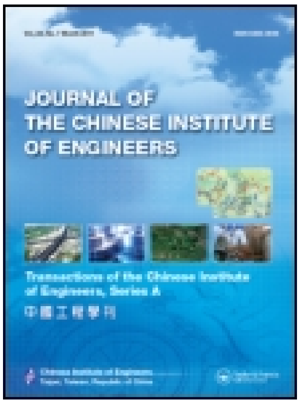

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Evolutionary-based virtual training in extracting fuzzy knowledge for deburring tasks

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EVOLUTIONARY-BASED VIRTUAL TRAINING IN EXTRACTING FUZZY KNOWLEDGE FOR DEBURRING TASKS

Shun-Feng Su*, Tar-Jyh Horng, and Kuu-Young Young

ABSTRACT

In this research, the problems of how to teach a robot to execute skilled operations are studied. Human workers usually accumulate their experience after executing the same task repetitively. In the process of training, a worker needs to find ways of adjusting his/her execution. In our system, the parameters for an impedance control scheme are considered as the targets for adjustment in the training process. The way to make adjustments is represented as a set of fuzzy rules in our research. Furthermore, a training scheme, called the evolutionary-based virtual training scheme, is proposed to extract knowledge (a set of fuzzy rules) for robotic deburring tasks. In this approach, an evolutionary algorithm is employed to find the best set of fuzzy rules and a simulation system is built to evaluate the execution performances of candidates. This learning scheme has been applied in finding a set of fuzzy rules that can adjust the parameters of impedance controllers required in deburring operations with satisfactory performance in deburring tasks.

Key Words: virtual training, evolutionary algorithms, fuzzy rule extracting, deburring tasks.

1. INTRODUCTION

Recently, industry has successfully employed robots to execute various tasks in which the working environment is harmful to human beings or operations are repetitive and/or require high accuracy. Usually, those tasks can be programmed into operations of robots because those tasks do not interact with the environment frequently and then human skill may not be necessary for the operations of the tasks. There may also exist tasks, such as deburring, grinding, milling, assembly, etc., which need interactions with the environment and thus, require decision-making while facing those interactions. Such tasks are very difficult to satisfactorily program into robot operations.

Several researchers have tried to discover relationships between human experts' intentions and operational strategies for tasks so that skills needed for accomplishing those tasks could be modeled and then possibly transferred into operations of robots. Asada *et al*. have employed neural networks (Asada and Liu, 1991a; Asada and Liu, 1993), adaptive control (Asada and Liu, 1991b), and fuzzy rules (Asada and Yang, 1992) to model and to transfer human skills into operations of robots. In (Guan, 1995), human skills are considered as the desired position commands to the controller of a robot manipulator during the execution of a compliant task. Other parameters, such as the parameters required in impedance control, are chosen as constants. The results in our simulation showed that the performance could be improved by changing those parameters. In order to acquire human skills, in (Asada *et al*., 1991), the joints of a robot manipulator are relaxed and then a human expert worker is asked to take the end-effector of the robot to accomplish a compliant task, for instance, deburring. The data of the deburring process, such as angles and torques of all joints are recorded. The approach then extracts useful rules or strategies for representing skills from the collected data. However, there are problems in that approach. First, the obtained rules or strategies based on this

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set of data may not be able to represent the skills sufficiently. Secondly, the rules or strategies extracted from the data are rather primitive and are sensitive to operational conditions. Thus, it may be desired to further generalize the obtained knowledge to cope with the variation of tasks.

In this research, we propose a novel idea of recoding knowledge for skilled tasks. The considered task is the deburring operation. The recorded knowledge in our research is the impedance controller characterized by a set of fuzzy rules. We attempt to use the parameters required in impedance to represent the operational skills for deburring to overcome various problems mentioned above. However, it is difficult to obtain these kinds of rules from expert knowledge or a set of training data. This paper then presents an approach using evolutionary algorithms in finding the best set of fuzzy rules for the impedance controller through simulation. It is called evolutionary-based virtual training in the paper. The simulation results have demonstrated good performance from the proposed approach in deburring operations.

The organization of the paper is as follows. Section II describes the concept of virtual training. In section III, the robotic impedance control is presented. The fuzzy rules used in coding knowledge for deburring tasks are proposed in section IV. In section V, the evolutionary algorithm used is described. We employed those mechanisms in our simulations. The detailed implementation environment and simulation results are presented in section VI. Finally, section VII concludes the paper.

II. THE CONCEPT OF EVOLUTIONARY-BASED VIRTUAL TRAINING

The idea of virtual training is to train operational schemes in a virtual environment, which is a simulation system that can truly model the considered environment. In such a system, when simulation results are not acceptable, operational schemes are modified, and then another simulation is conducted. Hopefully, after a period of training, an operational scheme yielding acceptable performance can be obtained. The name “virtual training” is adopted from an often-used terminology - virtual reality, which is also a simulation system for emulating scenarios in the real world.

In our research, a virtual robot environment is built. The performance of a deburring operation is evaluated by using results obtained from the virtual environment. From the training viewpoint, the system is trained to execute deburring tasks satisfactorily, and such knowledge is accumulated through practice. One advantage of this approach is that there is no cost for repetitive operations, and a mass amount of training becomes possible. Another advantage is that it is possible to capture all kinds of information or states that may be difficult or impossible to get in real world operations. Finally, due to the rapid growth of the techniques in virtual reality, to model a real world system accurately will eventually come true. Then, the concept of virtual training may become actually applicable.

Roughly speaking, there are two subsystems in our training system, the compliance controller and the learning module to record knowledge through training. The compliance controller used is an impedance control scheme. In this research, the knowledge to be learned is the rules for determining the parameters required in an impedance control scheme. Nevertheless, the representation of knowledge by using rules is discrete in nature, but the data obtained are for continuous variables. Thus, in order to soften the boundary between rules, the fuzzy set theorem (Zadeh, 1965) is adopted for rule reasoning in this research. The structure of fuzzy rules used for the operational skills is introduced in Section IV.

In the process of training, the system must find ways of adjusting its execution. In our system, the parameters for an impedance control scheme are used as the targets for adjustment. In our system, the performance of the current set of rules is evaluated through simulation. In a training paradigm, various patterns (sets of rules) must be used to explore all possibilities to search for the pattern that can yield the best performance. However, if the training patterns are tried in a random manner, the search for finding the best candidate may take lots of time. For our case, the number of possible sets of rules is extremely large, and the exhaustive search for all sets is impossible. Therefore, it is natural to think about the use of evolutionary algorithms to provide an effective way of finding the best candidate. Such an approach is called evolutionary-based virtual training in our research. The evolutionary algorithm used will be described in Section V.

III. ROBOTIC IMPEDANCE CONTROL

In this research, deburring tasks are used as the skilled operations for training. Various control schemes (Kazerooni *et al*., 1986; Kazerooni and Her, 1991) can be used as the compliance controller for deburring tasks. Impedance control was first proposed in (Hogan, 1985) and was proved to be stable in contact tasks in (Hogan, 1987; Hogan, 1988). The impedance control has been proven to be feasible for deburring operations. In this research, the impedance controller is used as the control scheme due to its flexibility and simplicity.

The control strategy of impedance control is to allow the end-effector of a robot manipulator to respond to an environmental force with desired target impedance. With simple physics, the following equation is obtained

$$\boldsymbol{M_d}\ddot{\boldsymbol{X}}+\boldsymbol{B_d}\dot{\boldsymbol{X}}+\boldsymbol{K_d}(\boldsymbol{X}-\boldsymbol{X_d})=\boldsymbol{F_{ext}} \tag{1}$$

where $\boldsymbol{M_d}$, $\boldsymbol{B_d}$ and $\boldsymbol{K_d}$ are the inertial, the damping and the stiffness matrices, respectively, in the Cartesian space specified by the designer. $\boldsymbol{X}$, $\dot{\boldsymbol{X}}$, and $\ddot{\boldsymbol{X}}$ are the end-effector's position, velocity and acceleration vectors in the Cartesian space, respectively. $\boldsymbol{X_d}$ is the goal position vector in the Cartesian space, and $\boldsymbol{F_{ext}}$ is the external force caused by the environment.

The impedance in Eq. (1) is a decoupled form in the Cartesian space. Since the control of a robot manipulator is always considered in the joint space, the above equation must be transformed into the joint space to derive the required control torque. Let $\boldsymbol{L}$ be the transformation between the joint space and the Cartesian space and denoted $\boldsymbol{X}=\boldsymbol{L}(\boldsymbol{q})$, where $\boldsymbol{X}$ is the position vector in the Cartesian space and $\boldsymbol{q}$ is the angle vector in the joint space. From the robot dynamics (Fu *et al.*, 1989):

$$\boldsymbol{H}(\boldsymbol{q})\ddot{\boldsymbol{q}}+\boldsymbol{V}(\boldsymbol{q},\dot{\boldsymbol{q}})+\boldsymbol{G}(\boldsymbol{q})=\boldsymbol{\tau_{act}}-\boldsymbol{J^T}\boldsymbol{F_{ext}} \tag{2}$$

where $\boldsymbol{\tau_{act}}$ is the generalized torque vector applied at joints, $\boldsymbol{q}$ is the vector of the joint variables, $\dot{\boldsymbol{q}}$ is the vector of the joint velocity, $\ddot{\boldsymbol{q}}$ is the vector of the joint acceleration, $\boldsymbol{H}(\boldsymbol{q})$ is the inertial acceleration-related symmetric matrix, $\boldsymbol{V}(\boldsymbol{q},\dot{\boldsymbol{q}})$ is the nonlinear Coriolis and centrifugal vector, $\boldsymbol{G}(\boldsymbol{q})$ is the gravity loading force vector, and $\boldsymbol{J}$ is the Jacobian matrix and is defined as $\dot{\boldsymbol{X}}=\boldsymbol{J}\dot{\boldsymbol{q}}$. With simple manipulation (Horng, 1996) and defining $\boldsymbol{W}=\boldsymbol{J}\boldsymbol{H}^{-1}\boldsymbol{J^T}$, the acting torque for robot joints is

$$\boldsymbol{\tau_{act}}=\boldsymbol{J^T}\boldsymbol{F_{ext}}+\boldsymbol{V}+\boldsymbol{G}+\boldsymbol{J^T}\boldsymbol{W}^{-1}\boldsymbol{M_d^{-1}}(\boldsymbol{F_{ext}}-\boldsymbol{B_d}\dot{\boldsymbol{X}}-$$
$$\boldsymbol{K_d}(\boldsymbol{X}-\boldsymbol{X_d}))-\boldsymbol{J^T}\boldsymbol{W}^{-1}\dot{\boldsymbol{J}}\dot{\boldsymbol{q}} \tag{3}$$

In the use of impedance control, one major issue is to select $\boldsymbol{M_d}$, $\boldsymbol{B_d}$ and $\boldsymbol{K_d}$ properly. In the work of (Guan, 1995), those parameters are chosen as constants in his work of transferring human skills. The results in later simulations showed that the performance could be improved by changing the parameters required in the impedance control mechanism. Thus, in order to obtain a better result for deburring operations, a way of determining when and how to change those parameters must be defined.

IV. FUZZY RULES FOR DEBURRING TASKS

Since Zadeh proposed the concept of fuzzy sets in (Zadeh, 1965), many applications of using fuzzy systems have demonstrated good performance (Kim *et al.*, 1994; Lin and Lee, 1996; Chen, 1998). Compared to the use of classical rules, fuzzy rules together with approximate reasoning mechanisms can provide various advantages.

In our implementation, the used fuzzy rules for adjusting the parameters of impedance controllers are of the form:

$$R_i\text{: IF (current-state} \in A_{pi}\text{) THEN } \Delta P=\theta_i$$
$$i=1, \cdots, n \tag{4}$$

where A_{pi} is the fuzzy label for the parameter P in the i-th rule, ΔP is the variable of the increment for the parameter P, θ_i is the incremental value assigned by this rule. This rule form is similar to that used in (Asada and Yang, 1992) except that their rules are identified from a human expert and then categorized based on expert linguistic information. It should be noted that in our rule form, θ_i is a crisp value. Thus, the fuzzy models used can be considered as a TSK fuzzy model (Takagi and Sugeno, 1985) and then the TSK fuzzy reasoning approach (Takagi and Sugeno, 1985; Lin and Lee, 1996; Jang *et al.*, 1997) is used for the reasoning process.

In this research, only line deburring tasks are discussed, and then the considered dimension is 2. In those rules, we either used the error on the burr axis (denoted as x_1) or the speed on the moving axis (denoted as x_2) as the current state to determine how to adjust those parameters. In our implementation, those parameters used for adjusting are $\boldsymbol{M_d}$, $\boldsymbol{B_d}$, $\boldsymbol{K_d}$, and $\boldsymbol{X_d}$, in Eq. (1). For simplicity, all variables are considered independently in our system. Thus, there are 8 groups of fuzzy rules and the fuzzy membership functions used are all triangular shapes with overlap ratios all 1 (Lin and Lee, 1996; Jang *et al.*, 1997). In this study, these fuzzy membership functions are selected as long as they are feasible. Since evolutionary algorithms are used in tuning rules, in order to have inheritance between generations the fuzzy membership functions are kept fixed in our study. Fig. 1 shows the membership functions for the rules of adjusting $\boldsymbol{M_d}$ on the x_1 axis and the other membership functions are similar and their center values are listed in Table 1. In the table, A_{pi}'s are fuzzy labels for the error on the x_1 axis and V_{pi}'s are fuzzy labels for the speed on the x_2 axis.

For the consequence parts of fuzzy rules, θ_i's, they are tuned in the training process. Various approaches (Takagi and Sugeno, 1985; Lin and Lee, 1996; Jang *et al.*, 1997; Juang and Lin, 1998) have been proposed to train parameters in fuzzy rules. However, those approaches are to tune the parameters

Table 1 The center values for all used fuzzy labels for parameters in our impedance control scheme

Parameter	Fuzzy label	Center values	Parameter	Fuzzy label	Center values
M_1	A_{M11}	-7.5×10^{-4}	K_1	A_{k11}	-1.5×10^{-3}
	A_{M12}	-2.5×10^{-4}		A_{k12}	-5.0×10^{-4}
	A_{M13}	5.0×10^{-4}		A_{k13}	5.0×10^{-5}
	A_{M14}	1.5×10^{-3}		A_{k14}	2.0×10^{-3}
	A_{M15}	2.5×10^{-3}		A_{k15}	4.0×10^{-3}
	A_{M16}	3.5×10^{-3}		A_{k16}	6.0×10^{-3}
M_2	V_{M21}	0.0	K_2	V_{k21}	1.0×10^{-2}
	V_{M22}	2.0×10^{-2}		V_{k22}	2.0×10^{-2}
	V_{M23}	4.0×10^{-2}		V_{k23}	3.0×10^{-2}
B_1	A_{B11}	-1.25×10^{-3}	X_{1d}	A_{X11}	-1.0×10^{-3}
	A_{B12}	-7.5×10^{-4}		A_{X12}	-3.0×10^{-4}
	A_{B13}	-2.5×10^{-4}		A_{X13}	-5.0×10^{-5}
	A_{B14}	4.0×10^{-4}		A_{X14}	5.0×10^{-5}
	A_{B15}	1.15×10^{-3}			
	A_{B16}	1.85×10^{-3}			
B_2	V_{B21}	-2.5×10^{-3}	X_{2d}	A_{X21}	0.0
	V_{B22}	1.25×10^{-2}		A_{X22}	2.0×10^{-2}
	V_{B23}	2.75×10^{-2}		A_{X23}	4.0×10^{-2}

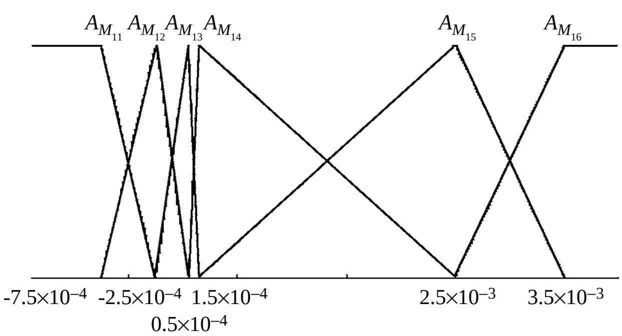

Fig. 1 The fuzzy membership functions for M_1

in a supervised and off-line manner. In other words, there must exist a subsystem that can tell the learning system what is correct and the training data must be available in a batch. In this research, due to the lack of a supervising block that can tell which one is desired, an evolutionary algorithm is used to search for θ_i's in the rules.

V. EVOLUTIONARY ALGORITHMS

Evolutionary algorithms are ways of finding a set of parameters that can optimize a fitness function and are traditionally referred to as genetic algorithms (Back *et al*., 1997), which are defined for the problems of finding the best combination of genes (binary) (Goldberg, 1989; Holland, 1975). Various applications can be found in robotics, such as solving inverse kinematics of redundant robots (Parker *et al*., 1989), motion planning and obstacle avoidance (Shibata and Fukuda, 1993), or navigation of mobile robot (Hashimoto *et al*., 1995). Evolutionary algorithms can also cooperate with fuzzy systems or neural networks to search for optimal solutions (Fukuda and Shimojima, 1995; Ishibuchi *et al*., 1995; Park *et al*., 1994). In (Ishibuchi *et al*., 1995), genetic algorithms are used to select fuzzy rules for classification problems. In (Park *et al*., 1994), a genetic-based method is proposed to look for an optimal fuzzy relation matrix in the New Fuzzy Reasoning Method (NFRM) (Cao *et al*., 1990) and to tune membership functions such that the obtained fuzzy rules can generate outputs as close to the actual data as possible. In this study, we also employed evolutionary algorithms to define fuzzy rules under the proposed virtual training system. We believe that other ways of combining fuzzy and evolutionary algorithms might have better learning performance than the one used here. However, this is not important in our problem because it can only reduce the learning time (generations) and has nothing to do with the deburring performance.

Due to the nature of adaptation to the problem in evolutionary algorithms, we proposed to build an evolutionary-based virtual training system to extract knowledge for robotic deburring tasks. Generally speaking, evolutionary algorithms are to search for better alternatives based on a given fitness function through the evolution of chromosomes. Chromosomes encode solutions to the problem and a fitness function is used to evaluate those chromosomes. At

Table 2 The initial population used in the simulation (10 chromosomes)

Corresponding fuzzy labels (scale)	1~10 chromosomes										Corresponding fuzzy labels (scale)	1~10 chromosomes									
A_{M11} ($\times 5.0\times 10^{-4}$)	-2	-2	-3	-3	-3	-2	-2	-2	-5	-5	A_{K11}	-5	-5	-5	-5	-4	-4	-5	-5	-5	-5
A_{M12} ($\times 5.0\times 10^{-4}$)	-1	-1	-1	-2	-2	-2	-2	-2	-2	-2	A_{K12}	-4	-4	-4	-4	-3	-3	-4	-4	-4	-4
A_{M13} ($\times 5.0\times 10^{-4}$)	1	1	1	1	1	1	1	1	1	1	A_{K13}	1	1	1	1	1	1	1	1	1	1
A_{M14} ($\times 5.0\times 10^{-4}$)	10	8	7	9	9	8	8	6	6	6	A_{K14}	5	3	3	3	3	3	5	3	3	2
A_{M15} ($\times 5.0\times 10^{-4}$)	20	12	15	11	11	15	15	14	14	12	A_{K15}	10	8	8	8	7	9	10	7	7	6
A_{M16} ($\times 5.0\times 10^{-4}$)	20	13	20	16	16	18	18	20	20	15	A_{K16}	13	10	10	10	9	9	13	9	9	7
V_{M21} ($\times 10^{-3}$)	-3	-1	-2	-3	-2	-2	-2	-2	-3	-3	V_{K21} ($\times 10^{-4}$)	-1	-2	-3	-4	-1	-1	-1	-1	-3	-3
V_{M22} ($\times 10^{-3}$)	5	3	3	5	5	4	3	3	5	5	V_{K22} ($\times 10^{-4}$)	20	15	12	10	8	6	16	18	18	15
V_{M23} ($\times 10^{-3}$)	10	8	7	7	6	6	5	10	7	7	V_{K23} ($\times 10^{-4}$)	30	25	20	15	10	12	22	20	20	30
A_{B11} ($\times 3.0\times 10^{-2}$)	-8	-6	-5	-5	-5	-5	-10	-10	-10	-8	A_{X11} ($\times 10^{-3}$)	-5	-5	-3	-4	-4	-2	-2	-2	-2	-2
A_{B12} ($\times 3.0\times 10^{-2}$)	-5	-4	-3	-4	-4	-4	-4	-4	-4	-5	A_{X12} ($\times 10^{-3}$)	-3	-3	-2	-2	-2	-2	-1	-1	-1	-1
A_{B13} ($\times 3.0\times 10^{-2}$)	-2	-1	-1	-2	-2	-2	-1	-1	-1	-2	A_{X13} ($\times 10^{-3}$)	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
A_{B14} ($\times 3.0\times 10^{-2}$)	1	1	1	1	1	1	1	1	1	1	A_{X14} ($\times 10^{-3}$)	0	0	0	0	0	0	0	0	0	0
A_{B15} ($\times 3.0\times 10^{-2}$)	2	2	2	3	3	2	2	2	2	2											
A_{B16} ($\times 3.0\times 10^{-2}$)	13	10	10	9	9	8	5	5	6	8											
V_{B21} ($\times 10^{-1}$)	-1	-1	-2	-2	-2	-2	-1	-2	-3	-1	A_{X21} ($\times 5.0\times 10^{-4}$)	2	2	2	2	2	2	2	2	2	2
V_{B22} ($\times 10^{-1}$)	5	3	3	3	4	4	5	5	7	5	A_{X22} ($\times 5.0\times 10^{-4}$)	0	0	0	0	0	0	0	0	0	0
V_{B23} ($\times 10^{-1}$)	20	15	12	12	10	10	20	18	11	20	A_{X23} ($\times 5.0\times 10^{-4}$)	-5	-4	-6	-6	-6	-5	-5	-5	-5	-5

first, an initial population is selected. Each chromosome in the population is evaluated in terms of its fitness. If given stopping criteria (for example, achieving a desired fitness value, no change in the old and new population for a long time, or reaching a specified computing time) are not met, evolutionary operations are performed to generate new chromosomes. In the generation process, chromosomes are selected from the population with probabilities proportional to their fitness values for reproduction. The whole process is repeated until the given stopping criteria are met. The solution is the best chromosome in the final population.

In this work, those θ_i's for 8 groups of fuzzy rules are ΔM_1, ΔM_2, ΔB_1, ΔB_2, ΔK_1, ΔK_2, ΔX_{1d}, and ΔX_{2d}, respectively, and are to be determined in the training process. By referring to Table 1, there are 34 attributes in each chromosome. The initial population (10 chromosomes) used is listed in Table 2. Those values are selected only because they are feasible. Since those attributes are real numbers, floating evolutionary operators are used. Consider two chromosomes $\zeta=<\zeta_1, \zeta_2, \cdots, \zeta_n>$ and $\eta=<\eta_1, \eta_2, \cdots, \eta_n>$. In our example, n=34. For the crossover operations, new chromosomes are obtained as $<\zeta_1+(\eta_1-\zeta_1)/a_1, \zeta_2+(\eta_2-\zeta_2)/a_2, \cdots, \zeta_n+(\eta_n-\zeta_n)/a_n>$ and $<\eta_1+(\zeta_1-\eta_1)/b_1, \eta_2+(\zeta_2-\eta_2)/b_2, \cdots, \eta_n+(\zeta_n-\eta_n)/b_n>$, where a_i and b_i are selected randomly in the interval [2, 5]. This interval is heuristically determined. For the mutation operation, the deviation value should be limited to a given range; otherwise the robotic operation might become unstable. When ζ_i is chosen for mutation, $\zeta=<\zeta_1, \cdots, \zeta_i, \cdots, \zeta_n>$ is changed to $\zeta^*=<\zeta_1, \cdots, \zeta_i+\delta, \ldots, \zeta_n>$, where δ is within the region [-3,3]. In our implementation, each attribute has its mutation probability, and there may exist more than one mutation in a chromosome. The mutation probability of each attribute is 0.03.

VI. SYSTEM IMPLEMENTATION AND SIMULATION RESULTS

The idea of our approach is to operate a robot simulator to execute a deburring task and when the execution is not acceptable, the rules for adjusting $\boldsymbol{M_d}$, $\boldsymbol{B_d}$, $\boldsymbol{K_d}$, and $\boldsymbol{X_d}$ of each dimension are then modified. Fig. 2 shows the block diagram of our system. First, a set of rules enters into the system. Then, the impedance controller uses those parameters during the task execution. After the task is accomplished, the fitness of the results is evaluated. The evolutionary algorithm is then used to produce new sets of rules for evaluation. Hopefully, with the evolutionary based training mechanism, a set of rules that can achieve satisfactory results is acquired.

There are several different forms of dynamics (Guan, 1995; Kazerooni and Her, 1991; Bone and Elbestawi, 1994; Kuan and Young, 1998) that can be used to describe the interaction between the robot end-effector and the working environment. A simple dynamic model used in (Guan, 1995) is adopted in this simulation. The deburring model used is shown in

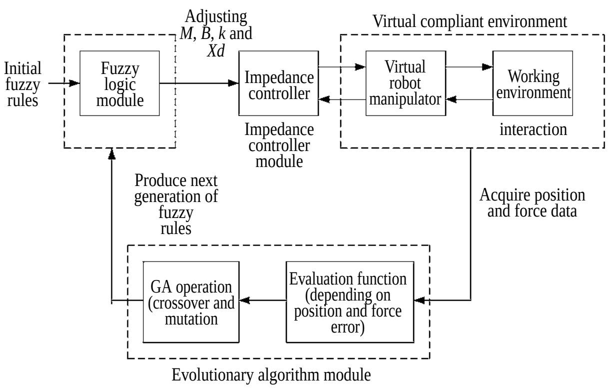

Fig. 2 The diagram of the evolutionary based virtual training system

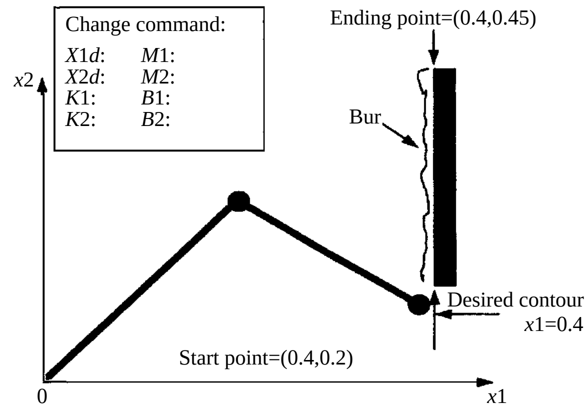

Fig. 3 The used virtual robot simulator

Fig. 3. The environment can be modeled as (Guan, 1995):

$$-\boldsymbol{F_{ext}}=\boldsymbol{M_e}\ddot{\boldsymbol{X}}+\boldsymbol{B_e}\dot{\boldsymbol{X}}+Ke(\boldsymbol{X}-\boldsymbol{X_e}) \tag{5}$$

where $\boldsymbol{M_e}$, $\boldsymbol{B_e}$ and $\boldsymbol{K_e}$ are the inertial, the damping and the stiffness matrices, respectively, of the environment, and $\boldsymbol{X_e}$ is the position vector of the environment. This external force is caused by the deformation of the workpiece. Usually, this type of dynamics of environment is adequate. The deburring behavior is characterized by:

$$\dot{X}_{e1}=-k_b\frac{F_{ext1}}{|\dot{x}_2|+\sigma} \tag{6}$$

where $\dot{X}_{e1}$ is the deburring effect, which is the change of the position vector on the x_1 axis, F_{ext1} is the external force on the x_1 axis, k_b and σ are positive constants. k_b represents the efficiency of deburring. When k_b is large, the efficiency of deburring is high. A small constant σ is to avoid dividing by zero in Eq. (6).

The requirements of deburring tasks in our training are described as follows. First, when the end-effector of the robot manipulator is in contact with the working environment, big impact should be avoided. Secondly, the line after deburring is asked to be as close to the desired line as possible, and then the position error is one index of the performance measure. Thirdly, the stability during the execution of the task needs to be assured. Finally, the execution time should not exceed a prescribed value. Besides, the weight of the position performance in the evaluation function is larger than that of the time consumption and of the force exertion.

According to the above task requirements, the fitness function used to evaluate the performance of a deburring operation is defined as:

$$score=\frac{W_1\times score_1}{2\times count}+\frac{W_2\times score_2}{2\times count}+(100-W_1-W_2)$$
$$\times\exp(-p_2\times count) \tag{7}$$

$$score_1=\sum_{i=0}^{n}[\mathrm{sgn}(0.4-X_{01i})\times\exp(-p_3\times(0.4-X_{01i}))] \tag{8}$$

$$score_2=\sum_{i=0}^{n}[\exp(-p_1\times(F_{ext1}-F_{lmt})^2)$$
$$\times\exp(-p_1\times(F_{ext2}-F_{lmt})^2)] \tag{9}$$

where W_1 and W_2 are the weights for the position and for the force performances, respectively. F_{lmt} is the desired force. p_1, p_2, and p_3 are the multipliers in different scores. 0.4 is the desired position and X_{01i} is the position after deburring for the ith point. $count=n$ is the number of points needed to accomplish a deburring task. Thus, $score_1$ is to evaluate the performance of X_{01i} (position) and $score_2$ is to evaluate the performance of external force. *count* is the measure of the execution time. In this simulation, the counting number cannot exceed a desired number. If it exceeds this desired number, the evaluation score is set as zero. In other words, if the speed of the deburring operation is too slow, the deburring operation will be regarded as a failed operation. In the same way, if the external force exceeds a tolerable force, the robot simulator alerts the user and also the evaluation score is set as zero. The values of robot simulator's parameters and other parameters used in our implementation are shown in Table 3.

First, the simulation result using the initial rules is shown in Fig. 4. In the figure, the horizontal axis is x_1, the vertical axis is x_2, and besides the original burr profile and the desired line (at x_1=0.4), the resultant positions (X_{01i}) for all points are shown. It is clearly evident that the performance is not good. Our

Table 3 The values for various parameters used in our implementation

Entities	Symbols	Description	Values
Parameters for the robot manipulator	l_1	The length of the first link	0.3m
	l_2	The length of the second link	0.32m
	m_1	The mass of the first link	2.815kg
	m_2	The mass of the second link	1.640kg
	I_1	The inertial of the first link	0.0234kg-m^2
	I_2	The inertial of the second link	0.0234kg-m^2
Parameters for the virtual environment	M_{e1}	The environment mass on the x_1-axis	0.0
	M_{e2}	The environment mass on the x_2-axis	0.0
	B_{e1}	The environment damping on the x_1-axis	0.5
	B_{e2}	The environment damping on the x_2-axis	0.5
	K_{e1}	The environment stiffness on the x_1-axis	100000
	K_{e2}	The environment stiffness on the x_2-axis	10000
	C_{fri}	The friction force coefficient on the x_2-axis	0.2
	k_b	The deburring coefficient	5
Parameters for the initial target impedance	M_{d1}	The desired mass on the x_1-axis	1.0
	M_{d2}	The desired mass on the x_2-axis	1.0
	B_{d1}	The desired damping on the x_1-axis	50
	B_{d2}	The desired damping on the x_2-axis	8
	K_{d1}	The desired stiffness on the x_1-axis	625
	K_{d2}	The desired stiffness on the x_2-axis	16
Parameters for the fitness function	W_1	The weight for the error score	50
	W_2	The weight for the external force	30
	p_1	The multiplier for the external force on the x_1-axis	0.005
	p_2	The multiplier for the external force on the x_2-axis	0.005
	p_3	The multiplier for the error (if $(0.4-X_{01n})>0.0$)	500
	p_3	The multiplier for the error (if $(0.4-X_{01n})\leq 0.0$)	200
	$F_{\lim it}$	The desired force	-15 NT

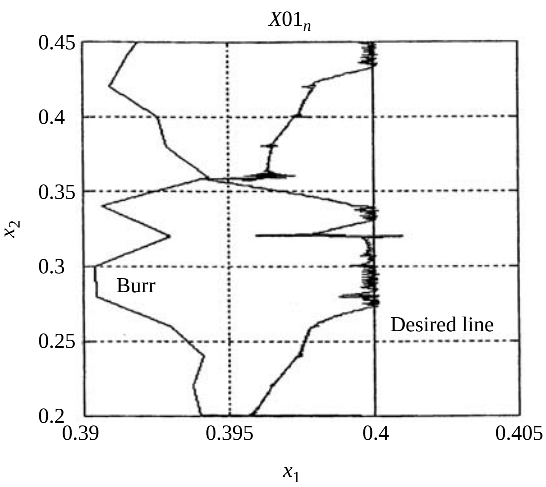

Fig. 4 The results by using the initial rule

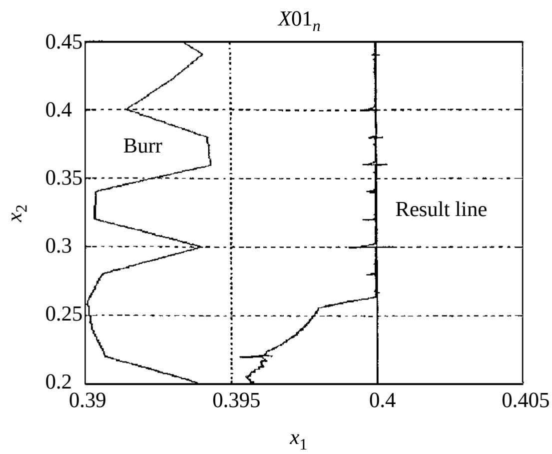

Fig. 5 The results of using the obtained rules (workpiece 1 and max=3000 points) with score 39.313

system is then trained by using the evolutionary algorithm with the maximal allowed points = 3000 to find a set of suitable rules. The deburring result by using the obtained fuzzy rules is shown in Fig. 5. It can be found that our approach indeed can train the fuzzy rules to perform deburring tasks nicely. Fig. 6 is another training result by using another burr profile. Again, the training is effective. Now, let the

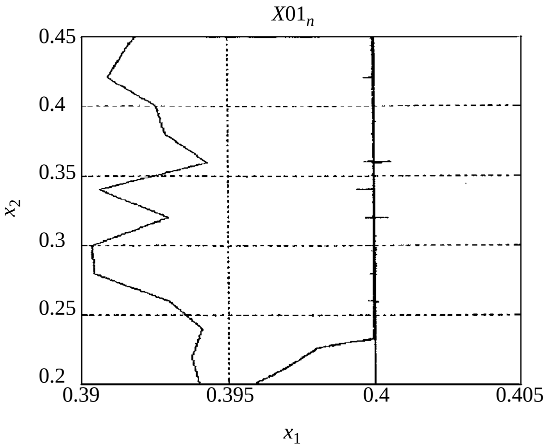

Fig. 6 The results of using the obtained rules (workpiece 2 and max=3000 points) with score 40.715

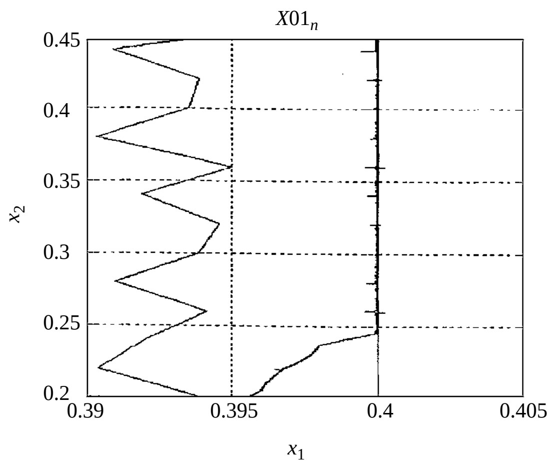

Fig. 7 The results of using the obtained rules (workpiece 1 and max=4000 points) with score 41.725

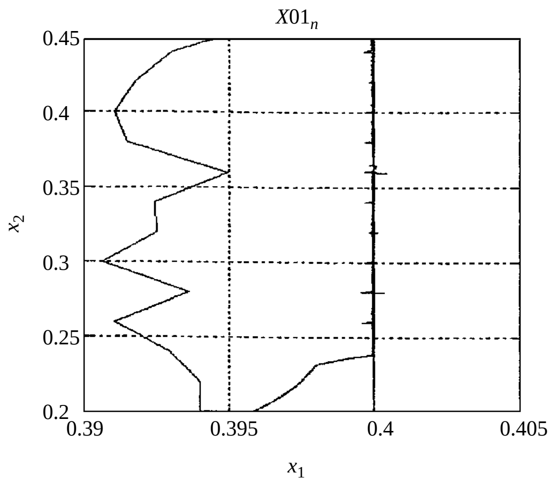

Fig. 8 The results of using the obtained rules (workpiece 2 and max=4000 points) with score 41.165

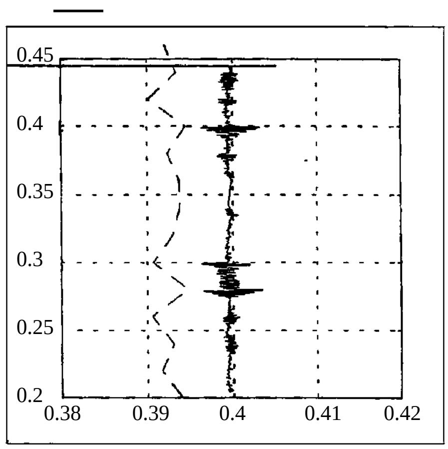

Fig. 9 The results reported in (Guan, 1995)

maximal allowed points become 4000; that is, a longer deburring process is allowed. The results are shown in Figs. 7 and 8. It can be found that the evaluated score are both higher than the former ones. For comparison, the results in (Guan, 1995) are also cited and shown in Fig. 9. It is evident that our results are much better than those in (Guan, 1995). It can be concluded that this approach can indeed achieve the purpose of training. In order to show that the idea of using the parameters in impedance controllers as knowledge is feasible, the obtained rules are applied to the workpieces with the same environmental parameters but different burr profiles. The set of rules obtained from the first case is used to debur the workpiece of the second case and the result is shown in Fig. 10. Similarly, the set of the rules obtained from the second case is also used to debur the workpiece of the first case and the result is shown in Fig. 11. It is evident that both cases are successfully performed.

VII. CONCLUSIONS

In this research, the problems of how to teach a robot to execute skilled operations are studied. The method of transferring human skills to robot operations is different from those proposed in the literature. Human workers usually accumulate their experience after executing the same task repetitively. Thus, in this work, we proposed an evolutionary-based system to extract knowledge for robotic deburring tasks through virtual training. This learning scheme has been successfully applied in finding ways of adjusting the parameters of impedance controllers required in deburring operations. Thus, the main focus of this paper is the idea of the proposed evolutionary-based virtual training scheme. Another focus is to transform the experience for skilled operations into

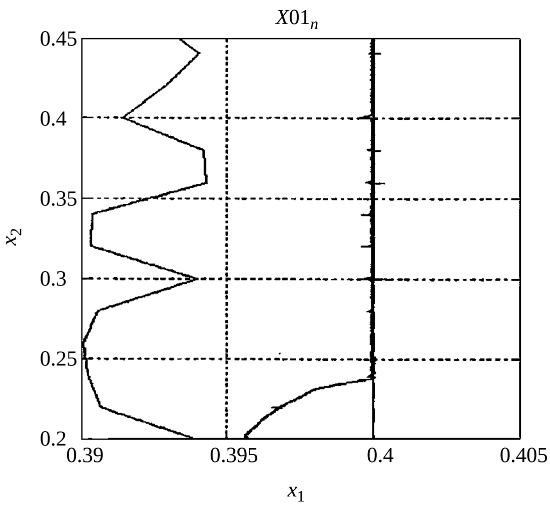

Fig. 10 The results of using the obtained rules from workpiece 1 for workpiece 2 (max=3000 points) with score 40.857

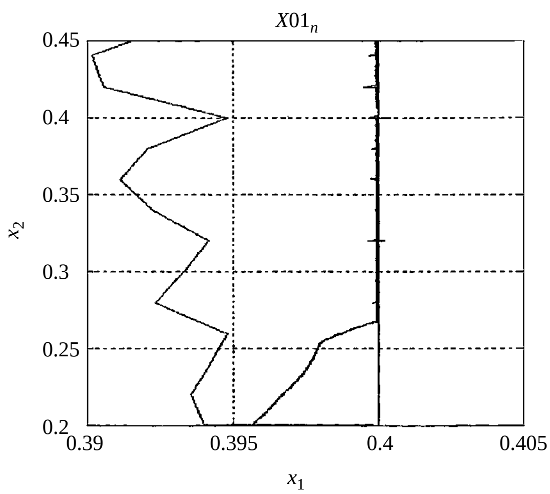

Fig. 11 The results of using the obtained rules from workpiece 2 for workpiece 1 (max=3000 points) with score 38.259

parameters in fuzzy systems. Such a numerical approach makes experience accumulation possible. From simulation, it is evident that our approach shows much better performance than previous work (Guan, 1995). We believe that the proposed mechanism can be used in training any skilled operations performed by robots.

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NOMENCLATURE

A_{pi}	the fuzzy labels for the error on the x_1 axis
$\boldsymbol{B_d}$	the damping matrices in the Cartesian space
$\boldsymbol{F_{ext}}$	the external force caused by the environment
$\boldsymbol{G}(\boldsymbol{q})$	the gravity loading force vector
$\boldsymbol{H}(\boldsymbol{q})$	the inertial acceleration-related symmetric matrix
$\boldsymbol{J}$	the Jacobian matrix
$\boldsymbol{K_d}$	the stiffness matrices in the Cartesian space
$\boldsymbol{M_d}$	the inertial matrices in the Cartesian space
ΔP	the variable of the increment for the parameter P
$\boldsymbol{q}$	the vector of the joint variables
$\boldsymbol{V}(\boldsymbol{q}, \dot{\boldsymbol{q}})$	the nonlinear Coriolis and centrifugal vector
V_{pi}	the fuzzy labels for the speed on the x_2 axis
$\boldsymbol{X}$	the end-effector's position vector in the Cartesian space
$\boldsymbol{X_d}$	the goal position vector in the Cartesian space
$\boldsymbol{\tau}_{act}$	the generalized torque vector applied at joints
θ_i	the incremental value assigned by a fuzzy rule

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