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The speed control of DC motors with Support Vector Machine

Abstract: *In recent years, the Support Vector Machine (SVM) has been commonly used as both classifier and control due to its advantages, which are sharp distinction surface detection and high accuracy, in the literature. In this study, the speed control of Direct Current (dc) motor system, which has variable parameters for resistance, is performed by using SVM controller. For this reason, the dc motor speed control performance of designed SVM controller is compared with the linear PI controller's. As shown from results, the dc motor speed control performance of designed SVM controller is very high. While the dc motor speed control performance of linear PI controller is degredation, the SVM controller's is robust versus to changes of controller parameter values.*

Streszczenie. *System SVM jest powszechnie używany w sterowaniu dzięki swym zaletom. W artylkule zastosowano system do sterowania prędkością siulnika napięcvia stałego. Porównonano sterowanie SVM z liniowym kontrolerem PI. Sysem SVM był bardziej odporny na zmiany praametrów. (**Sterowanie prędkością silnika stałoprądowego z wykorzystaniem sterownika SVM)***

Keywords: DC motor control, PI controller, intelligent SVM controller, robust control.
Słowa kluczowe: sterowanie, silnik prądu mstałego, sterownika SVM

1.Introduction

Direct current (dc) motors are very widely used in industry as the action elements. Today, the various control methods are used to improve the efficiency of direct current motor speed and position. Because, they provide the advantages of intelligent systems such as fuzzy logic, neural network and support vector machine (SVM) [1, 2]. There are many methods for dc motor speed control. In this study, the SVM controller is used due to its learning and generalization ability [3, 4]. The obtained dc motor speed control performance of SVM controller is robust versus to changes of parameter values, which are controller gain K and controller zero a, opposit to linear PI controller's. The selected nominal parameter values are used for the PI linear controller in this study.

2. DC Motors

The direct current motors are basically converter to convert electrical energy into mechanical energy [5], [6]. In general, a direct current motor has the magnetic flux created by permanent magnets or windings. Permanent magnet dc motors are used in the control system area. The dc motor used in this simulation studies is permanent magnet type. This closed loop DC motor control system has very fast electrical dynamics [7]. Therefore, the motor electrical dynamics in this simulation studies are neglected. Only the mechanical dynamics are discussed. Accordingly, Equation 1 refers to the relationship between dc motor withan angular velocity and torque;

(1) $$T_m(t) = J\frac{dw_m(t)}{dt} + Bw_m(t)$$

The Laplace transform of Eq.(1) can be given as below [6]:

(2) $$\frac{w_m(s)}{T_m(s)} = \frac{1}{Js + B}$$

are obtained. The J motor inertia and viscous friction coefficient, B as a DC motor transfer function,

(3) $$G(s) = \frac{1}{Js + B}$$

The Eq.(3) can be written as below:

(4) $$G(s) = \frac{K}{s + a}$$

In this simulation studies, this Eq.(4) is used for dc motor system model.

3. The Basic Structure of SVM

In literature, the Support Vector Machine (SVM) is used for two aim, which are classification and regression. The classification problems can include two classes or more than it [8]. The Support Vector Machines can separate a single class from all remaining classes [8], [9]. Many Support Vector Machines separate a pair of classes [10], [11].

The Support Vector Machines are used for classification task of only two-class problems. In Support Vector Machine, a separating hyperplane is used [8]. This hyperplane of Support Vector Machine is obtained by calculating the maximum distance to the closest data points of the training set.

These closest data points of the training set are named as Support Vectors. The data points of the training set may be linearly separated into the input space. These data points of the training set can be transformed to a High Dimensional Space by using a nonlinear transformation in this status. At the same time, The High Dimensional Space is named feature space. The variable kernel functions such as polynomial, sigmoid, linear, Gaussian radial basis function (RBF), spline, bspline etc. are used for realizing the nonlinear transformations. The all kernel functions must be suitable for Mercer condition [12-16]. A kernel function $Ke(.,.)$ can be given as below:

(5) $$Ke(x, x') = \langle c(x).c(x') \rangle$$

In here, $c(x)$ is a mapping from low dimension input space to a High Dimensional Space, x is each of input data points of the training set. The decision function of a Support Vector Machine can be shown in below:

(6) $$f(x) = \sum_{i=1}^{L} a_i y_i Ke(x, x_i) + b_i$$

Here, L is the number of data points of the training set. The a_i is Langrangian multiplier and may be calculated by solving a quadratic programming problem with linear constraints [8], [16]. The y_i are the target values, $y_i \in \{-1,1\}$ is the class label of training point x_i. The value of a_i is nonzero only for S*upport Vectors.* The Support Vector Machine is used to estimate an optimal hyperplane. This optimal hyperplane true classifiers input data points of the training set by dividing to two class. These are negative and positive [18]. This state is given in Fig. 1.

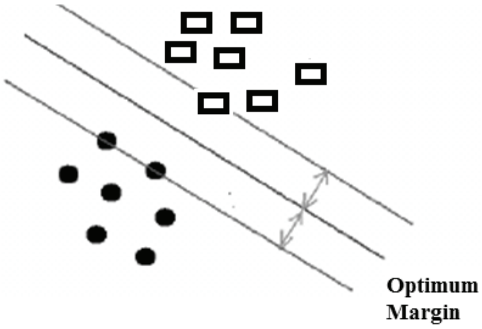

Fig. 1. A separate hyperplane.

Here, x_i is training data point, w is weight, b is bias vectors respectively. The optimum margin is the distance from the separating hyperplane to closest point for both triangle and square classes of data points. This optimum margin can be shown in Fig.1. [18], [19]. Moreover, this optimum margin is optimum hyperplane. The maximizing of margin formulation can be given as below:

(7) $$M\,arg\,in = \frac{2}{\|w\|}$$

All training data points are member of that class. They have to confirm the condition of $wx_i + b > 0$. Thew y_i outputs are set of labeled x_i input data points. When y_i is 1, the x_i input training data point is member of that class. If y_i is -1, the input training data point is not member of that class. It can be given as below:

(8) $$w.x_i + b \geq 1, \qquad \forall y_i = 1$$

$$w.x_i + b \leq -1, \qquad \forall y_i = -1$$

Morover, the Support Vector Machine can be used for regression. More information about it found in [20-23].

4. Structure of PI Controller

A linear PI controller consists of proportional and integral part of the recipient. PI controller is usually a permanent condition of the control system is used to minimize errors. Choose a location is suitable for zero damping, but also reduce errors [5]. A PI controller in continuous-time transfers in general function can be expressed as Eq(9):

(9) $$Gc(s) = K_p + \frac{K_i}{s}$$

where K_p is the proportional gain and K_i is the integral gain. If $K_p = K_k$ and $K_i/K_p = a_k$ in given Eq(10), then it can be written as below:

(10) $$Gc(s) = \frac{K_k(s + a_k)}{s}$$

Here, K_k is controller gain and a_k is the controller zero. In discrete-time, transfer function of a PI controller is expressed in Eq(11):

(11) $$Gc(z) = \frac{K_r(z - a_r)}{z - 1}$$

At Eq(11), K_r is discrete-time controller gain, a_r is the discrete-time controller zero. The Linear PI controller used in simulation studies designed for robustness versus to changes of parameter values, which are controller gain K and controller zero a. These robust parameters are used to control of a DC motor system with PI controller. The discrete time transfer function of this PI controller is also given in Eq(12). The values of K_i (integral gain) and K_p (proportional gain) of PI controller used in these simulation studies are taken as 0.0045 and 4.5 * 10^{-4} respectively. These values are kept constant throughout the simulation studies.

(12) $$Gc(z) = \frac{0.0045(z - 0.1)}{z - 1}$$

Linear PI controller is chosen for the nominal parameters of the system response. These are not exceeded. Moreover, the rise and settling time obtained by the SVM controller system can be considered to be the best values.

5. DC motor control using SVM Controller

In Fig. 2.a and Fig. 2.b, the SVM inverse modelling and control blocks are given respectively. In these simulation studies, mentioned blocks are used for SVM control of dc motor.

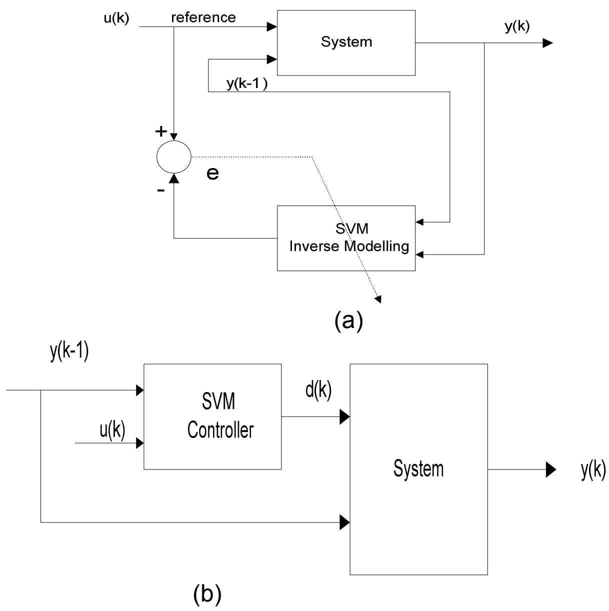

Fig. 2.(a) The SVM inverse modelling block and (b) control block used in this study.

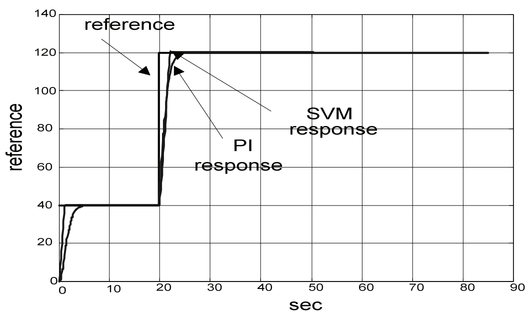

Fig.3. K = 100 and a = 2 nominal parameter values are used in the SVM controller and PI controller for the system response.

Then, SVM generalization process is realized by using the inverse modelling block given in Fig. 2.b. The obtained control results for the nominal values of system parameters $K = 1/J$ = 100 and $a = B/J$ = 2 (J = 0.01 kgm^2 and B = 0.02 Nms/rad) are shown in Fig. 3. Beside, + / - 15 values of the saturation function are used for limiting the outputs of all controllers in the simulation study.

When, the zero of controller (*a*) is constant value, response of the PI is not distorted as long as the value of K decreases in from 100 to 55. Because, the system response of PI slows down as the gain (K) is decreased. Therefore, the system response of SVM fixes as the gain (K) is decreased.

As shown in Figure 4, the system response of SVM controller is beter than the system response of PI controller for values of K is 100 and value of a is 9.

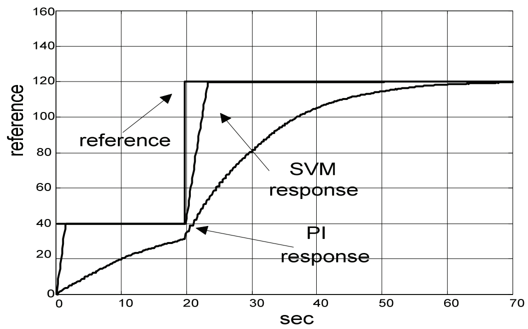

Fig. 4. The comparing the system responses of PI and SVM controllers for parameters for the K = 100 and a = 9.

As shown in Fig. 5, the system response of SVM controller is beter than the system response of PI controller for values of K is 100 and value of a is 0.4.

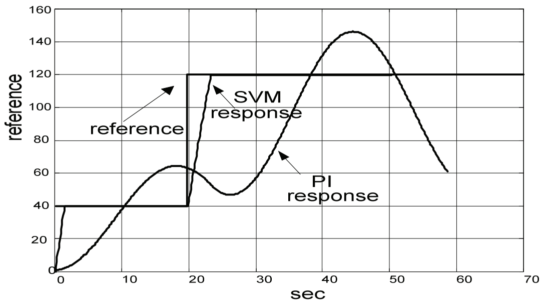

Fig. 5. The comparing the system responses of PI and SVM controllers for parameters for the K = 100 and a = 0.4.

6. Results and discussion

This work is performed in order to create a foundation of future applications in computer simulation in this area. In these simulation studies, a dc motor system is handled. The PI controller and SVM controller are applied to this dc motor system for speed control by changing the values of controller parameters $K = 1/J$ and $a = B/J$ within definite limits respectively.

The dc motor speed control performance of designed SVM controller is compared with the linear PI controller's. As shown from results, the dc motor speed control performance of designed SVM controller is very high (Figs. 3-5). While the dc motor speed control performance of linear PI controller is degredation, the SVM controller's is robust versus to changes of controller parameter values. So, control performance of designed SVM controller is beter than linear PI controller's. Nevertheless, the rise and settling time obtained by the SVM controller system can be considered to be the best values.

REFERENCES

[1] J. A. Fernández Pierna, V. Baeten, A. Michotte Renier, R. P. Cogdill, and P. Dardenne, Combination of support vector machines (SVM) and near-infrared (NIR) imaging spectroscopy for the detection of meat and bone meal (MBM) in compound feeds, Journal of Chemometrics, Volume 18, Issue 7-8 , Pages 341 – 349, (2004).

[2] A. Osareh, M. Mirmehdi, B. Thomas, R. Markham, Comparative exudate classification using support vector machines and neural networks, *In: T. Dohi, R. Kikinis (Eds.), Fifth International Conference on Medical Image Computing and Computer-Assisted Intervention, Lecture Notes in Computer Science*, vol. 2489, Springer, Berlin, pp. 413–420, (2002).

[3] Kosko, B., 1991, Neural Networks and Fuzzy Systems, A Dynamical Systems Approach, *Englewood Ciffs., NJ: Prentice Hall.*

[4] J. H. Friedman, Anotherapproach to polychotomous classification. *Technical report, Department of Statistics, Stanford University*, (1997).

[5] Franklin, G. F., Powell, J. D. and Workman, M. L., 1990, Digital Control of Dynamic Systems, *Addison Wesley*, s.130-132.

[6] Kuo, B. C. , Çeviri: Bir, A., 1999, Otomatik Kontrol Sistemleri, Literatür Yayınları:35, s.186-187

[7] Krishnan, R., 2001, Electric Motor Drives Modeling, Analysis and Control, *Prentice Hall*.

[8] Y. Yao, P. Frasconi, and M. Pontil, Fingerprint Classification with Combinations of Support Vector Machines, *AVBPA 2001*, *LNCS 2091*, pp. 253-258, (2001).

[9] V.N.Vapnik. Statistical Learning Theory. Wiley, New York, (1998).

[10] E. Avci, I. Turkoglu, M. Poyraz, Intelligent Target Recognition Based on Wavelet Packet Neural Network, *Experts Systems with Applications*, 29(1), 2005.

[11] P.I.J. Keeton, F.S. Schlindwein, Application of Wavelets in Doppler Ultrasound, vol. 17, *MCB University Press*, No. 1, pp. 38–45, (1997).

[12] M. Akay, Wavelet applications in medicine, *IEEE Spectrum* 34, p.p. 50–56, (1997).

[13] H. Liang, I. Nartimo, A feature extraction algorithm based on wavelet packet decomposition for heart sound signals, *in: Proceedings of the IEEE-SP International Symposium*, pp. 93–96, (1998).

[14] MATLAB 6.5 version Wavelet Toolbox, MathWorks Company.

[15] A. Bakhtazad, A. Palazoglu, J.A. Romagnoli, Processdata de-noising using wavelet transform, *Intelligent Data Analysis*, 3 267–285, (1999).

[16] W. M. Campbell, E. Singer, P. A. Torres-Carrasquillo and D. A. Reynolds, Language Recognition with Support Vector Machines, Odyssey 2004, May 31st -June 4th, Toledo, Spain, (2004)

[17] E. Frias-Martinez , A. Sanchez and J. Velez, Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition, *Engineering Applications of Artificial Intelligence*, in press.

[18] Gunn SR. Support Vector Machines for Classification and Regression. Technical report, Image speech and intelligent systems research group, *University of Southampton*, UK, 1998. Available on http://www.ecs.soton.ac.uk/·~rp/publications/pdf/SVM. pdf [Accessed on 30 July 2004].

[19] J. Kindermann, G. Paass and E. Leopold, Error Correcting Codes with Optimized Kullback-Leibler Distances for Text Categorization, *PKDD 2001*, p.p. 266-276, (2001).

[20] V. N. Vapnik. Statistical Learning Theory. Wiley, New York, (1998).

[21] Avci, E., Selecting of the optimal feature subset and kernel parameters in digital modulation classification by using hybrid genetic algorithm–support vector machines: HGASVM, *Expert Systems with Applications*, *Volume 36, Issue 2, Part 1*, *March 2009*, *Pages 1391-1402.*

[22] Avci, E., Avci, D., "A novel approach for digital radio signal classification: Wavelet packet energy–multiclass support vector machine (WPE–MSVM)", *Expert Systems with Applications*, 34(3), 2140-2147, (2008).

[23] Turkoglu, I., Avci, E., "Comparison of wavelet-SVM and wavelet-adaptive networkbased fuzzy inference system for texture classification", *Digital Signal Processing,* 18(1), 15-24, (2008).

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