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Synthesis of the neural coordinated control algorithm for the model of CNC machine

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Abstract. Objectives: Increase quality factor of the CNC machine model in comparison with the Uncoupled System by synthesizing Neural Coordinated Control. Synthesis: We synthesized the Neural Coordinated Control algorithm based on the coordinated control algorithm and neural control. Experiment: Using mathematical modeling we compared the synthesized algo-rithms and the uncoupled system using the following criteria: contour error, contour speed error, and score function. Results: The four NCC algorithms were synthesized and trained. The experiment shows that synthesized algorithms have better score function values and better quality factor values in comparison to the reference Uncoupled System. Conclusion: The quality factor of the CNC machine model was successfully in-creased by using the synthesized Neural Coordinated Control algorithm.

1 Introduction

Increase of quality factor – ratio of contour speed to contour error – of contour tracking is a relevant task, because systems with high quality factor can make more accurate operations or make the same operations faster, that increases performance of the machine [1-6].

Modern developments in computing technologies allow us to implement on practice more computation complex algorithms, for example: neural network control [7-10], coordinated control algorithms [1-3, 11, 12], fuzzy logic control [13,14], and other [15-18].

In this paper we propose the neural coordinated control (NCC) which is based on the coordinated control algorithm and neural control. This combination is chosen by the following reasons:

- The coordinated control algorithm is an algorithm with the coupled structure which has several advantages over systems with the uncoupled structure (for example the Uncouple System) [1,4-6]: contour error is minimized directly – the Uncoupled System minimizes contour error indirectly through minimizations of coordinated errors; it is possible to set control priorities by choosing ratio of contour error and contour speed error. In many cases low contour error is preferable to low contour speed error; etc [4];
- Neural network regulators can be used to form complex non-linear combinations of input parameters on its outputs. This can be used to create unique and specialized control for specific control tasks with relatively small amount of dynamic information [7-9].

The goal of the paper: Increase quality factor of the CNC machine model in comparison with the Uncoupled System by using Neural Coordinated Control.

The tasks:

1. Synthesize several NCC with different neural network structures and different training sets;
2. Train the neural networks using the chosen score function and gradient descent learning algorithm;

Compare the synthesized algorithms and the Uncoupled System using the following criteria: the root mean square quality factor, the minimum quality factor, the root mean square contour speed error and the score function.

2 Synthesis

The simplified CNC machine model (1) fig. 1 has been chosen as the plant.

$$\begin{cases} T_L \cdot \ddot{x} + \dot{x} = U_x \\ T_L \cdot \ddot{y} + \dot{y} = U_y \end{cases} \quad (1)$$

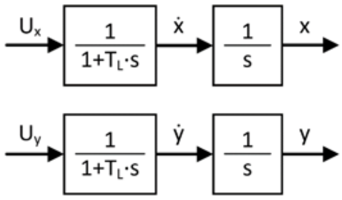

Fig. 1. The plant structure.

As previously been mentioned the NCC is based on the coordinated control algorithm [1,2,4,19]. The main

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idea of the coordinated control algorithm is forming the speed control vector as combination of two vectors fig. 2: the tangent speed (V_τ), which sets movement along the trajectory, and the normal speed (V_n), which minimizes contour error.

Contour error (E_k) – minimal distance between the end effector position and the trajectory.

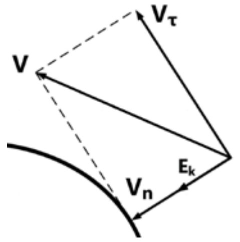

Fig. 2. The speed control vector as a combination of the tangent speed and the normal speed.

The structure of NCC is shown on the Fig. 3.

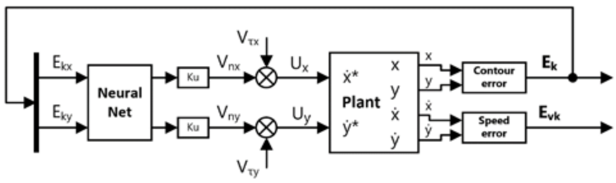

Fig. 3. The structure of NCC.

The trajectory is the circular arc:

$$y^2 + x^2 = R^2 \tag{2}$$

The tangent speed for circular arc:

$$\begin{cases} V_{\tau x} = V_k * cos\left(\dfrac{\pi}{2} - \tan^{-1}\left(\dfrac{y}{x}\right)\right) \\ V_{\tau y} = -V_k * sin\left(\dfrac{\pi}{2} - \tan^{-1}\left(\dfrac{y}{x}\right)\right) \end{cases} \tag{3}$$

The neural regulator for NCC has one of these structures fig. 4. They are used to form the normal speed (4), where K_u is a positive gain.

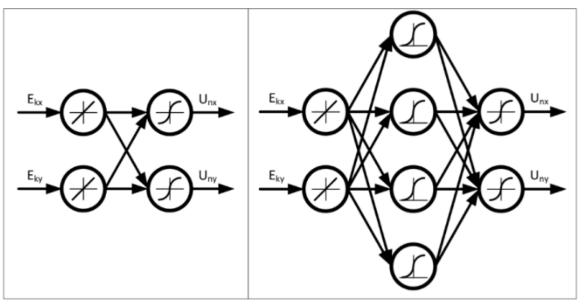

Fig. 4. The structures of the neural regulators. Left – neural network without hidden layers; Right – neural network with one hidden layer.

$$\begin{cases} V_{nx} = K_u \cdot U_{nx} \\ V_{ny} = K_u \cdot U_{ny} \end{cases} \tag{4}$$

The neural networks are trained using gradient descent learning algorithm [20]. The learning criterion or the score function (5) is the linear convolution [21] of the two criteria: the root mean square of contour error and the root mean square of contour speed error. In practice a low value of contour speed is usually preferable to a low value of contour speed error, hence α_2 is chosen to be lower than α_1.

$$Score = \alpha_1 \langle E_k \rangle + \alpha_2 \langle E_{vk} \rangle \tag{5}$$

Contour error (E_k) and contour speed error (E_{vk}) for the circular arc are:

$$\begin{cases} E_k = \sqrt{x^2 + y^2} - R \\ E_{vk} = \dot{x}^2 + \dot{y}^2 - V_k^2 \end{cases} \tag{6}$$

3 Experiment

The experiment was conducted using mathematical model calculation.

We synthesized and trained four algorithms: NR_L0E1, NR_L0E3, NR_L1E1 and NR_L1E3, where:

- L0 and L1 – number of hidden layers: 0 and 1 accordingly;
- E1 and E3 – size of training set: 1 and 3 elements accordingly.

The synthesized algorithms were compared with the Uncoupled System fig. 5. .

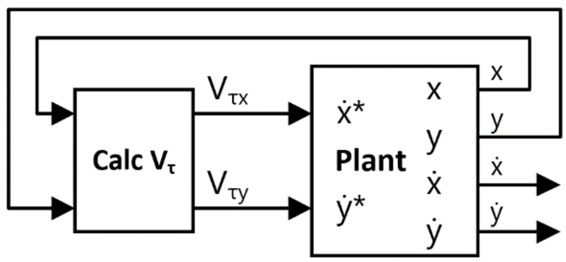

Fig. 5. The structure of the reference Uncoupled System.

Parameters:

- The plant parameter fig. 1:
  $T_L = 0.001\ [s]$
- Contour speed for all algorithms (3, 6)
  $V_k = 0.4\ [m/s]$
- The training sets (2):
  E1: R = 9 [m]
  E3: R = 9, 11, 13 [m]
- The initial position, speed and residuals:
  $x_0 = -R\ [m];\quad y_0 = 0[m];\quad E_{k0} = 0$
  $\dot{x}_0 = 0\ [m/s];\quad \dot{y}_0 = 0[m/s];\quad E_{vk0} = -V_k^2$
- The neural regulator gain (4):
  $K_u = 0.8$
- The score coefficients (5):
  $\alpha_1 = 1;\quad \alpha_2 = 0.001$
- The simulation time:
  $T_{sim} = 10\ [s]$

- Initiation of the neural networks weights and biases:

Weights: W_{ij} = -0.1…0.1

Biases: b_{ij} = -0.1…0.1

Since the score function is generally not convex [10] – i.e. have several local minimums – the neural networks were initialized randomly and were trained several times.

The experiment results are presented in table 1.

Table 1. The results of the experiment.

Type	R, m	Score	<v>, 1/s	<Evk>, m/s	v_min, 1/s
US	9	0.0287	13.9373	0.0080	7.8125
	10	0.0259	15.4440	0.0080	8.6768
	11	0.0235	17.0213	0.0080	9.5465
	12	0.0216	18.5185	0.0080	10.3896
	13	0.0199	20.1005	0.0080	11.2676
NR_L0E1	9	0.0086	46.5116	0.0242	17.8571
	10	0.0050	80.0000	0.0241	29.1971
	11	0.0034	117.6471	0.0241	59.7015
	12	0.0044	90.9091	0.0241	66.6667
	13	0.0062	64.5161	0.0241	50.6329
NR_L0E3	9	0.0019	222.2222	0.0257	78.4314
	10	0.0024	173.9130	0.0257	50.0000
	11	0.0034	117.6471	0.0258	38.4615
	12	0.0045	88.8889	0.0259	32.2581
	13	0.0054	74.0741	0.0259	28.5714
NR_L1E1	9	0.0082	48.7805	0.0120	19.7044
	10	0.0047	85.1064	0.0120	31.7460
	11	0.0030	133.3333	0.0120	63.4921
	12	0.0038	105.2632	0.0119	76.9231
	13	0.0055	72.7273	0.0119	57.9710
NR_L1E3	9	0.0131	30.5344	0.0105	14.1343
	10	0.0095	42.1053	0.0105	18.8679
	11	0.0065	61.5385	0.0105	25.9740
	12	0.0042	95.2381	0.0105	37.7358
	13	0.0025	160.0000	0.0105	60.6061

Using data from table 1 we plotted comparative graphs fig. 6.

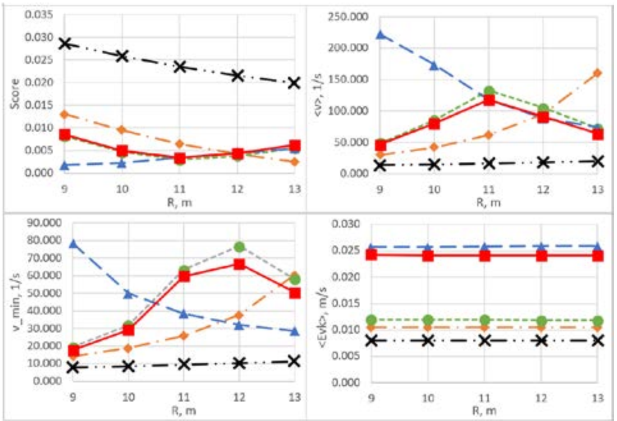

Fig. 6. The experimental comparative graphs. Top Left – The score function to radius (of the circular arc); Top Right – The root mean square quality factor to radius; Bottom Left – The minimal quality factor to radius; Bottom Right – The root mean square contour speed error to radius. Legend: US – the black dash-dot-dotted line (-..-) with cross markers (x) ; NR_L0E1 – the red solid line (—) with square markers (□) ; NR_L0E3 – the blue dashed line (--) with triangular markers (Δ) ; NR_L1E1 – the green dotted line with circular markers (○) ; NR_L1E3 – the orange dash-dotted line with diamond markers (◊)

4 Results

The four NCC algorithms were synthesized and trained. The experiment table 1 and fig. 6 shows that synthesized algorithms have better score function values and better quality factor values in comparison to the reference Uncoupled System. The synthesized algorithms have lower contour speed error than the Uncoupled System it is a consequence of choosing the relatively small score function (3) coefficient $\alpha_2 = 0.001$.

None of the synthesized algorithms is pareto optimal by the score function. It is probably connected with the non-convexity of the score function, i.e. during learning process the neural regulators got into local minimums

5 Conclusion

From the results we can conclude that the quality factor of the CNC machine model was increased – in comparison to the Uncoupled System – by using the Neural Coordinated Control.

Choosing more complex neural network or having more training examples does not lead to a pareto optimal by score solution. The reason behind this may be non-convexity of the score function.

The synthesized algorithms have worse – than the Uncoupled System – speed error due to the chosen score coefficients.

6 Discussion

The score function has coefficients which might be used to set control priorities, i.e. how does these coefficients influent the criteria?

How more complex neural network's structures and bigger training sets will influence the criteria?

The neural networks might be trained using different algorithms, for example using a generic algorithm, which should better handle non-convex score functions

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