DECISION TABLE TUNING USING A GENETIC ALGORITHM

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Abstract

A genetic algorithm based procedure for direct decision table adjusting is proposed to solve dynamic discrete-time optimal control problem. A decision table controller is applied to second order process and ITSE performance measure is used. Linear and nonlinear decision table elements distribution is investigated and results compared.

Introduction

Although genetic algorithms have been successfully applied to various static optimization problems [1], application of the genetic algorithm to dynamic discrete-time optimal control problems have been only initially studied [2][3][4][5]. The main direction of research was to use the genetic algorithm to tune various parameters of fuzzy controller. Most of research efforts to find robust design procedure fall into one of four main fields: selection of scaling factors, derivation of optimal membership functions, elicitation of a rule-base and on-line modification of the rule-base [6][7][8][9]. For time-critical applications fuzzy controller is replaced with the decision table controller derived from fuzzy algorithm [10]. Published results [11][12] indicate that the genetic algorithm can effectively adjust the decision table independently of fuzzy procedure and knowledge about process.

Decision table controller

A decision table controller (DTC for short) is a controller which changes its output in regular discrete time instances and whose transfer function is defined by decision table, Fig. 1.

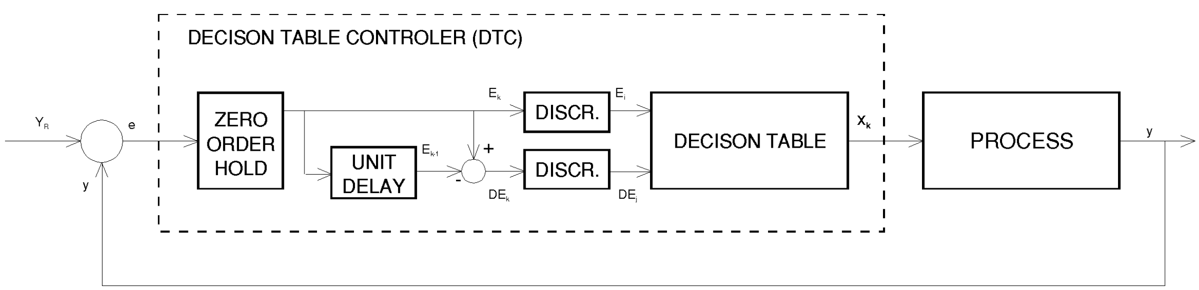

Fig. 1 Decision table controller

In this research two-input single-output DTC was used:

$$x_{ij} = f(E_i, DE_j) \quad , \qquad (1)$$

where x_{ij} is controller output in period from time instance t_k to t_{k+1}, E_i is discrete error in time instance t_k, DE_j is discrete change-in-error in time instance t_{k-1}, and f defined with decision table. E_k and DE_k are converted to discrete values E_i and DE_j respectively and used as inputs for decision table. There are four parameters that have to be established for decision table: number of discrete error values N_E, number of discrete change-in-error values N_{DE} (i.e. resolution of error and change-in-error), function f_E ; $E_i=f_E(E_k)$ and function f_{DE} ; $DE_j=f_{DE}(DE_k)$, i.e. distribution of error and change-in-error diskrete values. Apart from finding general DTC idea applicability, the main purpose of this research was to find rules to determine these parameters. In this research N_E=2,3,5,7,21 and N_{DE}=2,3,5,7,21 were used. The decision table discrete error value is defined as:

$$LE_{i-1} \le E_i < LE_i \quad ; \quad i = 0,1,...,(N_E - 1) \quad ; \tag{2}$$

$$LE_{i-1} < LE_i \quad ; \quad LE_{-1} = -\infty \quad ; \quad LE_{(N_E - 1)} = +\infty \quad , \tag{3}$$

The decision table discrete change-in-error value is defined analogous. In this research we try to find general rules to determine values for LE_i and LDE_j, i.e. f_E and f_{DE}.

	$LE_{-1} \le E_0 < LE_0$	$LE_0 \le E_1 < LE_1$	$LE_1 \le E_2 < LE_2$
$LDE_{-1} \le DE_0 < LDE_0$	x_{00}	x_{01}	x_{02}
$LDE_0 \le DE_1 < LDE_1$	x_{10}	x_{11}	x_{12}
$LDE_1 \le DE_2 < LDE_2$	x_{20}	x_{21}	x_{22}

Table 1: Example of decision table for N_E=3, N_{DE} =3.

In traditional fuzzy controller algorithm linear distribution was used, but we found out that nonlinear distribution gives better results. In the case of linear distribution LE_{i-1}-LE_i=const.

Experiments were conducted with distributions:

$$LE_i = |E_{\max}| \cdot \left(-1 + \frac{2}{N_E - 2} \cdot i \right)^n \quad , \quad i = 0,1, \ldots , (N_E - 2) \quad , \tag{4}$$

$$LDE_j = |DE_{\max}| \cdot \left(-1 + \frac{2}{N_{DE} - 2} \cdot j \right)^m \quad , \quad j = 0,1, \ldots , (N_{DE} - 2) \quad , \tag{5}$$

where:

$\|E_{max}\|$	absolute expected maximal error value,
$\|DE_{max}\|$	absolute expected maximal change-in-error value,
n	error nonlinearity factor, n=2·r+1, r=0,1,2 ..., (for n=1 distribution is linear),
m	change-in-error nonlinearity factor, m=2·r+1, r=0,1,2 ..., (for m=1 distribution is linear).

In this research: E_{max}=0.3, DE_{max}=0.001, sampling interval=0.1, n=1,3 and m=1,3 were used.

Genetic algorithm parameters

This work was conducted using the SUGAL Genetic Algorithm package (v2.1), written by Dr. Andrew Hunter at the University of Sunderland, England. Following GA parameters were used:

- crossover onepoint, rate = 0.7,
- datatype floating point,
- elitism on,
- mutation uniform (per gene, decay rate = 0.98, decay rate step = 1, rate=0.5),
- normalisation direct,
- population size=100,
- replacement uniform (unconditional, rate = 1),
- selection roulette.

Process behavior is optimized with respect to ITSE criteria (fitness) for various test patterns:

$$J = \tanh\left(\frac{1}{\sum_{p=0}^{VT}\sum_{t=0}^{TMAX} e_P^2 \cdot t \cdot \Delta t}\right) \tag{6}$$

where:

J	fitness (to be maximized),
e_p	error (difference between reference and process output for p-test pattern),
VT	total number of test patterns, in this research VT=11,
t	time,
Δt	sampling interval (in this research Δt=0.1),
TMAX	total test pattern interval (in this research TMAX=400).

The decision table was tuned for various disturbances and various reference inputs in order to explore the whole decision table space. It is necessary because with only one reference input and one disturbance step input there are regions of decision table which never act and are not explored by algorithm. The whole decision table is coded as single chromosome:

$$x_{ij} = X_{\max} \cdot \tanh\left(\text{SuGetNativeFloat(chrom- > string, } (\text{i} \cdot \text{N}_{\text{DE}} + \text{j})\ \right) \tag{7}$$

where X_{max} is maximal output level of the controller (here X_{max}=1), *SuGetNativeFloat(chrom->string, s)* is SUGAL expression to extract s-th parameter from floating point chromosome (details on SUGAL parameters can be found in [13] and [14]). *Tanh* function is used to limit x_{ij} in the range [-X_{max},X_{max}], because SUGAL have no limiting chromosome facility. A population is a set of decision tables and the best population member is the best decision table.

Simulations

Simulations were conducted on second order process with transfer function:

$$T(s) = \frac{1}{(s+1)^2} \tag{8}$$

Tab. 1 shows results, i.e. ITSE values for various decision table parameters. The best results are achieved with n=3, m=1, i.e. nonlinear error and liner change-in-error decision table distribution. It is interesting to note that [5,5][3,1] table gives better result than [21,21][1,1] and [21,21][3,1] table. It leads to a conclusion that the decision table distribution is a critical parameter and is more important than number of table elements.

$[N_E, N_{DE}]$ [n,m]	[1,1] [1,1]	[3,3] [1,1]	[5,5] [1,1]	[5,5] [3,1]	[7,7] [1,1]	[7,7] [3,1]	[7,7] [1,3]	[7,7] [3,3]	[21,21] [1,1]	[21,21] [3,1]
ITSE	1.09	14.88	2.84	0.74	1.65	0.76	1.50	0.84	0.86	0.82

Tab. 2 ITSE values for various decision table parameters

Figs. 2 and 3 show process output of DTC controlled second order process with GA tuned decision table.

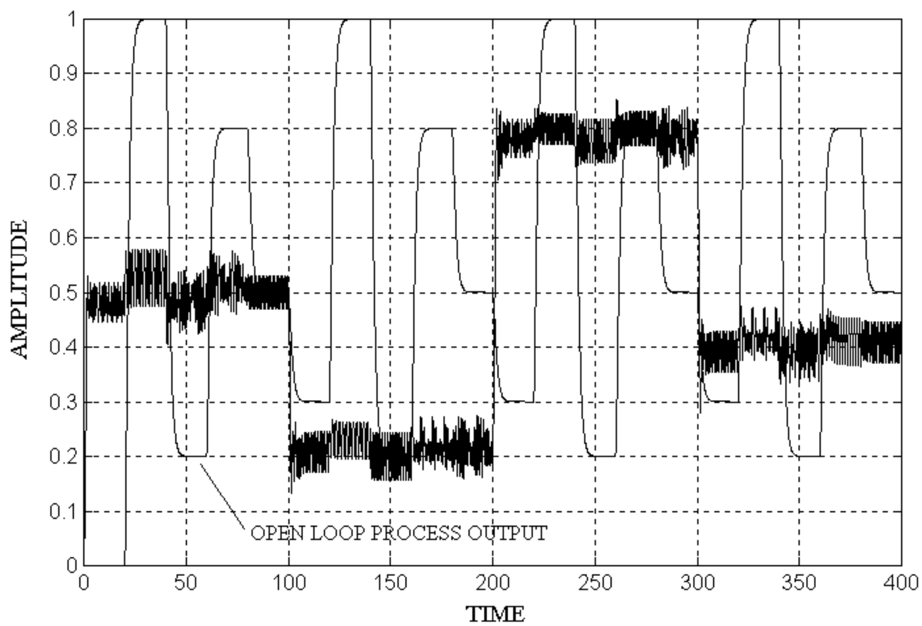

Fig. 2 DTC controlled process response with the [1,1][1,1] decision table (bang-bang controller)

Fig. 2 shows open loop process output input and DTC controlled process output with [1,1][1,1] decision table (bang-bang controller). Note that sampling interval is 0.1, so that oscillations amplitude is relatively big. It is reasonable to use DTC controller with n>1 if better result than with bang-bang controller can be achieved.

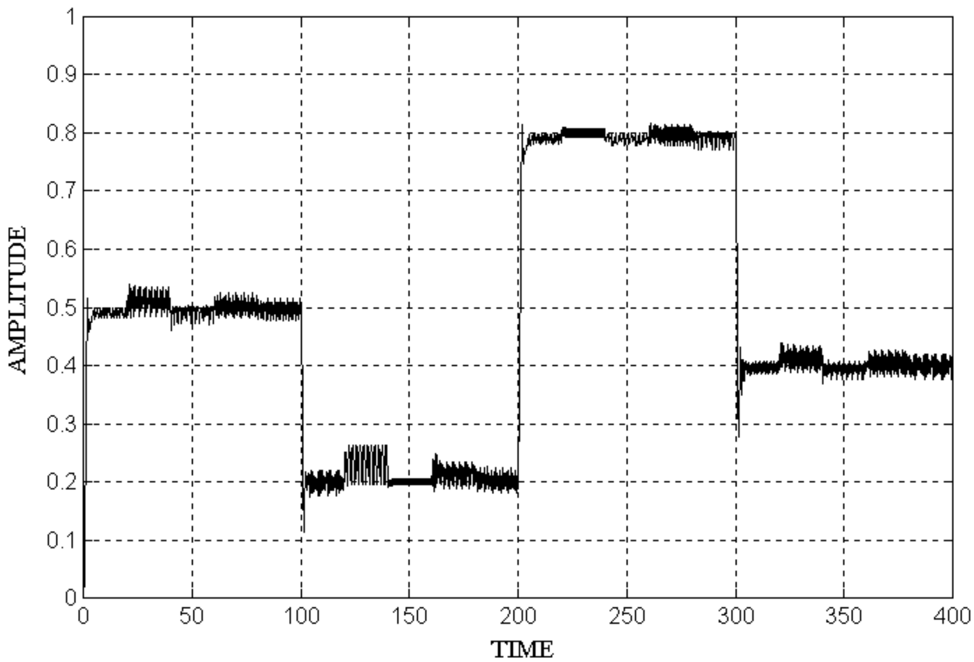

Fig. 3 DTC controlled process response with the [7,7][3,1] decision table

Fig. 3 shows process output with [7,7][3,1] decision table. There is no significant difference in performance between [5,5][3,1] and [7,7][3,1] decision table. Here proposed distributions f_E and f_{DE} are empirically achieved and their optimal values have yet to be investigated. Here they served the purpose to indicate the importance of decision table elements distribution.

Conclusions

The genetic algorithm based procedure for direct decision table adjusting is investigated applied to the second order process with ITSE performance measure. The parameters of decision table are investigated and the results for various parameters compared. It is found that table elements distribution is of main importance. Nonlinear table elements distribution is superior to linear one for the same number of table elements, and can even successfully replace linear tables with more elements.

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