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Self–learning controller of active magnetic bearing based on CARLA method

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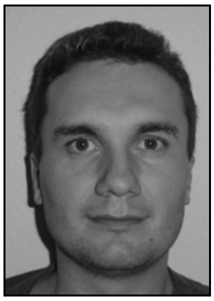

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Abstract

The active magnetic bearing control through analytically designed linear PD regulator, with parallel nonlinear compensation represented by automatic approximator is described in this contribution. Coefficient (parameter) values come from actions of Continuous Action Reinforcement Learning Automata (CARLAs). Influence of CARLAs parameters to learning is discussed. Parameters influence is proved by simulation study. It is shown that learning improvement can be reached by selecting appropriate parameters of learning.

Keywords: active magnetic bearing control, continuous action reinforcement learning automata.

Samo uczący się sterownik aktywnego łożyska magnetycznego oparty na metodzie CARLA

Streszczenie

W artykule przedstawiono sterowanie aktywnego łożyska magnetycznego za pomocą analitycznie dobranego regulatora PD z nieliniową kompensacją równoległą. Współczynniki kompensacji są wyznaczane automatycznie z użyciem metody CARLA (Continuous Action Reinforcement Automata). Zbadano wpływ parametrów metody na proces uczenia się kompensatora w oparciu o eksperymenty symulacyjne. Wykazano, że właściwy dobór parametrów metody prowadzi do poprawienia skuteczności procesu uczenia się.

Słowa kluczowe: sterowanie aktywnego łożyska magnetycznego, metoda CARLA.

1. Introduction

The active magnetic bearing (AMB) inhibits contact between rotor and stator and so it eliminates limitations of classic bearing. Therefore it is possible to use AMB in specific and extreme circumstances where classic bearing is inapplicable. Electromagnets located in stator of the bearing create magnetic field. The force caused by magnetic field keeps the rotor levitating in desired position in the middle of air clearance. So the control of magnetic field is necessary.

Nonlinearity of controlled system causes problems when linear regulators are used for control. It is possible to control AMB by linear regulator near desired position only. Performance of regulator decreases with raising amplitude of deviations. Nonlinear compensating element connected parallelly to the regulator can be used to reduce deviations. CARLA method is used to detect the parameters of compensation automatically.

CARLA method belongs to the group of learning automats. It is capable of learning the value of parameter without knowledge of mathematic model of controlled system. This property is used to find unknown parameter values of nonlinear compensation. Performance of CARLA method depends on properly set learning parameters. It can be shown that properly set learning parameters can improve the speed of learning.

2. AMB model

Simplified model of AMB with one DOF (see fig. 1) is used for simulation studies of one axis behavior. Rotor is replaced by mass point, gravitation is neglected (assumed as compensated one) and the nonlinearity is considered for electromagnetic subsystem only.

$$\begin{aligned} m\ddot{x} + b\dot{x} + F_{m1} - F_{m2} &= F_e \\ Ri_1 + L\dot{i}_1 &= u_1 \,,\; x \in \langle 0, d \rangle \,. \\ Ri_2 + L\dot{i}_2 &= u_2 \end{aligned} \tag{1}$$

$$F_{m1} = A\left(\frac{i_1}{x+a}\right)^2 ,\; F_{m2} = A\left(\frac{i_2}{-x+d+a}\right)^2 ,\; A > 0 ,\; a > 0 \,. \tag{2}$$

Tab. 1. Parameters of model of AMB
Tab. 1. Parametry modelu AMB (aktywnego łożyska magnetycznego)

Parameter	Description	Value	Unit
m	mass of rotor	$0,07$	$[\mathrm{kg}]$
b	damping	13	$[\mathrm{Ns/m}]$
A	parameter of magnetic force model	$4,9 \cdot 10^{-6}$	$[\mathrm{Nm^2/A^2}]$
a	parameter of magnetic force model	$1,43 \cdot 10^{-3}$	$[\mathrm{m}]$
d	air clearance	$1,4 \cdot 10^{-3}$	$[\mathrm{m}]$
R	resistance of electromagnets	3	$[\Omega]$
L	inductance of electromagnets	$2,6 \cdot 10^{-3}$	$[\mathrm{H}]$

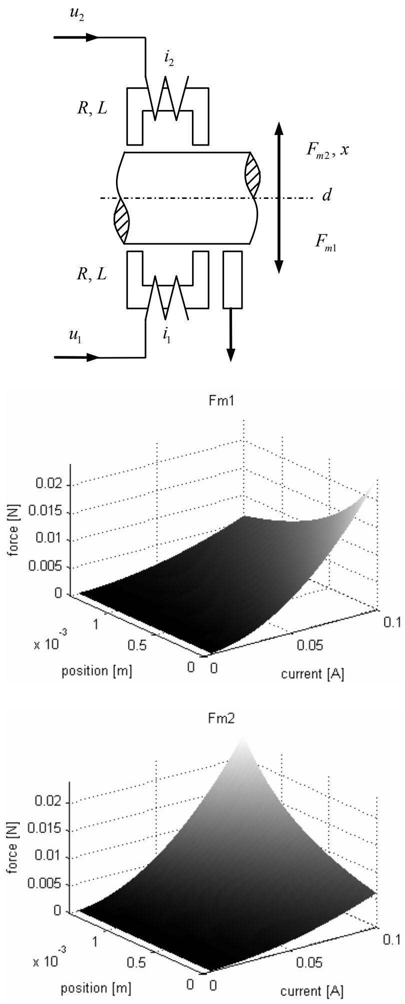

Fig. 1. Model of AMB and relation between magnetic force and position of stator and current

Rys. 1. Model aktywnego łożyska magnetycznego oraz zależności siły magnetycznej od położenia wirnika i prądu sterującego

3. Analytic design of controller

Original work [1] used one controller (PID regulator). The regulator controlled the position of rotor by one feeding voltage only. Polarity of voltage determined which electromagnet was switched on. Results published in this paper use two analytically derived controllers to linearize the description of AMB (see fig. 2).

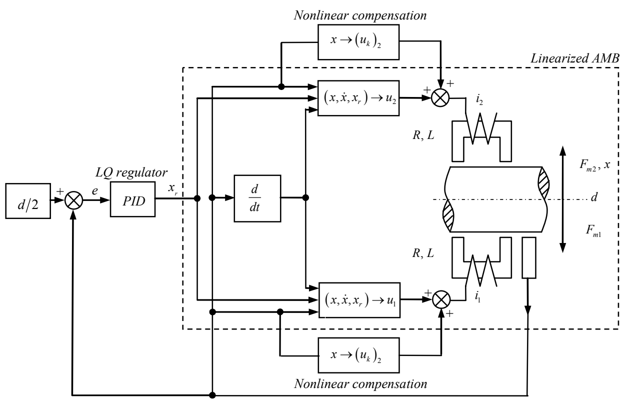

Fig. 2. Schema of basic controller and PID regulator with parallel nonlinear compensation

Rys. 2. Schemat podstawowego sterownika i regulatora PID z nieliniową kompensacją równoległą

We are able to model the nonlinear characteristic of magnetic force, so it is possible to use this knowledge to derive nonlinear controller. For example it is possible to take the linearization method as the basis:
When magnetic forces will behave according to (3)

$$F_{m_{1L}} = \frac{k}{2}\left(x + 2\varepsilon x_r\right),$$
$$F_{m_{2L}} = \frac{k}{2}\left(-x + 2x_r\left(1+\varepsilon+\gamma\right)\right), \tag{3}$$
$$k > 0,$$

the whole system will behave like

$$m\ddot{x} + b\dot{x} + kx = F_e + \frac{1}{2}kx_r + \frac{1}{2}\gamma kx_r, \tag{4}$$

where F_e is force loading of AMB, γ is constant, that can be used to compensate constant force (e.g. gravitation), k is stiffness of system and x_r is desired position of AMB (usually the middle of air clearance). This goal is accomplished by

$$i_1 = \frac{1}{2}\frac{\sqrt{2A\beta_1}}{A}\alpha_1,$$
$$i_2 = \frac{1}{2}\frac{\sqrt{2A\beta_2}}{A}\alpha_2, \tag{5}$$

where

$$\alpha_1 = x + a,$$
$$\beta_1 = k\left(x + 2\varepsilon x_r\right),$$
$$\alpha_2 = d - x + a,$$
$$\beta_2 = k\left(-x + 2x_r\left(1+\varepsilon+\gamma\right)\right).$$

We can obtain equations of controller by constituting equations (5) into equations (1)

$$u_1 = \frac{R}{2}\frac{\sqrt{2A\beta_1}}{A}\alpha_1 + \frac{L}{2}\left(\frac{\alpha_1 k}{\sqrt{2A\beta_1}} + \frac{\sqrt{2A\beta_1}}{A}\right)\dot{x}, \tag{6}$$

$$u_2 = \frac{R}{2}\frac{\sqrt{2A\beta_2}}{A}\alpha_2 + \frac{L}{2}\left(\frac{\alpha_2 k}{\sqrt{2A\beta_2}} + \frac{\sqrt{2A\beta_2}}{A}\right)\dot{x}. \tag{7}$$

We obtain parameters of linear PD controller for regulation close to the desired position through linearization of control laws (6) and (7) using first two terms of Taylor expansion of function $f_{1,2}$ for small deviations around the desired position x_r in simplified notation $u_{1,2} = f_{1,2}(x) + g_{1,2}(x)\dot{x}$

$$u_{1,2} \approx \left(K_c\right)_{1,2} + \left(K_p\right)_{1,2}\left(x - x_r\right) + \left(K_d\right)_{1,2}\dot{x}, \tag{8}$$

where

$$\left(K_c\right)_{1,2} = f_{1,2}\left(x_r\right),$$
$$\left(K_p\right)_{1,2} = \frac{\partial}{\partial x} f_{1,2}\left(x\right)\Big|_{x=x_r},$$
$$\left(K_d\right)_{1,2} = g_{1,2}\left(x_r\right).$$

4. Optimal control design

AMB controlled by previously derived controllers can be treated like linear system. Its behavior is described by (4). It is assumed that desired position x_r is the input and real position x is the output of linearized AMB.

Many methods exist to design a controller of linear system. Linear Quadratic (LQ) design was used to design the controller of desired position of linearized AMB (see fig. 2). It gives optimal parameters of PID regulator

$$x_r = \left(K_p\right)_{LQ} e + \left(K_i\right)_{LQ} \int e\,dt + \left(K_d\right)_{LQ} \frac{de}{dt}. \qquad (9)$$

Parameters of PID regulator were computed by minimizing weighted cost function (10)

$$J = \int_0^\infty \left(y^T Q y + x_r^T R x_r\right) dt , \qquad (10)$$

where

$$y = \left[\int e\,dt, e, de/dt\right]^T ,$$

$$Q = \begin{bmatrix} 10^3 & 0 & 0 \\ 0 & 10 & 0 \\ 0 & 0 & 10^{-2} \end{bmatrix}$$

and

$$R = [1].$$

5. Nonlinear compensation

AMB force load causes nonzero control error. Linearized control laws (8) are designed to linearize behavior of AMB near desired position only. Parallel nonlinear compensation which amplifies actions is added to compensate the deviations. Compensation is required only if nonzero control error exists and it has to reduce the deviation as much as possible. These conditions are fulfilled by following compensator (assumed desired position is $d/2$)

$$\left(u_k\right)_{1,2} = \left(K_n\right)_{1,2} \cdot \operatorname{sgn}\left(x - \frac{d}{2}\right) \cdot \sqrt{\left|x - \frac{d}{2}\right|} . \qquad (11)$$

CARLA method is used to detect the value of $\left(K_n\right)_{1,2}$ coefficient. It minimizes the square value of control error $(x\text{-}d/2)^2$.

6. CARLA method

CARLA method [3, 4] was developed as an extension of the discrete stochastic learning automata. It replaces the discrete action space with a continuous one. It is more appropriate for engineering applications that are continuous in nature.

CARLA method is working in interactions with generally unknown system by randomly selecting its parameter values. Learning consists in increasing the probability of selecting the successful parameter values.

7. Influence of some of learning parameters to CARLA method

Successful application of every parameterized learning method is conditioned by properly set learning parameters. CARLA method can be used to learn on real AMB so it should learn quickly to reach good performance in shortest possible time. The variance of selected actions is the measure of learning stage of CARLA method. Number of learning steps to reach the limit variance can be used to compare values of parameters.

Comparison of values of learning parameters is done on learning of previously defined controller of AMB. Random load was applied to AMB with standard deviation $0.1\,[\mathrm{N}]$ and mean $0.9\,[\mathrm{N}]$ during $t = \langle k; k+0.5\rangle [\mathrm{s}]$ and $0.5[\mathrm{N}]$ during $t = \langle k+0.5; k+1)[\mathrm{s}]$, $k = 0,1,2,...,n$.

7.1. Influence of parameters of gaussian function – gh, gw [2]

Increasing value of g_h parameter increases the influence of last successful action to CARLAs probability density. It leads to increase of learning speed. But value too high decreases the stability of CARLA method. Best value is g_h=0.35 .

Parameter g_w indirectly indicates variance of selected action after successful learning. Its too high value leads on too high variance, but too small value noticeably decreases speed of learning. Best value according to speed of learning and reachable variance of selected actions is g_w=0.03 .

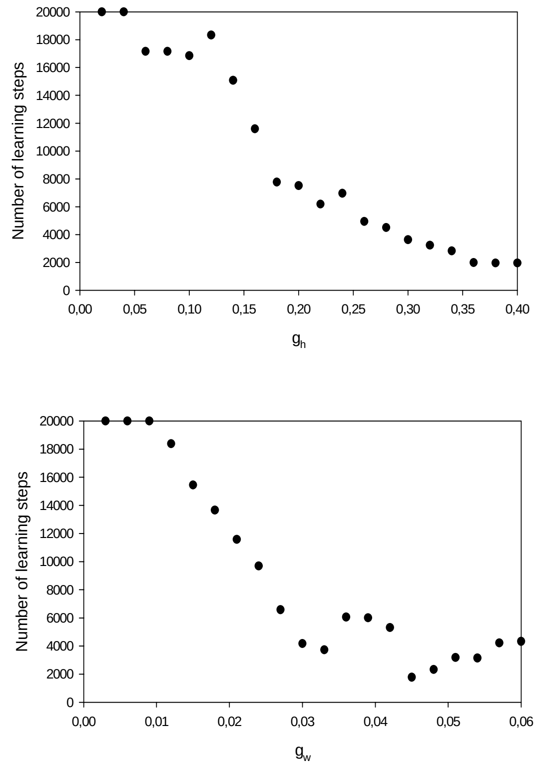

Fig. 3. Influence of parameters of gaussian function – g_h, g_w
Rys. 3. Wpływ parametrów g_h i g_w funkcji Gaussa

7.2. Influence of number of samples to save probability density (N) [2]

Probability density cannot be fully saved due to the limited memory. It is possible to store limited number of samples only. Values between samples have to be computed by (linear) interpolation. In this case N=20 is minimal number of samples. Increase of number of samples above this value does not lead to improvement of learning speed, but increases required memory and computation time.

7.3. Influence of number of last costs to compute performance (R) [2]

Number of last costs to compute performance has little influence to speed of learning in this case. But it can be shown that properly set number of last cost to compute performance increases speed of learning of different controlled system. Value R=20 has best performance.

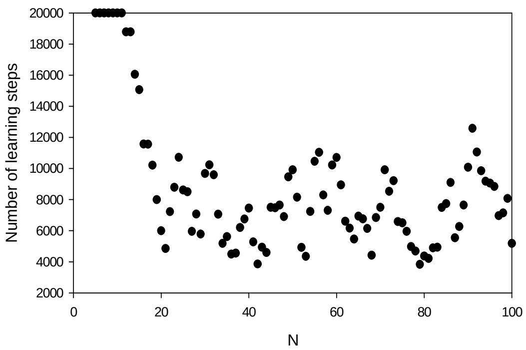

Fig. 4. Influence of number of samples to save probability density
Rys. 4. Wpływ liczby próbek potrzebnej do zapamiętania gęstości prawdopodobieństwa

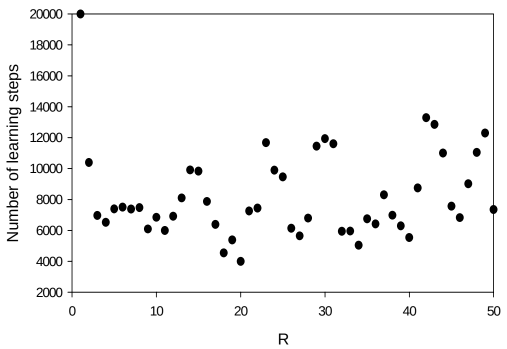

Fig. 5. Influence of number of last cost to compute performance
Rys. 5. Wpływ liczby ostatnich wartości funkcji celu, wykorzystywanych do oceny działania, na szybkość uczenia się

8. Simulation results

Parameters of simulation are the same like were used to test influence of learning parameters. Tested learning parameters are the only exception. They are set to detected best values.

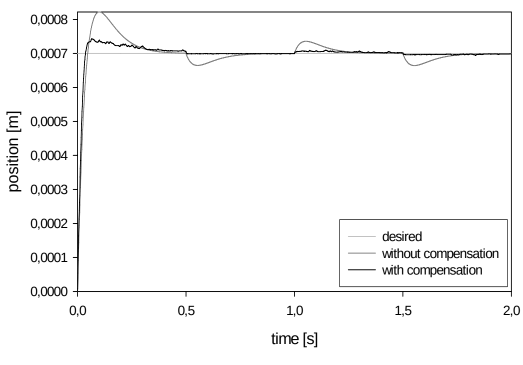

Fig. 6. Ideal conditions
Rys. 6. Warunki idealne

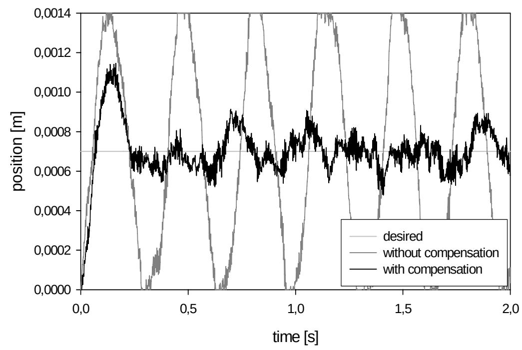

Fig. 7. Robustness against the measurement error and action delay
Rys. 7. Odporność na błąd pomiaru i opóźnienie działania

8.1. Ideal conditions

This test shows behavior of AMB, when no delay of action exists and error in measured value is zero. The compensation minimized the deviation to negligible value even when loading force is changed. The learned values were $(K_n)_1 \approx 83$ and $(K_n)_2 \approx -75$.

8.2. Robustness against the measurement error and action delay

Standard deviation of error in measured value was set to $1 \cdot 10^{-5}$ [m] and delay of action was set to $4 \cdot 10^{-4}$ [s]. The compensation was able to control the position of AMB when controller without compensation oscillated. Learned values were $(K_n)_1 \approx 50$ and $(K_n)_2 \approx -36$.

9. Conclusion

The nonlinear compensation is capable of keeping very small deviation from desired center position. The values of compensator coefficients were detected by CARLA method. Properly set values of learning parameters can increase the speed of learning. Optimal values of coefficients depend on controlled system. It is necessary to detect values of learning parameters for every developed system to reach the best performance.

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Artykuł recenzowany