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# Learning fuzzy controllers in mobile robotics with embedded preprocessing

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ABSTRACT

The automatic design of controllers for mobile robots usually requires two stages. In the first stage, sensorial data are preprocessed or transformed into high level and meaningful values of variables which are usually defined from expert knowledge. In the second stage, a machine learning technique is applied to obtain a controller that maps these high level variables to the control commands that are actually sent to the robot. This paper describes an algorithm that is able to embed the preprocessing stage into the learning stage in order to get controllers directly starting from sensorial raw data with no expert knowledge involved. Due to the high dimensionality of the sensorial data, this approach uses Quantified Fuzzy Rules (QFRs), that are able to transform low-level input variables into high-level input variables, reducing the dimensionality through summarization. The proposed learning algorithm, called Iterative Quantified Fuzzy Rule Learning (IQFRL), is based on genetic programming. IQFRL is able to learn rules with different structures, and can manage linguistic variables with multiple granularities. The algorithm has been tested with the implementation of the wall-following behavior both in several realistic simulated environments with different complexity and on a *Pioneer 3-AT* robot in two real environments. Results have been compared with several well-known learning algorithms combined with different data preprocessing techniques, showing that IQFRL exhibits a better and statistically significant performance. Moreover, three real world applications for which IQFRL plays a central role are also presented: path and object tracking with static and moving obstacles avoidance.

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## 1. Introduction

The control architecture of mobile robots usually includes a number of behaviors that are implemented as controllers, which are able to solve specific tasks such as motion planning, following a moving object, wall-following or avoiding collisions in real time. These behaviors are implemented as controllers whose outputs at each time point (control commands) depend on both the internal state of the robot and the environment in which it evolves. The robot sensors (e.g. laser range finders, sonars, cameras, etc.) are used in order to obtain the augmented state of the robot (internal state and environment). When the robot operates in real environments, both the data obtained by these sensors and the internal state of the robot present uncertainty or noise. Therefore, the use of mechanisms that manage them properly is necessary. The use of fuzzy rules is convenient to cope with this uncertainty, since it combines the interpretability and expressiveness of the rules with the ability of fuzzy logic for representing uncertainty.

The first step for designing controllers for mobile robots consists of the preprocessing of the raw sensor data: the low-level input variables obtained by the sensors are transformed into high-level variables that are significant for the behavior to be learned. Usually, expert knowledge is used for the definition of these high-level variables and the mapping from the sensorial data. After this preprocessing stage, machine learning algorithms can be used to automatically obtain the mapping from the high-level input variables to the robot control commands. This paper describes an algorithm that is able to perform the preprocessing stage embedded in the learning stage, thus avoiding the use of expert knowledge. Therefore, the mapping between low-level and high-level input variables is done automatically during the learning phase of the controller.

The data provided by the sensors is of high dimensionality. For example, a robot equipped with two laser range finders can generate over 720 low-level variables. However, in mobile robotics it

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is more common to work with sets or groupings of these variables, (e.g. "frontal sector") that are much more significant and relevant for the behavior. As a result, it is necessary to use a model that is capable of grouping low-level variables, thus reducing the dimensionality of the problem and providing meaningful descriptions. The model should provide propositions that are able to summarize the data with expressions like "part of the distances in the frontal sector are high". This kind of expressions can model the underlying knowledge in a better way than just using average, maximum or minimum values of sets of low level variables. Moreover, these expressions also include the definition of the set of low-level variables to be used. Since these propositions involve fuzzy quantifiers (e.g. "part"), they are called Quantified Fuzzy Propositions (QFPs) [1]. QFP provide a formal model that is capable of modeling the knowledge involved in this grouping task.

Evolutionary algorithms have some characteristics that make them suitable for learning fuzzy rules. The well-known combination of evolutionary algorithms and fuzzy logic (genetic fuzzy systems) is one of the approaches that aims to manage the balance between accuracy and interpretability of the rules [2,3]. As it was pointed out before, fuzzy rules can be composed of both conventional and QFPs (therefore, they will be referred to as QFRs). Furthermore, the transformation from low-level to high-level variables using QFPs produces a variable number of propositions in the antecedent of the rules. Therefore, genetic programming, where the structure of individuals is a tree of variable size derived from a context-free grammar, is here the most appropriate choice.

This paper describes an algorithm that is able to learn QFRs of variable structure for the design of controllers with embedded preprocessing in mobile robotics. This proposal, called Iterative Quantified Fuzzy Rule Learning (IQFRL), is based on the Iterative Rule Learning (IRL) approach and uses linguistic labels defined with unconstrained multiple granularity, i.e. without limiting the granularity levels. This proposal has been designed to solve control (regression) problems in mobile robotics having as input variables the internal state of the robot and the sensors data. Expert knowledge is only used to generate the training data for each of the situations of the task to be learned and, also, to define the context-free grammar that specifies the structure of the rules.

The main contributions of the paper are: (i) the proposed algorithm is able to learn using the state of the robot and the sensors data, with no preprocessing. Instead, the mapping between low-level variables and high-level variables is done embedded in the algorithm; (ii) the algorithm uses QFPs, a model able to summarize the low-level input data; (iii) moreover, IQFRL uses linguistic labels with unconstrained multiple granularity. With this approach, the interpretability of the membership functions used in the resulting rules is unaffected while the flexibility of representation remains. The proposal was validated in several simulated and real environments with the wall-following behavior. Results show a better and statistically significant performance of IQFRL over several combinations of well-known learning algorithms and preprocessing techniques. The approach was also tested in three real world behaviors that were built as a combination of controllers: path tracking with obstacles avoidance, object tracking with fixed obstacles avoidance, and object tracking with moving obstacle avoidance.

The paper is structured as follows: Section 2 summarizes recent work related with this proposal and Section 3 presents the QFRs model and its advantages in mobile robotics. Section 4 describes the IQFRL algorithm that has been used to learn the QFRs. Section 5 presents the obtained results, and Section 6 shows three real world applications of IQFRL in robotics. Finally, Section 7 points out the most relevant conclusions.

## 2. Related work

The learning of controllers for autonomous robots has been dealt with by using different machine learning techniques. Among the most popular approaches can be found evolutionary algorithms [4,5], neural networks [6] and reinforcement learning [7,8]. Also hibridations of them, like evolutionary neural networks [9], reinforcement learning with evolutionary algorithms [10,11], the widely used genetic fuzzy systems [12–18], or even more uncommon combinations like ant colony optimization with reinforcement learning [19] or differential evolution [20] or evolutionary group based particle swarm optimization [21] have been successfully applied. Furthermore, over the last few years, mobile robotic controllers have been getting some attention as a test case for the automatic design of type-2 fuzzy logic controllers [8,5,20].

An extensive use of expert knowledge is made in all of these approaches. In Ref. [12] 360 laser sensor beams are used as input data, and are heuristically combined into 8 sectors as inputs to the learning algorithm. On the other hand, in Refs. [9,13–16,18,19,21] the input variables of the learning algorithm are defined by an expert. Moreover, in Refs. [13,14,16,18,20] the evaluation function of the evolutionary algorithm must be defined by an expert for each particular behavior. As in the latter case, the reinforcement learning approaches need the definition of an appropriate reward function using expert knowledge.

The approaches based on genetic fuzzy systems use different alternatives in the definition of the membership functions. In Ref. [10,12,16] the membership functions are defined heuristically. In Refs. [14,15] labels have been uniformly distributed, but the granularity of each input variable is defined using expert knowledge. On the other hand, in Refs. [13,17–19,21] an approximative approach is used, i.e., different membership functions are learned for each rule, reducing the interpretability of the learned controller.

The main problem of learning behaviors using raw sensor input data is the curse of dimensionality. In Ref. [7], this issue has been managed from the reinforcement learning perspective, by using a probability density estimation of the joint space of states. Among all the approaches based on evolutionary algorithms, only in Ref. [4] no expert knowledge has been taken into account. In this work, the number of sensors and their position are learned from a reduced number of sensors.

In Ref. [22] a Genetic Cooperative-Competitive Learning (GCCL) approach was presented. The proposal learns knowledge bases without preprocessing raw data, but the rules involved approximative labels while the IQFRL proposal uses unconstrained multiple granularity. Moreover, in this approach it is difficult to adjust the balance between cooperation and competition, which is typical when learning rules in GCCL. As a result, the obtained rules where quite specific and the performance of the behavior was not comparable to other proposals based on expert knowledge.

## 3. Quantified Fuzzy Rules (QFRs)

### 3.1. QFRs for robotics

Machine learning techniques in mobile robotics are used to obtain the mapping from inputs to outputs (control commands). In general, two categories can be established for the input variables:

- High-level input variables: variables that provide, by themselves, information that is relevant and meaningful to the expert for modeling the system (e.g. the linear velocity of the robot, or the right-hand distance from the robot to a wall).
- Low-level input variables: variables that do not provide by themselves information for the expert to model the system (e.g. a single

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