In: 7th German Conference on Robotics, Robotik 2012, Munich, Germany

Rule based Intention Generalization through Human-Robot Interaction

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Abstract

Humans have the capability of concept generalization. They can generalize an operation specific to an object on different objects present in the scene. In this paper we introduce a novel approach of rule based human intention generalization. The generalization is performed through Human-Robot Interaction (HRI) by inducing the rules online. The online rule induction corresponds to the performed human action on a known object with known characteristics. The novel generalization of an induced rule is performed based on the acceptance, rejection or correction by the human in response to the robot reaction while HRI. A novel method of conflict resolution is also proposed for the generalized rules. The experiments performed for the rule based intention generalization and online rule induction include teaching the robot of a specialized human intention. The robot tries to generalize the taught human intention by applying the actions on the related objects. The robot generalizes the human intention while HRI, based on acceptance, rejection or correction by the human. The intention generalization is performed by embedding the generalized rule into the probabilistic finite state machine. A finite state machine represents a human intention.

1 Introduction

Generalization of a concept corresponds to the reduction of the number of conditions present in the selection criterion of the concept. The lesser the conditions in the selection criterion of a concept the more general is the concept and vice versa.

There exist concepts related to generalization, e.g., applying the knowledge obtained from one case to another case and transferring the knowledge obtained from one scenario to another. This relates to Case Based Reasoning (CBR) [4] and Knowledge Transfer (KT) [9, 12] which are the examples of Lazy Learning algorithms. CBR may use different feature representations, e.g., Rough Sets [22]. The Lazy Learning algorithms use different kinds of distance functions to calculate the similarity between cases [23]. Association based rule learning in Data Mining [10, 21, 7] requires a huge amount of data to generate rules with certain probabilistic measures. Learning from Demonstration (LfD) [5, 17] use the term generalization for the robot to learn comprehensively from many times performed demonstration in different conditions for a certain task. The approach proposed in [11] describes that correction based HRI gives better results in LfD. HRI is used to correct the task performed by the robot [2], for behaviour adaption [15], and to learn the environment dynamics [19]. There exist generalization approaches for mobile robot, e.g., [3] describes navigational generalization based on evolutionary algorithms and [18] discusses Differential Equations based motor skill generalization. All the above described approaches do not consider generalization as concept generalization. The most related approach to concept generalization is [15]. It is also known as Version Space strategy. This approach can be successfully applied in classification. The HRI based concept generalization can not be performed using [15]. Since [15] does not suggest what to do in correction performed by the human while interaction. Similarly [15] also does not explicitly describes the rule conflict resolution. There exist also approaches for conflict resolution, e.g., [6] uses the classification frequencies of the rules (that cover the example to be classified) with respect to the classes to classify a conflicting example. The approach in [8] uses the product of prior probability of the class with the product of conditional probabilities of the rule with respect to that class. The class with higher value is selected. In [20] each conflicting rule votes for its predicted class with a weight and the weight of all the classes are summed up and the class with the highest weight is selected. The conflict resolution in [14] is the same as [8] if there is no training example in the intersection of the conflicting rules. If there are training examples in the intersection of conflicting rules then it [14] uses the conditional probabilities of the intersecting rules with respect to the class. The suggested approach in [13] introduces the idea of new induction from the examples that are covered by the rules in conflict. The above described approaches discuss the resolution of conflict using probability and the frequency of the class and by inducing new rules. No approach tries to focus on the antecedents of the rule that influence classification. Along with concept based generalization, the conflict resolution of rules is also suggested based on the importance of individual antecedents of the rule. The presented approach is confined to the generalization relating to the reduction of the concept criterion as described earlier. The application of these generalized rules in the intuitive HRI improves the interaction capabilities of the robot as the robot can interact more intelligently by performing the actions that are not explicitly taught to the robot.

The remainder of this paper is organized as follows. In the Section 2 a brief introduction of the probabilistic state machines representing the human intentions is given. Section 3 describes the online rule induction and generalization approach. Section 4 discusses the rule conflict resolution. Section 5 describes the experiments, performed using the proposed approach. In the end, the Section 6 concludes the approach described in this paper.

2 Probabilistic State Machines

The probabilistic Finite State Machines (FSMs) [1] are used to recognize and react according to the human intentions. Each FSM consists of a tuple, i.e., $FSM = \langle Q, \Sigma, S_1, S_n, \delta \rangle$. The set Q consists of the states $S_i \quad i = 1,..,n$ of a FSM. The set Σ corresponds to the set of the human actions $a_{xi} \; x = 1,...,m$ for a state $S_i \in Q$. Each action a_{xi} has a probability value with respect to a state S_i, i.e., $P(a_x \mid S_i)$. There exists an action $a_{ki} \in \Sigma$ for each state $S_i \in Q$ such that the probability of a_{ki} for the state S_i is greater than the probability of all the other actions $a_{ji} \in \Sigma$ at the state S_i, i.e.,

$$\forall S_i \in Q : \exists a_{ki} \in \Sigma : \underset{j=1, j \neq k}{\overset{m}{\forall}} a_{ji} \; it \; holds \; that \left[P(a_k \mid S_i) > P(a_j \mid S_i) \right]$$

For each state S_i the sum of the probabilities of all the action adds up to 1, i.e.

$$\forall S_i \in Q \wedge \forall a_{xi} \in \Sigma \; it \; holds \; that \sum_{x=1}^{m} P(a_x \mid S_i) = 1$$

The start and final states of the FSM are represented by S_1 and S_n. In a general probabilistic FSM (**Figure 1**), the action a_{ji} represents the j^{th} action at the state S_i such that and it leads to the same state S_i. The action a_{ki} represents the k^{th} action at state S_i and it leads to next state S_{i+1}.

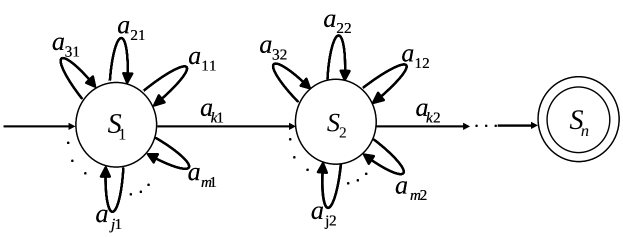

Figure 1 A General Finite State Machine

3 Rule Generalization

We introduce an approach for human intention generalization based on the rule generalization. The rule generalization corresponds to the generalization of the transition conditions of FSMs. The transition conditions correspond to the actions a_{ki} for the FSMs, discussed in Section 2. Each transition condition corresponds to a rule that is generalized using HRI. After recognizing the human intention the robot also reacts according to the generalized rules that will be described in the Section 5. The rules are induced online while HRI. The rule generalization is performed by HRI based on the idea of concept generalization. The robot generalizes the induced rules by applying them on a group of related objects. The group of objects corresponds to those objects that are similar to the object in some respect on which the human has performed the operation. The process of rule generalization is performed according to the following steps

3.1 Grouping of the objects
3.2 Online rule induction
3.3 Rule application
3.4 Rule generalization

3.1 Grouping of the objects

The objects of similar characteristics are grouped together. The system is given the characteristics of the objects and it classifies the object based on the similar characteristics. For example, if we have a group of the following objects, i.e., jug, plate, bowl, book, note book, shirt and, trousers. Then the jug, plate and bowl will fall into one class, book, and note book will fall into second class and shirt, and trousers will fall into third class. The reason is that the jug, plate and bowl have the similar characteristic of being broken along with other characteristics. The book, note book, shirt, and, trousers do not have the characteristic of being broken. Similarly the shirt and trousers can be dirty and book and note book do not have the characteristic of dirtiness. There may be more than one different characteristics present in the different classes.

3.2 Online rule induction

The objects present in the scene are known to robot. They belong to classes which are already known too. The robot also understands the human actions and the changes in the scene occurred due to the human action. The characteristics of the objects present in the scene are also known to the system. If an action sensible by the robot is performed by the human on an object with known characteristics, then the robot induces a rule considering the characteristics of the object as the antecedents and the performed action as the consequent of the rule.

3.3 Rule application

For generalization based on HRI, the robot applies the induced rules on the suitable objects present in the scene.

A set S of hypotheses is created, i.e. $S = \{<L, R, O>_1,\ldots,< L, R, O>_h\}$. The set S consists of h hypotheses. Each hypothesis $\langle L,R,O\rangle_i$ consists of a list L_i, a rule R_i, and object O_i. The List L_i corresponds to a set of characteristics that are similar in the object O_i present in the scene and the antecedents of rule R_i, in hypothesis i.

3.4 Rule generalization

In the process of generalization the robot applies the rule R_h on the object O_h of the h hypothesis of set $S=\{\langle L,R,O\rangle_1,\ldots,\langle L,R,O\rangle_h\}$. The robot expects the feedback from the human for the application of rule R_h on the object O_h. Generalization is performed based on the human action in response to robot's rule application.

The robot expects three kinds of responses from the human. The human can accept the robot's action. The robot's action can be rejected or can be corrected by the human along with rejection. In the generalization algorithm (**Figure 2**), the input of the algorithm includes set S of hypotheses that is generated in the rule application step. The robot can recognize the n objects present in the scene and the related characteristics of the n objects.

Input :

- *Human feed back*
- *n known objects O in the scene*
- *Changes in scene due to human action are known*
- *Characteri stics of the objects in the scene*
- $S = \{\langle L,R,O\rangle_1,\ldots,\langle L,R,O\rangle_h\}$

  Hypotheses generated in rule applicatio n section

Output :

Possible Generaliza tion of rules

Procedure :

1 – FOR *all h Hypotheses*
2 – $\quad$ $Exectue(Consequent(R_h), O_h)$
3 – $\quad$ IF $Reward(Accepted)$
4 – $\qquad$ $RULE\_UPDATE(L_h, R_h)$
5 – $\quad$ END IF
6 – $\quad$ IF $Reward(Rejected)$
7 – $\qquad$ $\mathbf{L} = R\_DIFFERENCE(R_h, L_h)$
8 – $\qquad$ $RULE\_UPDATE(\mathbf{L}, R_h)$
9 – $\quad$ END IF
10 – $\quad$ IF $Reward(Rejected + Corrected)$
11 – $\qquad$ $\mathbf{L} = RC\_DIFFERENCE(R_h, O_h)$
12 – $\qquad$ $RC\_RULE\_UPDATE(\mathbf{L}, R_h, A_{Correction}, O_h)$
13 – $\quad$ END IF
14 – END FOR

Figure 2 HRI based rule generalization

The human feedback and the changes occurred in the scene due to the human actions are also known to the robot. The output of the algorithm is the possible generalization of the rules in the hypotheses set S. The algorithm proceeds by applying the consequent part of rule R_h on the object O_h for each hypothesis $\langle L,R,O\rangle_h$ in the set S (line 1-2, **Figure 2**). If the human accepts the robot's action then the rule R_h is updated (line 4, **Figure 2**) by replacing the antecedents of rule R_h with the list L_h (line 1-3, **Figure 3**).

1 – $RULE\_UPDATE(L, R)$
2 – $R.Antecedent = \{\ \}$
3 – $R.Antecedent = L$

Figure 3 Update of the antecedents of rule R by list L

If the robot action is rejected by the human (line 6, **Figure 2**) then the difference between the rule R_h and the L_h is performed (line 7, **Figure 2**). The difference between R_h and L_h results in a list **L** that contains the elements that belong to R_h but do not belong to L_h (line 1-5, **Figure 4**).

1 – $R\_DIFFERENCE\ (R, L)$
2 – $R: \{a_1, a_2, a_3, \ldots, a_p\}$
3 – $L: \{ch_1, ch_2, ch_3, \ldots, ch_q\}$
4 – $A: R \setminus L\ \ st\ a_i \in R\ \wedge\ a_i \notin L\ \wedge\ i \geq 1$
5 – RETURN A

Figure 4 Relative complement of L with respect to R

The rule R_h is updated (line 8, **Figure 2**) by replacing the antecedents of rule R_h with the list **L** (line 1-3, **Figure 3**). The list **L** is produced at line 7, **Figure 2**. If the human not only rejects the robot action but also corrects the robot action (line 10, **Figure 2**) then once again the difference between the rule R_h and the characteristics of the object O_h is performed (line 11, **Figure 2**). The O_h corresponds to the characteristics of the object O in the h hypothesis of set S. The set S exists in the input of algorithm given in **Figure 2**. The difference results in a list **L** that contains the elements that belong to O_h but do not belong to R_h (line 1-5, **Figure 5**).

1 – $RC\_DIFFERENCE\ \ (R, O)$
2 – $R: \{a_1, a_2, a_3, \ldots, a_p\}$
3 – $O: \{ch_1, ch_2, ch_3, \ldots, ch_q\}$
4 – $A: O \setminus R\ \ st\ ch_i \in O\ \wedge\ ch_i \notin R\ \wedge i \geq 1$
5 – RETURN A

Figure 5 Relative complement of R with respect to L

The rule R_h is updated (line 12, **Figure 2**) by replacing the antecedents of rule R_h with the list **L** (line 1-3, **Figure 6**). The list **L** is produced at line 11, **Figure 2**. The consequent of rule R_h is replaced by the human correction (line 4, **Figure 6**). The Induced Rule (*IR*) for the newly constructed rule is also updated (line 5, **Figure 6**).

1 – $RC\_RULE\_UPDATE(L, R, A, C)$
2 – $R.Antecedent = \{\ \}$
3 – $R.Antecedent = L$
4 – $R.Concequent = A$
5 – $R.IR.Antecedent = C,\quad R.IR.Consequent = A$

Figure 6 Update of rule R and related Induced rule (*IR*)

The rules that are generalized by the process of REJECT and REJECT plus CORRECT are tested before they are moved into the transition pool. The rule generalized by REJECT may lead to false generalized rule. There can be two cases of false generalizations. In Case 1, if the (Induced Rule) *IR* is applied on an object of another class then the intermediate generalized rule (*IGR*) will be false generalization. The *intermediate generalized rules* (*IGRs*) correspond to the rules that are produced by the result of ACEPT, REJECT or REJECT plus CORRECT, performed by the human while the process of generalization (**Figure 2)**. For example, if *IR* and the characteristics of the object are as under

IR : IF {*Dirty*, *Plate*, *Intact*} THEN *W.B* (*Wash Basin*)
Object : {*Shirt*, *Dirty*, *Good*}

Then the *IGR* due to REJECT (line 6-9, **Figure 2**) will be

IGR : IF {*Plate*, *Intact*} THEN *W.B*

In Case 2, if *IR* is applied on the object of the same class and if the *IGR* does not contain all the necessary antecedents then *IGR* will be a false generalization. For example, if *IR* and the characteristics of the object are as under

IR : IF {*A*, *B*, *C*, *D*} THEN A
Object : {*A*, *B*, *D*}

Then the *IGR* due to REJECT (line 6-9, **Figure 2**) will be

IGR : IF {*C*} THEN A

If *B* and *C* are the necessary antecedents with respect to the action A then *IGR* is a false generalization. Similarly in case of REJECT plus CORRECT, there exist two cases. In Case 1, if *IR* is applied on an object of another class then the *IGR* will be a false generalization. For example, if *IR* and the characteristics of the applied object are as under

IR : IF {*Dirty*, *Plate*, *Intact*} THEN *W.B*
Object : {*Shirt*, *Dirty*, *Good*}

Then the *IGR* due to REJECT plus CORRECT (line 10-13, **Figure 2**) will be as under

IGR : IF {*Shirt*, *Good*} THEN *W.M* (*Wash Machine*)
IR : IF {*Shirt*, *Dirty*, *Good*} THEN *W.M*

In Case 2, if the necessary antecedents are not considered then the *IGR* will be a false generalization. For example, if *IR* and the characteristics of the object are as under

IR : IF {*A*, *B*, *C*, *D*} THEN A
Object : {*A*, *B*, *D*, *E*}

Then the *IGR* due to REJECT plus CORRECT (line 10-13, **Figure 2**) will be as under

IGR : IF {*E*} THEN **A**
IR : IF {*A*, *B*, *D*, *E*} THEN **A**

If *B* and *E* are the necessary antecedents with respect to the action **A** then *IGR* is a false generalization. Therefore the *IGRs* are first tested with the procedure (**Figure 7**) and then moved into the transition pool. The false generalization only occurs if the object belongs to a different class. The input to the procedure (**Figure 7**) is the set **IGR**. Each IGR_i, $i=1,\ldots, M$ has its corresponding *IR*. The output of the procedure (**Figure 7**) is the set of *IGRs* with corrected generalization problems. All the *IGRs* are tested for all the related objects (line 1, 2 **Figure 7**) present in the scene. The related object with respect to an IGR_i corresponds to the object that has all the characteristics concerned to the IGR_i. After IGR_i is applied (line 3, **Figure 7**), the human responds by accepting, rejecting or rejecting and correcting the robot reaction.

If the human accepts the robot reaction then intersection is performed between the IR_i concerned to IGR_i and the characteristics of the object O_j and IGR_i is updated (**Figure 3**) with the results of intersection (line 4-6, **Figure 7**). The intersection (line 5, **Figure 7**) is performed due to the fact that it results in all the necessary antecedents.

Input : *Set* IGR *of Intermediate Generalized Rule* (*IGR*) *and concerned Induced Rule* (*IR*)
Output : *IGRs*
Procedure :
1 – For *all* IGR_i
2 – For *all applicable Objects* O_j *for* IGR_i
3 – *Apply* IGR_i *on* O_j
4 – IF(*REWARD* =="ACCEPT")
5 – $\mathbf{L} = INTERSECT\,(Characteristic(O_j), IGR_i.IR)$
6 – $RULE\_UPDATE\,(\mathbf{L}, IGR_i)$
7 – ELSE IF(*REWARD* =="REJECT")
8 – $\mathbf{L} = R\_DIFFEENCE\;(IGR_i.IR, Characteristic(O_j))$
9 – $RULE\_UPDATE\,(\mathbf{L} \cup IGR_i.Antecedents, IGR_i)$
10 – IF(*REWARD* =="REJECT + CORRECT")
11 – $\mathbf{L} = RC\_DIFFERENCE\,(IGR_i.IR, Characteristic(O_j))$
12 – $RC\_RULE\_UPDATE\left(\mathbf{L}, IGR_i, A_{Correction}, Characteristic(O_j)\right)$
13 – END IF
14 – END FOR
15 – END FOR

Figure 7 Evaluation of *IGRs* for false generalization

The intersection (line 5, **Figure 7**) considers the similar characteristics of the object O_j (on which the robot has performed the action) and the antecedents of the induced rule of the IGR_i. For example, if we consider the example of Case 2 in REJECT case described earlier, i.e.

IR_i : IF {*A*, *B*, *C*, *D*} THEN A,
IGR_i : IF {*C*} THEN A,
and O_j : {*E*, *B*, *G*, *F*, *C*}.

The object O_j will contain all the necessary antecedents as the action is accepted for O_j. After acceptance (line 4-6, **Figure 7**) the IGR_i will be as under

IGR_i: IF {*B*, *C*} THEN A.

If the human rejects the robot reaction then the difference (see **Figure 4)** is performed (line 7-8, **Figure 7**). The difference specifies the unconsidered necessary antecedents that are added to IGR_i (line 9, **Figure 7**). The updated IGR_i is made available in the set **IGR** as it may require further necessary antecedents. If an IGR_i generated due to REJECT plus CORRECT and results in a false generalization. Then that IGR_i is corrected by adding the necessary antecedents. If the human rejects and corrects the reaction then the IGR_i is updated (line 11-12, **Figure 7**). This rule IGR_i is once again made available in the set **IGR** to be tested. The $IGR_i.IR$ corresponds to the characteristics of O_j and $A_{Correction}$ (line 12, **Figure 7**). The IGR_i generated only due to accept (line 4-6, **Figure 7**) are added to the transition pool.

3.5 Transition pool

The *IGRs* are added to the transition pool. In the process of generalization of *IGRs* (see **Figure 8),** each IGR_i present in the transition pool is matched against another rule IGR_j. If both the rules match, i.e., the consequent of both the rules IGR_i and IGR_j are similar and at least one antecedent in both the rules is similar.

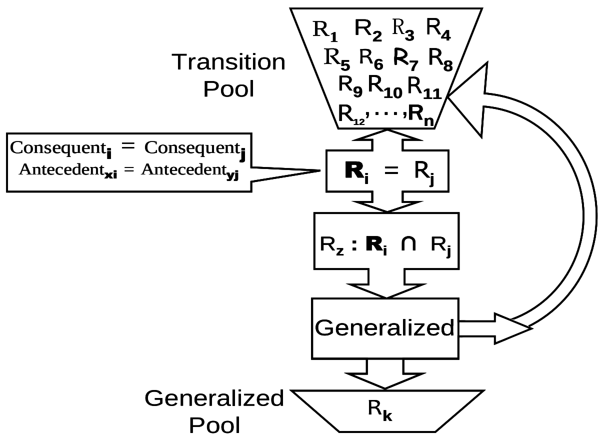

Figure 8 Generalization of *IGRs* in transition pool

Then intersection of the antecedents of the both the rules is performed, i.e.

$$IGR_z : IGR_i \cap IGR_j$$
$$a_z \in IGR_i.antecedent$$
$$a_z \in IGR_j.antecedent$$
$$a_z \in \{antecedents\ of\ IGR_z\} \quad z \geq 1$$
$$IGR_z.consequent = IGR_{i||j}.consequent$$

The rules IGR_i and IGR_j are dissolved into another rule IGR_z with the similar consequent and possibly few numbers of antecedents as compared to IGR_i and IGR_j. If the rule is completely generalized then it is moved into pool of generalized rules otherwise it is sent back to the pool of intermediate generalized rules (**Figure 8**). The *IGRs* are kept in the transition pool until they are completely generalized. There are two cases in which the rules are considered completely generalized. The Case 1 corresponds to the rules that have only one antecedent left. The Case 2 corresponds to the rules that can not be further generalized after **C** cycles of generalization in the transition pool. A generalization cycle corresponds to the fact that an IGR_i in the transition pool once again come into the transition pool (**Figure 8**).

4 Rule Conflict Resolution

The proposed approach for rule conflict resolution takes into account the significance of each antecedent of a rule to resolve the conflict. An antecedent of a rule corresponds to a known characteristics of a known object observed in the scene. The significance of an antecedent is termed as the *importance factor*. The importance factor of an antecedent can have the value in an interval of 1 and 0, i.e., $Imprtance\ Factor\ (A) \in [1,0]$. The importance factor of an antecedent is calculated as under

$$Importance\ Factor = \sigma / \Omega$$

σ : *Number of times a characteristics is selected*

Ω : *Number of times a characteristics is considered*

Each characteristic known to the robot is assigned an importance factor. The importance factor of the characteristics are updated while HRI. For example, an object has characteristics ch_1, ch_2 and ch_3 and the robot has performed an action A on that object according to the IR, i.e.

$$IR \quad : \text{IF} \quad \{ch_1, ch_2, ch_5\} \quad \text{THEN} \quad A$$
$$\text{Object} \quad : \{ch_1, ch_2, ch_3\}$$

If the human has accepted the action A then the rule will be generalized as under

$$IGR : \text{IF} \quad ch_1, ch_2 \quad \text{THEN} \quad A$$

The considered (Ω) characteristics are the antecedents corresponding to the induced rule, i.e., ch_1, ch_2 and ch_5. The selected (σ) characteristics correspond to the antecedents that remain in the rule, i.e., ch_1 and ch_2.

5 Experiments

The experiments are performed with a robotic arm of 6 degrees of freedom. HRI based experiments are performed by performing different known actions (**Figure 9**). The human picked and placed a specific speckled object into the speckled object rack (**Figure 9**). The robot picked and placed all the speckled objects into the concerned rack. Although the robot has not observed the human actions concerning all speckled objects, but due to the generalization capability picked and placed all the speckled objects.

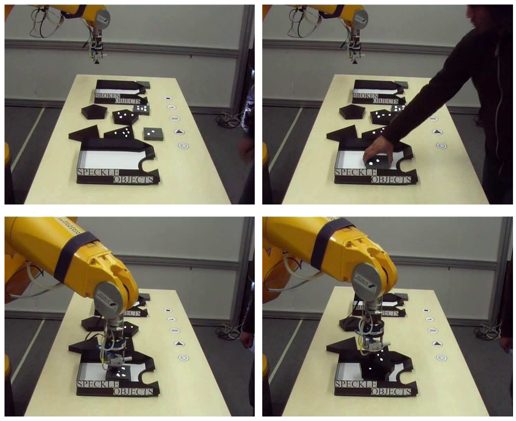

Figure 9 Intention generalization by HRI

The graph (**Figure 10** Left) represents the generalization capability of the robot. The generalization axis represents the no of objects acted upon by the robot while reacting to the recognized human intention. The green bars represent the results with generalization and brown bars represent without generalization. The graph (**Figure 10** Right) shows the rule conflict results.

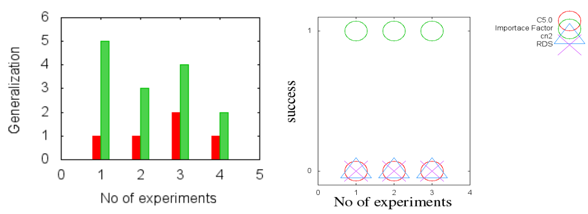

Figure 10 Graphs for intention generalization by HRI

The RDS [8], CN2 [6] and C5.0 [20] produce false result as they use probability for conflict resolution. They do not consider importance of individual antecedents in a rule.

6 Conclusion

In this paper we have introduced a generalization approach for the human intention generalization. The intention generalization corresponds to the understanding of the key concept of the human intention and to react according to that concept. The approach describes the rule generalization by HRI. This rule is then embedded into the probabilistic FSM [1]. That is used to recognize the general human intention and to react generally. The generalization capability of the robot increases the range of intuitive reactions. As future work the robot will be able to distinguish between the situations if he needs to react based on the generalization or specialization according to the human intention. If it is known that only one characteristic is significant for the concerning action and the objects belong to one class then the algorithm in **Figure 2** is enough for generalization.

7 Literature

[1] Awais, M., and Henrich, D. Human-Robot Collaboration by Intention recognition using Probabilistic State Machines. In Proceedings of 19th International Workshop on Robotics in Alpe-Adria_Danube Region (RAAD), 2010.

[2] Argall, B., Sauser, E., and Billard, A. "Tactile guidance for policy refinement and reuse," in Proc. 9th IEEE Int. Conf. on Development and Learning (ICDL), 2010, pp. 7–12.

[3] Berlanga, A., Sanchis, A., Isasi, P., and Molina, M. Generalization capabilities of co-evolution in learning robot behavior. Journal of Robotic Systems, 19(10):455-467, 2002.

[4] Bartsch-Spöl, B., Lenz, M., and Hübner, A. 1999. Case-Based Reasoning – Survey and Future Directions. Proc. Of the 5th German Biennial Conference on knowledge-Based Systems, Springer Verlag, 67-89.

[5] Billing, E., and Hellström, T. A Formalism for Learning from Demonstration. 2010. PALADYN Journal of Behavioral Robotics, VERSITA, DOI:10.2478/s13230-010-0001-5.JBD.1()1.2010.1-13

[6] Clark, P., and Boswell, R. Rule induction with CN2: some recent improvements. In proceedings of the Fifth European Working Session on Learning, pages 151-163, Berlin, 1991. Springer-Verlag

[7] Cohen, W. (1995), Fast Effective Rule Induction. In Proceedings of ICML-95, 115-123

[8] Compumine - Rule Discovery System™

[9] Frommberger, L. 2007. Generalization and transfer learning in noise-affected robot navigation tasks. In: Neves, J., Santos, M.F., Machado, J.M. (eds.) EPIA 2007. LNCS (LNAI), vol. 4874, pp. 508–519. Springer, Heidelberg

[10] Goodman, M., and Smyth, P. Rule induction using information theory. In G. Piatetsky-Shapiro and W. J. Frawley, editors, Knowledge Discovery in Databases (KDD-1991). MIT Press, 1991.

[11] Giovannangeli, C., and Gaussier, P. Human-Robot interactions as a cognitive catalyst for the learning of behavioral attractors. In 16th IEEE International Symposium on Robot and Human interactive Communication (RO-MAN 2007), pages 1028–1033, August 2007.

[12] Hart, S., Sen, S., and Grupen, R. Generalization and transfer in robot control, in 8th International Conference on Epigenetic Robotics (Epirob08), 2008.

[13] Lindgren, T., and Boström, H. Resolving rule conflicts with double induction. In Proceedings of the 5th International Symposium on Intelligent Data Analysis. Springer-Verlag, 2003.

[14] Lindgren, T., and Boström, H. Classification with intersecting rules. In Proceedings of the 13th International Conference on Algorithmic Learning Theory (ALT' 02), Pages 395-402. Springer-Verlag 2002.

[15] Mitchell. T. Generalization as search, Artificial Intelligence 18 (2) (1982) 203-226.

[16] Mitsunaga, N., Smith, C, Kanda, T., Ishiguro, H., and Hagita, N. Robot behavior adaptation for human-robot interaction based on policy gradient reinforcement learning," in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2005), 2005.

[17] Nicolescu, N., and Maja, M. Natural Methods for Robot Task Learning: Instructive Demonstrations, Generalization and Practice, Second International Joint Conference on Autonomous Agents and Multi-Agent Systems Melbourne, Australia, 2003

[18] Pastor, P., Hoffmann, H., Asfour, T., and Schaal, S. Learning and generalization of motor skills by learning from demonstration, In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), 2009

[19] Quinton, J., and Inamura, T. (2007), Human-Robot Interaction Based Learning for Task-Independent Dynamics Prediction. In Proceedings of 17th International Conference on Epigenetic Robotics

[20] RuleQuest Research See 5: an informal tutorial, 2003

[21] Spruit, M. Discovery of association rules between syntactic variables, In Proceedings of the 17th Meeting of Computational Linguistics in the Netherlands (2007).

[22] Salamo, M.., and Golobardes, E. Rough Sets Reduction Techniques for Case-Based Reasoning, In Proceedings of 4th ICCBR (International Conference on Case Based Reasongin) 2001

[23] Wettschereck, D., and Aha. D. A Review and Empirical Evaluation of Feature Weighting Methods for a Class of Lazy Learning Algorithms. Artificial Intelligence Review 11: 273-314, 1997 Kluwer Academic Publishers.