Knowledge Transfer Between Robots with Identical Tasks Execution

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Abstract:- This paper considers the transfer of knowledge expressed in the form of a collection of fuzzy or linguistic inference rules, also called knowledge or rule-base, from one robot (teacher) to another robot (student) in the case where both robots are supposed to perform the same task. Some rules are assumed taught or transferred to the student; i.e., they are known, and others are missing. The objective of this study is to have the student robot uncover the missing rules through self-experience and using the transferred rules. This objective is achieved by devising a novel method that enables the student robot to complete the knowledge-base. The completed rule-base would not necessarily turn out to be identical to the one possessed by the teacher robot. But, once it is used in the execution of the same task, it leads to satisfactory performance from a comparative perspective.

Key-Words:- Knowledge transfer; Robots; Fuzzy inference; Knowledge-base; Rule-base; Self-experience; Learning

1 Introduction

Fuzzy logic extends the conventional binary logic to allow the handling of partial truth values; i.e., values between "completely true" and "completely false." Fuzzy inference, which use fuzzy or linguistic rule-bases, also called knowledge-bases, permit the approximate modeling of complex humanistic processes in a more natural and relevant manner as compared to models based on precise classical mathematical approaches [1, 2].

The rule-base of a fuzzy inference system or fuzzy controller is formed by a collection of conditional "if-then" rules of the form: If x is A and y is B, then z is C. In the expressed rule, x and y are the input variables of the fuzzy controller and z is the output variable. A and B are fuzzy sets assigned over the input variables and C is a fuzzy set over the output variable. Fuzzy set C could also be a singleton or crisp value.

Fuzzy inference and knowledge-bases have, in recent years, been used in the area of robotics to equip robots with the necessary linguistic knowledge in the execution of a specific task [3-7]. One way to come up with an appropriate knowledge-base is through the use of numerical input-output data, representing the experience of a human operator, and the application of learning methods [6-8]. It is assumed, therefore, that a knowledge-base, obtained in this or in some other justifiable methodology, permits a suitable and good task execution resembling to a large degree that of a human expert. A robot equipped with a knowledge-base of the noted type is called, in this study, a teacher robot.

This study addresses the transfer of knowledge from one robot (teacher) to another robot (student) in the case where both robots are required to perform the same task. The teacher robot is assumed to possess a complete knowledge-base, which, once invoked, leads to an adequate execution of the task. The student robot has an incomplete knowledge-base. That is, some rules are assumed taught or transferred to the student; i.e., they are known, and others are missing. The objective is to have the student robot learn or uncover the missing rules through self-experience and using the transferred knowledge.

Hence, this study considers devising a novel procedure that can be applied to configure the missing rules based on numerical input-output data acquired from the experience of the student robot. The learning method and the data employed in the configuration of the knowledge-base of the teacher robot are considered unknown and, as a result, cannot be used since this robot is assumed to have its own learning manner and experiential situations. What can and should be used are the rules that are taught to the student robot. The described situation resembles to a large degree the real teacher-student relationship. After learning some of the teacher's skills, the student, then, has to develop his own learning procedures and define experiential situations he finds suitable to acquire the other needed skills in the task execution.

Consequently, the learning procedure that needs to be devised has to differ from the one used to obtain the rule-base of the teacher robot. In addition, it has to be based on tailoring specific student-related and teacherindependent experiential situations from which convenient data can be obtained in order to facilitate the determination of the missing rules using the known or transferred ones.

In the next section, the general structure of the fuzzy inference system that is used in this study is given. Also, some properties of the system are emphasized. Then, based on the system structure and properties, a procedure that permits the identification of the missing rules given a number of available rules will be described in Section 3. The described procedure will then be applied to a case study and tested for appropriateness in Section 4. This is done through the comparison of the performance of the obtained completed knowledge-base with that possessed by the teacher robot. Section 5 provides conclusive comments.

2 Fuzzy Inference System and Properties

The structure of the fuzzy inference system considered in this study consists of a set of "if-then" rules of the form:

$$\text{If } x \text{ is } A_n \text{ and } y \text{ is } B_m, \text{ then } z \text{ is } C_{nm} \qquad (1)$$

A_n, for $n = 1, 2, \ldots, N$ and B_m for $m=1, 2,\ldots, M$ are the fuzzy sets assigned respectively over the input variables x and y of the system and whose membership functions are denoted by $\mu_{An}(x)$ and $\mu_{Bm}(y)$.

All the (n,m) combinations are considered to form the antecedents or "if" parts of the rules. Hence, the number of rules is equal to the product $N \times M$. Further, the membership functions of the fuzzy sets assigned over a single input variable are such that the sum of the grades of membership of a specific crisp input value in these fuzzy sets is 1. Hence, the membership functions of the fuzzy sets A_n and B_m are as in Figure 1. C_{nm} is the crisp consequent or "then" part of rule nm.

Based on the above-described fuzzy system structure and using the defuzzification method developed in [9] as an improved version of the weighted-average defuzzification method [10], the crisp output obtained from a crisp input pair, denoted (x_0, y_0), is written as follows:

$$z_o = \sum_{n=1}^{N} \sum_{m=1}^{M} [\mu_{An}(x_0) \times \mu_{Bm}(y_0)]\, C_{nm} \qquad (2)$$

Now, we consider the grid partitioning of the input space based on the breakpoints of the assigned membership functions as shown in Figure 1. Using the indicated $x_1, x_2, \ldots, x_N$ points on the x-axis as well as the $y_1, y_2, \ldots, y_M$ points on the y-axis, then the following can be obtained with regard to the output in Equation (2) when fixing y to one of the noted y's and letting x be anywhere between any two consecutive x's or vice-versa.

For $y = y_m$, where $m = 1,2, \ldots, M$ and $x_n \le x \le x_{n+1}$ for $n= 1,2,\ldots, N-1$, then the output can be expressed as follows:

$$z = [\mu_{An}(x) \times \mu_{Bm}(y_m)]C_{nm} + [\mu_{A(n+1)}(x) \times \mu_{Bm}(y_m)]C_{(n+1)m} \qquad (3)$$

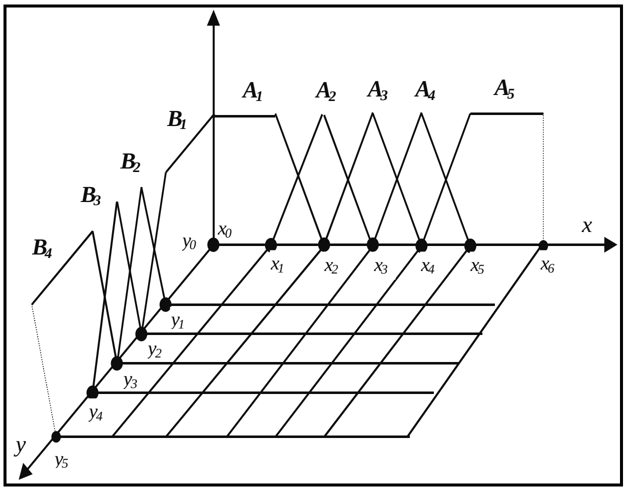

Fig. 1. Membership-function partitioning of the input space.

Since $\mu_{Bm}(y_m) = 1$ and $\mu_{An}(x) + \mu_{A(n+1)}(x) = 1$, then the output in Equation (3) becomes:

$$z = \mu_{An}(x)[C_{nm} - C_{(n+1)m}] + C_{(n+1)m} \qquad (4)$$

Similarly, for $x = x_n$, where $n =1, 2,\ldots, N$ and $y_m \le y \le y_{m+1}$, where $m =1, 2, \ldots, M - 1$, then the output can be expressed as:

$$z = [\mu_{An}(x_n) \times \mu_{Bm}(y)]C_{nm} + [\mu_{An}(x_n) \times \mu_{B(m+1)}(y)]C_{n(m+1)} \qquad (5)$$

Here, $\mu_{An}(x_n) = 1$ and $\mu_{Bm}(y) + \mu_{B(m+1)}(y) = 1$. Hence, the output in Equation (5) becomes:

$$z = \mu_{Bm}(y)[C_{nm} - C_{n(m+1)}] + C_{n(m+1)} \qquad (6)$$

It can be observed here that the part of the membership function of A_n that is used in Equation (4) is the one between x_n and x_{n+1}. It is therefore, the decreasing part of A_n. Similarly, the decreasing part of B_m is used in Equation (6). Hence, if the indicated parts of the membership functions of A_n and B_m are linear, as in Figure 1, then Equations (4) and (6) become also linear. They represent, therefore, straight-line segments, which could be increasing or decreasing depending on the sign of the difference ($C_{nm} - C_{(n+1)m}$) in Equation (4) and ($C_{nm} - C_{n(m+1)}$) in Equation (6).

We finally verify in this section the continuity property of the system input-output characteristic when one input variable is fixed and the output is taken as a function of the second input variable. Considering Equation (4) again, then the output for $y = y_m$ and $x_{n+1} \le x \le x_{n+2}$ can be expressed as:

$$z = \mu_{A(n+1)}(x)[C_{(n+1)m} - C_{(n+2)m}] + C_{(n+2)m} \qquad (7)$$

The evaluation of the outputs in Equations (4) and (7) at $x = x_{n+1}$; i.e., at the boundary point between the two indicated x regions and where $\mu_{A(n+1)}(x)=1$ and $\mu_{An}(x)=0$, results in these outputs being equal to $C_{(n+1)m}$. Further, Equation (6) and its modified version for $x = x_n$ and $y_{m+1} \le y \le y_{m+2}$ result in an output at $y=y_{m+1}$ being equal to $C_{n(m+1)}$.

3 Procedure for the Identification of Missing Rules

Based on the structure of the fuzzy inference system considered in Section 2 and the verified properties of the input-output characteristic when one input is fixed and the other varies between specific limits, a procedure for the identification of the missing rules is devised in this section. It is assumed that the membership functions of the input fuzzy sets are given in addition to some number of crisp rule consequents. These are to be used to determine the consequents of the missing rules. As mentioned in Section 1, the student robot is to uncover the missing rules through self-experience. This means that some convenient input points need to be specified for which the measured outputs need to be determined. The obtained input-output data points are also to be used to determine the consequents of the missing rules.

Looking back at Equations (4) and (6), it can be seen that two rule consequents are involved in each of these equations. This means that if one involved consequent in an equation is known and measured data along the corresponding line segment is used to come up with the equation of the linear input-output curve over this segment for fixed x or y, then the slope of the obtained linear equation can be equated with the slope of the curve expressed in (4) or (6). This will then lead to the determination of the unknown consequent involved in Equation (4) or (6). Hence, it is required that some data approximation or interpolation procedure be applied to come up with a linear curve interpolating between the available measured input-output data. The linear least-mean-square (LMS) algorithm for data approximation is chosen here.

The line equation obtained from the LMS will be of the form:

$$z = q\,r + h \qquad (8)$$

To obtain this line equation, we start by taking input points, which lie on the previously noted line segments. Hence, r would represent the input variable x if the input points are for fixed y and varying x. It would represent the input variable y if the input points are for fixed x and varying y. The output for each of these inputs is then measured. Afterwards, the following two quantities are calculated:

$$s_{rr} = \sum_{i=1}^{D} r_i^2 - \frac{1}{D}\left(\sum_{i=1}^{D} r_i\right)^2 \qquad (9)$$

and

$$s_{rz} = \sum_{i=1}^{D} r_i z_i - \frac{1}{D}\sum_{i=1}^{D} r_i \sum_{i=1}^{D} z_i \qquad (10)$$

where r_i and z_i are respectively the input and output of each point, and D is the number of data points taken. Note that, for Equation (4), $r_i = x_i$ while for (6), $r_i = y_i$. The slope of the line in Equation (8) is calculated using (9) and (10) as

$$q = s_{rz} / s_{rr} \qquad (11)$$

This slope is then equated to that of Equation (4) or (6), depending on the one we are using, to get the missing consequent. Note that, in Equation (4), $\mu_{An}(x)$ can be written as $ax + b$, where a and b depend on the considered membership function. The same applies to Equation (6) where $\mu_{Bm}(y)$ takes the form $ay + b$. Therefore, the slope q, calculated according to Equation (11), can be written as:

$q = a\times$ [quantity inside brackets in Eq. (4) or (6)] (12)

Now, due to the continuity property that has been verified in Section 2 regarding the system input-output characteristic for a fixed input and varying second input, Figure 2 is drawn and it is used to complete the description of the procedure for the identification of the missing rule consequents. The consequents on the horizontal line segments are obtained based on Equations (4) and (7). Those on the vertical line segments are obtained based on Equation (6) and its continuity counterpart equation.

As can be seen in Figure 2, it is sufficient that only one rule consequent be known in order to be able to determine the consequents of all other rules in the system. This can be done in a chaining manner. Every time an unknown consequent is determined over a line segment, then this consequent can be used over the next segment with corresponding measured outputs and LMS to determine another unknown consequent.

For example, if C_{11} is known, then the use of measured outputs for some number of input points at $y = y_1$ and for $x_1 \le x \le x_2$, gives C_{21}. Now, using the measured data in the appropriate ranges, C_{21} can be used, in turn, to obtain C_{31} and C_{31} gives C_{41}, etc. Also, C_{11} can be used to obtain C_{12} and C_{12} gives C_{22}. C_{22}, in turn, gives C_{32}, etc.

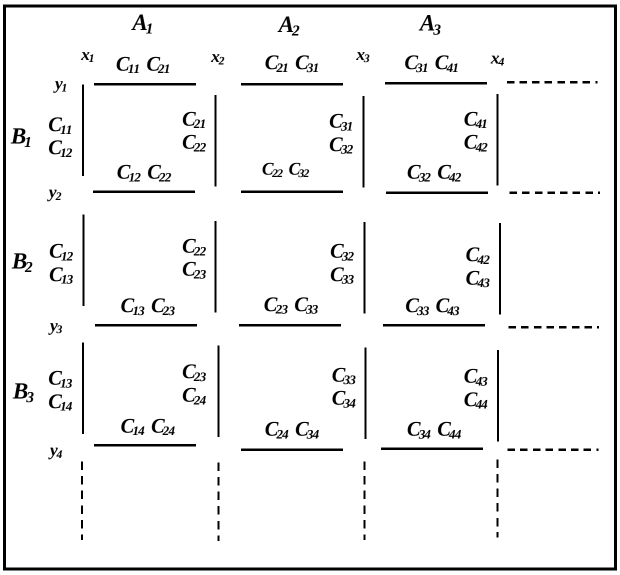

Fig. 2. Consequents on line segments drawn using the fuzzy system continuity property.

But, since each consequent determined in the above-noted manner contains some error, then this error can accumulate as we go from one segment to the next. The error accumulation would be lessened whether more than one rule consequent is known. In such a situation, every unknown consequent needs to be determined based on what can be called the minimum distance or shortest path concept. That is, the smallest number of line segments leading from each known consequent to a specific unknown one needs to be determined. Then, the known consequent that needs to be used to obtain the specific unknown one is the consequent whose shortest path is the smallest. The smallest number of line segments (steps) leading from one consequent, C_{ij}, to another, C_{lp}, can be obtained using the following formula:

$$d_{min} = |i - l| + |j - p| \tag{13}$$

Let, for example, C_{12} and C_{34} be the only known consequents. The consequent C_{43}, say, can be determined using C_{12} and also using C_{34}, which could lead to different values of C_{43}. Due to the error accumulation issue explained before, it is preferable to determine C_{43} using the closest known consequent. In this example, it is C_{34} not C_{12} since, according to Equation (13), the minimum distance between C_{12} and C_{43} is 4 while that between C_{34} and C_{43} is 2. This also appears clearly in Figure 2.

4 Case Study and Testing

In this section, the fuzzy inference system or fuzzy controller that was designed in [7] for robot navigation among moving obstacles and based on the data-driven learning algorithm developed in [8] is used to test the procedure for the identification of missing rules as described in Section 3. The system has 7 input membership functions over the input variable denoting "angle" and 8 membership functions over the second input variable denoting "distance." Thus, the total number of used rules is 56 (Section 2). The system output represents the "deviation angle" that the robot needs to implement at every specified time step in order to avoid collision with the moving obstacles and remain as close as possible to the direct path between the current robot position and the target point.

Some of the system rule-base consequents are put aside (assumed missing or unknown) and others are considered known. The use of the procedure introduced in Section 3 will give the missing consequents. The completed rule-base will be tested for appropriateness through the comparison of its input-output characteristic with that of the system obtained in [7] and considered to be the teacher robot knowledge-base.

Due to the error accumulation issue that was discussed in Section 3, the number of missing rule consequents has been increased gradually in the experimentation in order to determine how many out of a total of 56 consequents can be ignored while still having the completed knowledge-base perform satisfactorily; i.e., provide an input-output characteristic that is sufficiently close to the one obtained in [7].

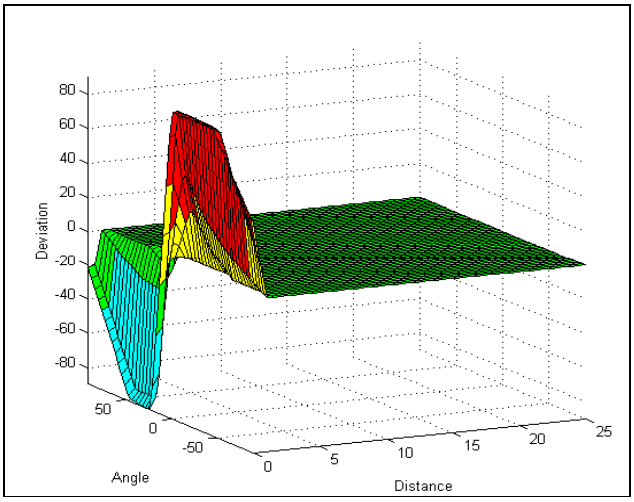

Fig. 3. Input-output characteristic of the student robot knowledge-base.

Figure 3 provides the input-output characteristic of the completed (student) rule-base obtained by the procedure introduced in Section 3 with 20 missing consequents. The comparison of Figure 3 control surface with that given in [7] shows that they are sufficiently close and, hence, a satisfactory performance is obtained with a good number of missing consequents. In fact, the use of a smaller and smaller number of missing rule consequents provided a closer and closer characteristic to that obtained in [7]; i.e., the characteristic of the teacher robot knowledge-base. This shows the efficiency of the rule completion procedure introduced in this study.

5 Conclusion

This study has addressed the transfer of knowledge from what has been termed a teacher robot to a student robot. Having the knowledge represented in the form of a rule-based fuzzy or linguistic inference system, it has been assumed that a part of the rule-base consequents are taught or transferred to the student robot. The missing consequents need to be identified by this robot through self-experience and using the transferred knowledge.

For this purpose, this paper has presented a novel procedure for the determination of the missing consequents. The procedure has been introduced based on the structure and verified properties of the fuzzy system that uses an improved weighted-average defuzzification method. In this manner, the procedure turned out to be permitting the student robot to complete its knowledge-base through its own learning method and specifically tailored experiential situations that allowed the use of the knowledge transferred from the teacher robot.

The described procedure can be used to allow interaction between machines in terms of knowledge transfer and learning and in a manner that resembles to a large degree what takes place between a teacher and a student in real life. In a car-driving school, for instance, the student cannot be taught all the driving rules in all possible situations. Some rules can be taught to the student. The other rules need to be discovered and learned by the student through self-experience.

The performance testing of the devised procedure has shown that it is capable of accomplishing efficient rule completion under a relatively good number of missing consequents. This has been verified by comparing the input-output characteristic of the completed rule-base with that of the rule-base possessed by the teacher robot in the case of robot navigation among moving obstacles.

Future research should address the problem of improving the efficiency of the provided procedure for missing rules identification in such a manner that the completed knowledge-base would still have a close performance to the teacher robot knowledge-base but under a larger number of missing consequents. Moreover, devising a procedure for the configuration of the whole inference system components should be addressed. In addition to the rule consequents, the number and type of the membership functions should be of interest. This would lessen the dependence of the student robot on the teacher and raises the level of intelligence of the student robot as a learning machine.

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