Application of WINROSA for Controller Adaptation in Robotics and Classification in Quality Control

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Abstract

This paper presents two applications of the WINROSA software tool. In the first application a data–based generated fuzzy modul is used to adapt the parameters of the position controller of an industrial robot to optimise the continuous path accuracy. It is shown how to learn from good and poor control strategies. The second application is the classification of automatic gear boxes by 149 characteristics. It is demonstrated that a data–based generated fuzzy modul is a promising approach for handling this very complex problem. A new method for complexity reduction is used to reduce the number of necessary process characteristics by analysing their relevance for the classification.

1 Introduction to WINROSA

The application of fuzzy models and fuzzy controllers depends on efficient data based methods as direct design by experts is often not possible. The Fuzzy–ROSA[2] method [Krone94] is a concept for generating a fuzzy rule–based model from the input–output behaviour of a dynamic system. With the WINROSA software tool the Fuzzy–ROSA method can easily be used for solving complex problems even if there is only little process knowledge available. It can be used for generating positive and negative rules from observation data. Positive rules are interpreted as recommendations and negative rules are interpreted as warnings or vetoes.

Due to the need for acceptable computing time, the generation process is divided into five main steps. The approach of the Fuzzy–ROSA method does not aim at reaching the global optimum (which would be impossible), but at reaching a good result in an acceptable time.

There are alternative strategies available for each step, so that the method can be adapted to different application requirements and problem sizes.

Project Definiton: Before rules are generated, the membership functions of the input and output variables of the considered system are extracted by cluster analysis [Krone98a], heuristic or prior knowledge.

Rule Generation: Depending on the size of the search space, a complete search or an evolutionary search [Krone97] can be chosen. By the concept of a relevance test [Krone98a, Jessen98] and a rating for each individual rule, the problem of finding a good rule base is reduced to the problem of finding individually good rules. The rule set is built up by an incremental collecting of good rules.

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[1] Daimler Benz AG, Stuttgart

[2] **R**ule **O**riented **S**tatistical **A**nalysis

Off–line Rule Reduction: The number of generated rules is reduced by off–line rule reduction methods [Krone96b] that meet different requirements, for example the complete covering of all input situations, the modelling error or a strictly bounded number of rules.

Optimisation: The input–output behaviour of the fuzzy system obtained is optimised by adjusting the remaining free parameters.

Analysis: The analysis of the rule base allows a judgement of the design process and of the model quality and provides feedback for the problem formulation.

2 Application 1: Controller adaptation in robotics

In the case of continuous path motions particular applications require high accuracy of a six–axis robot arm in the cartesian space. As the use of additional sensing mechanisms for the cartesian space control is expensive and problematic, it is near at hand to minimise the positioning error in the joint space. The motion equations of the robot arm under examination are given by a set of nonlinear coupled differential equations. Control schemes, which consider these circumstances, require theoretically based models of adequate exactness. On the other hand, a considerable improvement of control performance can be attained by adaptive control techniques. In the conducted studies the parameters of the axis controller are modified according to the operating point. In order to learn the best control parameters for the different operating points, the robot arm is moved along several selected cartesian path trajectories. Along the paths the main–influencing variables (positions, velocities and accelerations of the axes 1, 2 and 3) are recorded, where constant controller parameters are active. The three parameters are varied on three levels, so that the robot arm is moved forward and backward along each path $3^3 = 27$ times.

2.1 Learning from good and poor control strategies

As the Fuzzy–ROSA method finds a statistical relevant compromise in contradictory data, it will do the same, when observation data of different control strategies and control performances are used. This, however, will lead to the problem, that bad controller outputs in the observation data are integrated in the compromise and different control strategies are mixed up in an uncontrolled way. In order to overcome these disadvantages, caused by the contradictoriness of the data, the following concept is proposed [Krone96a]: First the observation data sets are rated with regard to the achieved control performance. A linear or nonlinear function transforms the values of this performance index to a rating factor. The rating factors are used to achieve rated degrees of matching of the conclusions. The rated degrees of matching of the conclusions are finally used to generate positive and negative rules. Consequently, all aspects of control performances are integrated in finding the most relevant and performance–orientated rules. The result is a set of relevant fuzzy rules, which in a certain situation recommend those control parameters, which lead to good control performances, and warn against those control parameters, which lead to poor control performances. Since the axis controller has three parameters, the conclusions of the fuzzy rules refer to a vector of the control parameters. Therefore, for the processing of recommendations as well as warnings the two–way fuzzy concept is extended to the case of multiple output variables. For a further improvement of the flexibility of the adaptation process the concept of the inference filter is as well extended to the case of multiple output variables [Schwane98].

2.2 Results

Exemplary, in the following the improvement of the control of axis 1 is illustrated, which can be achieved by the adaptive concept. Figure 1 and 2 show the control error for constant control parameters along a path. The proportional–action and the derivative–action components are the same in both cases, whereas the integral–action component is adjusted to a very low and to a very high value, respectively. With the fuzzy adaptation of the control parameters using positive rules only the dynamic control error of the axis can be considerably decreased (Fig. 1). Further improvements are possible by making use of negative rules and the inference filter in addition (Fig. 2).

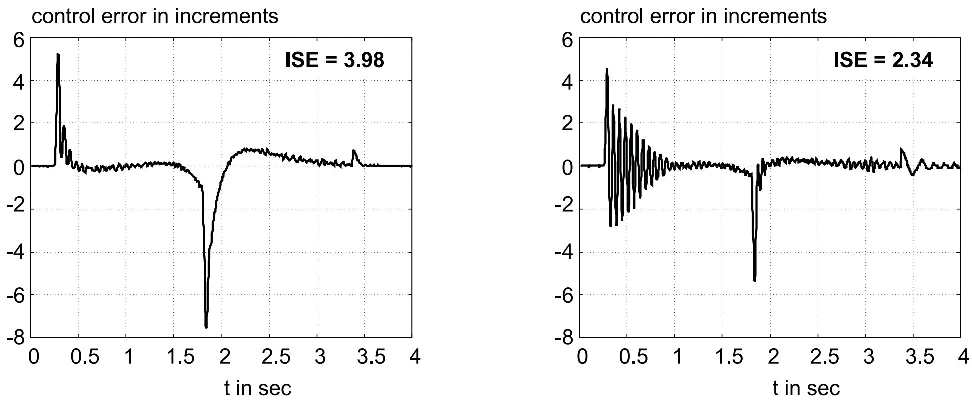

Figure 1: Control error of axis 1 along a continuous path achieved with constant control parameters with low (left) and high (right) integral–action component

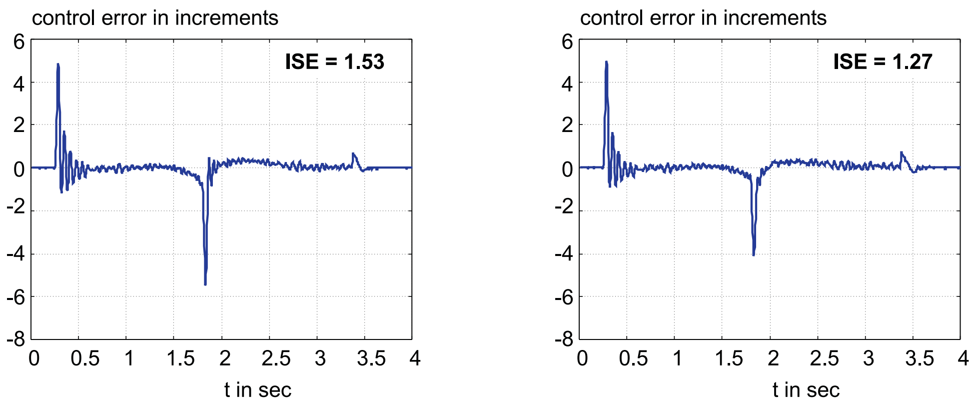

Figure 2: Control error of axis 1 with the fuzzy adaptation along a continuous path achieved by automatic generation of fuzzy rules by the Fuzzy–ROSA method with positive rules only and COS–defuzzification (left) and two–way fuzzy adaptation with inference filter (right)

3 Application 2: Classification in quality control

In quality control different parameters are inspected during a test to detect material faults, production faults, assembling faults or unusual sounds during operation. Nowadays, all gear boxes produced by an automobile manufacturer are being tested acoustically by human specialists. Acoustic tests of these components are performed for two reasons. Feasible components are sorted out and faulty components are identified by their characteristic acoustic patterns. Object of the classification presented here are automatic gear boxes. Due to their complex structure, the high number of moving parts and the influence of different operating states, a high number of acoustic characteristics has to be derived from the measured signals. To support and finally automate the human tester's decision an automatic fuzzy–classificator is developed. The tester's decision can be 'all right' ('o.k.') or 'faulty' ('not o.k.').

3.1 Data–based generation of a fuzzy classificator

With 149 input characteristics the design of a fuzzy–classificator is a very complex problem. Therefore a knowledge–based approach is very time consuming and needs a lot of process understanding. Nevertheless, it is possible to design a fuzzy–classificator by hand. With about 200 rules and a maximum combination depth of 16 linguistic statements in the rule premise, it is possible to classify more than 95 % of the gear boxes correctly.

In an alternative approach a data–based fuzzy classificator was generated with the WINROSA software tool based on 1060 data sets (1000 'o.k.' / 60 'not o.k.'). In order to demonstrate that no process knowledge is necessary each of the 149 input characteristics was only identified by a number. Five equidistant membership functions were chosen heuristically for each characteristic.

With a combination depth of 6 this configuration leads to about 10^{17} possible rules. In this huge search space an evolutionary search was chosen for finding relevant rules. For the rule test and rating strategy the relevant hit rate was taken. In about 20 hours it was possible to generate a rule base with several thousand rules and a classification rate up to 100 % on the learning data.

To get a small and transparent rule base the number of rules was reduced as follows. By reducing all rules with a rating index smaller than one, only rules with a hit rate of 100 % were left in the rule base. Therefore, each single rule always produces the right classification for the learning data set if applicable. A rerating of the rule base with the relevance index leads to higher indexes for rules for faulty gear boxes. These rules are more important for the classification. If the number of rules is reduced by taking out the rules with the lowest relevance indexes, it is possible to reduce the rule base down to less than a hundred rules with a correct classification rate of 100 %.

To proove that also gear boxes which are not part of the learning data can be classified only 90 % of the available data sets were taken for learning. The correct classification rate on the data sets not taken for learning was 92 % (95 % for 'ok' and 70 % for 'not o.k').

These promising results show, that a fuzzy–classificator can be generated data–based. In further works the data–based and the knowledge–based approach will be compared in detail.

3.2 Finding a handy set of relevant process characteristics

An essential point in the modelling of a complex technical system is the choice of a handy set of relevant input variables. In the case of the classificator described above the input variables are the acoustic characteristics and the output is the tester's decision. To reduce the number of potentially relevant input variables to a handy set a method for complexity reduction is applied [Praczyk98]. With it characteristics are analysed for their relevance for the classification and for redundancy relating to other characteristics.

The general idea of the method is to analyse how good a variable can be deduced from another variable concerning the available data. To quantify this, a measure of definiteness has been defined which is based on fuzzy logic. It quantifies the definiteness of linear as well as nonlinear relations between variables.

The method is divided into two main steps. In the first step the relation of each input variable with the output variable is analysed. If the definiteness of the relation quantified by the defined measure is lower than a certain threshold, the input variable can be removed because no information about the output variable can be obtained from this input variable. In the second step the redundancy of each input variable relating to each other input variable is analysed. The measure of definiteness is derived for all combinations of input variables. If the measure for a pair of two input variables is greater than a certain threshold, no additional information can be obtained by using both variables as input variables. Therefore, only one of the variables has to be included into the set of relevant process characteristics. Preferably, the input variable with the less definte relation with the output variable is removed.

By applying this method to the available data of the gear boxes, the number of relevant, not redundant characteristics could be reduced to 93. This means a reduction of more than one third of the characteristics compared to the original number. With this reduced number of characteristics a fuzzy–classificator was generated in the same way as described above. For a correct classification rate of 100 % a slightly higher number of rules was necessary.

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