Journal of Engineering Science and Technology Review
Special Issue on Telecommunications, Informatics, Energy and Management 2019

Conference Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Artificial Adaptive Filter for Robotic Systems

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Received 28 September 2019; Accepted 24 February 2020

Abstract

Several neurorobotic studies have demonstrated that ability to learn skilled animal movements depends on the cerebellum.Models based on Marr-Albus have been applied for different behaviours, such as the vestibulo-ocular reflex that suggests that cerebellum can act as an internal model like a state estimator. The prime focus is on the brain motor control system, the function of cerebellum as an adaptive filter and on the model of vestibulo-ocular reflex (VOR). In this paper simple Vestibulo-Ocular Reflex model was used to simulate oculomotor planton Matlab/Simulink.Main task of the VOR is to convert the vestibular signalto motor commands to the oculomotor plant, in other words head velocityto eye velocity. This paper covers in detail the model of basic VOR system and how cerebellum inspired adaptive control can be realised.

*Keywords:*Vestibulo-ocular reflex (VOR); Cerebellum, Adaptive filter, Robotics.

1. Introduction

This paper covers in detail the model of basic VOR system and how cerebellum inspired adaptive control can be realized. Bioinspired and biomimetic attitudes are extensively researched in robotics with the aim to improve cognitive, motor, autonomic functions of machines. The motor control stabilizes by using bioinspired adaptive control algorithms. To maintain gaze stable VOR operates to counter-rotate the eyes to prevent retinal slip. Experiments of implementation and evaluation of bioinspired adaptive control algorithm in the control of a robot eye showsignificant performance. For example actuation by pneumatic artificial muscles as a model of cerebellar function, which is analogue to the VOR [1].

It is important that these excellent results be extended to neurorobotics. To this end, it is necessary to further investigate the neurorobotic adaptive control in order to validate and extend current research findings [2 - 4].

The objective of the VOR inspired motor learning process is to let the brainstem B in combination with the cerebellum C get the inverse model of the motor plant P. The training signal is the sensory error e(t), which is represents the retinal slip signal in the biological system.

2. Material and method

2.1 Basic linear system model

Diagram of circuitry that mediates thehorizontal VOR is presented in the Fig1. Result of the moving of imageextremely fast across retina is the vision degradation. The retinal slip would beproduced by movements of the head, as it happens in locomotion. The VOR operatesto counter-rotate the eyes to prevent retinal slip for maintaining the stable gaze [1].

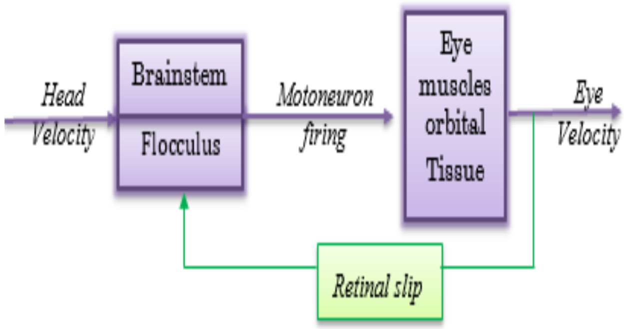

Fig 1. Bio-control circuit.

Cerebellar flocculus receives information about head velocity, eye movement commands and retinal slip. The adaptive control is used to be sure that the inverse plant model is accurate. The information about system output has to be used for learning. According to Fig 1 and Fig 2training signal is retinal slip, which is sent to the flocculus, also consistent with flocculus being the adaptive part of the controller.

Characteristics of basic VOR system model are shown on Fig 3.The output is a motor command $u(t)$; input is a conjunction of the vestibular system $r(t)$ and the cerebellar output $z(t)$.

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ISSN: 1791-2377 © 2020 School of Science, IHU.

P – the first order dynamic model of oculo motor plant, with transfer function P(s) betweeneye-in-head velocity x(t)and motor command u(t) as a Laplace transform in equation 1 [6-7].

$$P(s) = \frac{ks}{s+1/T_p}, \qquad (1)$$

where$T_p = 0.2$ s is time constant, $k = 1$ is a gain.
B – brainstem, which is modeled as a first-order leaky integrator plus a pure dc gain. Transfer function of brainstem model B(s) is presented as Laplace transform in equation 2 [6].

$$B(s) = G_d + \frac{G_i}{s+1/T_i}, \qquad (2)$$

where$G_d = 1$ is the direct path gain and $G_i = 1/T_p = 5$ is the indirect path gain and $T_i = 0.5$s is a time constant.

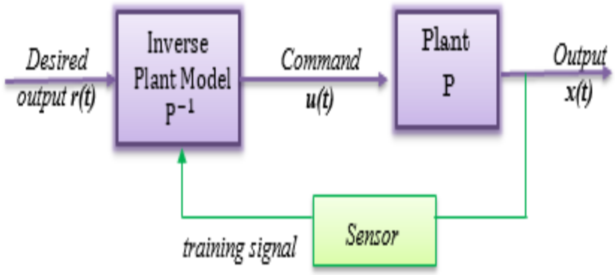

Fig 2. Control circuit

Further simulations were executed with different values of the parameters T_p, G_d, G_i, T_i.It has to be noted, that the exact values are not important at this stage, but time constants should be in the 100 ms range.
Brainstem provides a control, which the cerebellum improves by adjusting the response via the filter weights. The perfect compensation of plant could be achieved by brainstem itself, when $T_i = \infty$, $G_d = 1$, $G_i = 1/T_p$.
The cerebellum is implemented as an adaptive FIR (finite impulse response) filter C, with output z(t), which is given in equation 3.

$$z(t) = \sum_{i=0}^{L} w_i p(t - i \cdot \Delta T) \qquad (3)$$

where input u(t) to the adaptive filter C, which was splited into number of L components $p_1(t), \dots, p_n(t)$, with delays between them of ΔT. $\Delta T = 0.02$s (2 s in total).
w_i –weight of the componentp_i.

2.2 Learning algorithm

Weights of adaptive filter have to be changed to reduce the perceived visual slip from the input. The inverse oculomotor plant is realized when the learning algorithm is successfully applied and adjustment of the weights is done in combination with the brainstem. The sensory error e(t) is a direct result of the performance of the adaptive filter C.

$$e(t) = (P - B^{-1} + C) \cdot x(t) \qquad (4)$$

As it can be seen in equation 4 error is reduced to zero when $C = B^{-1} - P$.

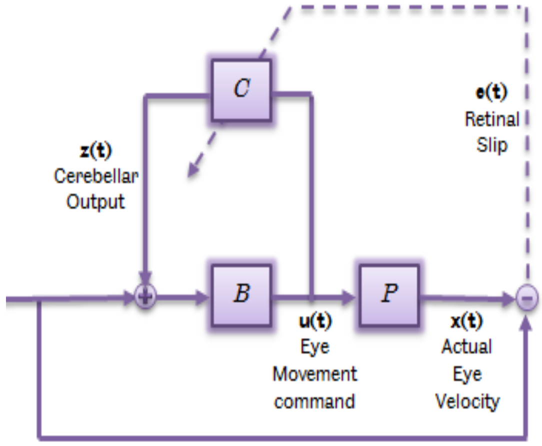

Fig 3. The basic VOR system.

Efficiently, this learning topology subsequently does not need a translation of the sensory error into a motor-command error. For that reason, the observed visual slip is expected to build the suitable teaching signal for the adaptation of the filter. Rule to adjust the weights is shown in equation 5.

$$\delta w_j = -\beta \langle p_j(t) \cdot \hat{u}(t) \rangle, \qquad (5)$$

where δw_j is the change in the jth weight w_j, β – a constant of learning rate. The value of that is adjusted to give rapid learning without instability. $\hat{u}(t)$– the value of retinal slip at time t, $p_j(t)$ – the value of the jth filter signal at time t, ⟨ ⟩ – denotes the expected value of the enclosed quantity over the time period used for training.

The feature of learning rule is that it is identical to the least means square rule of adaptive control theory.
The system architecture of the model has been programmed by means Matlab and Simulink software. Block-diagram in Simulink software is shown in Fig 4.Simulation results have been done for a simple first order plant in order to prove usefulness of the algorithm.

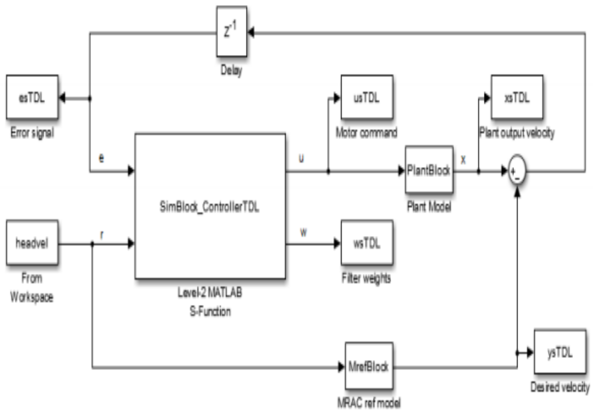

Fig 4. Block-diagram in Simulink software

3. Results and discussion

Model architecture of the system was programmed by using Matlab and Simulink. Experiments below were done for simple, first order plant, to prove the usefulness of the algorithm [8].

Performance of the system to band limited white noise input, i.e.head velocity, gave rise to retinal slip with low frequency, which is expected because of the existing brainstem controller. It can be stated that it is unable to maintain eccentric gaze. The time course of the plant and the brainstem is directly effected on how fast eye position returns to initial value.

The performance of the model when training element is implemented made with the same characteristics of P and B. Learning starts at 30 seconds. For testing how the value of learning rate effects on performance, each time the same set of signals are used as input r.

The difference between retinal slip of pre-training and post-training experiments gives better understanding howadaptive component reduces error (Fig5).

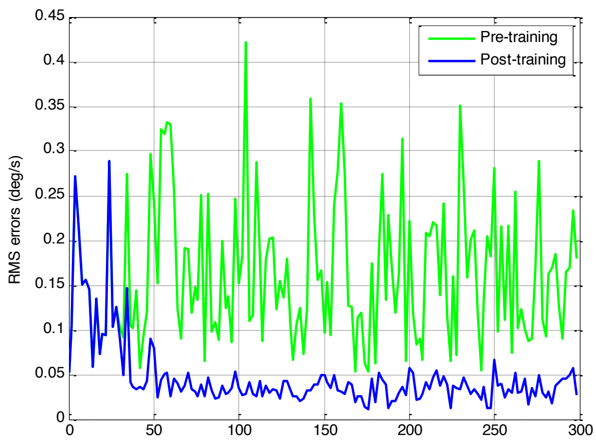

Fig 5. Retinal slip before and after training (learning began at 30 s).

Next experiment adaptation to change in plant parameters, implemented via a change in the gain of the plant, is studied after 150s.The performance of the system is illustrated in the Fig 6.

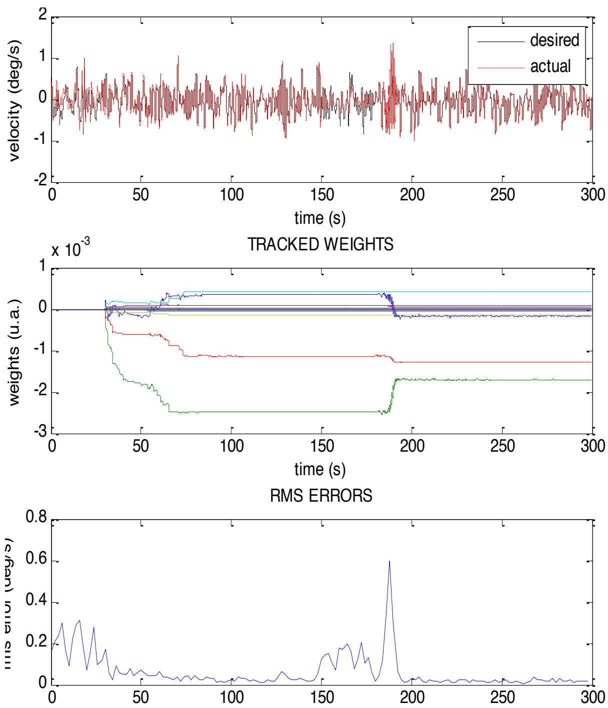

Fig 6. Performance of the system with dynamic plant

Zoom of the Fig 6 shown in Figs 7, 8, 9, start, when plant's gain changed and end of learning respectively.

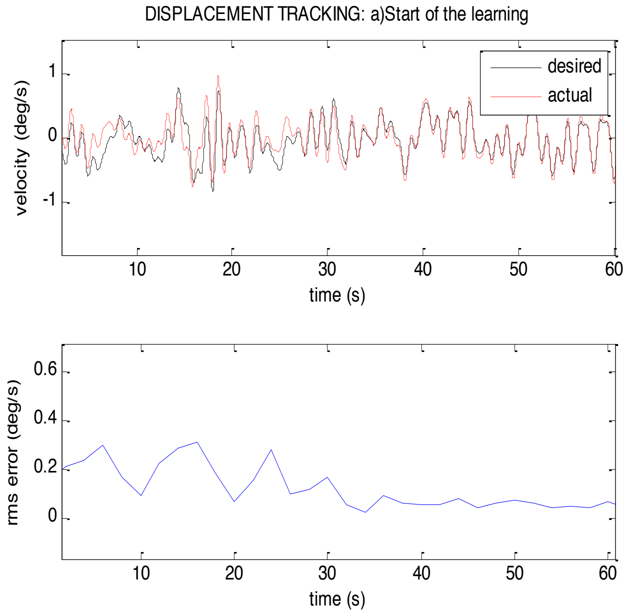

Fig 7. Start of the learning

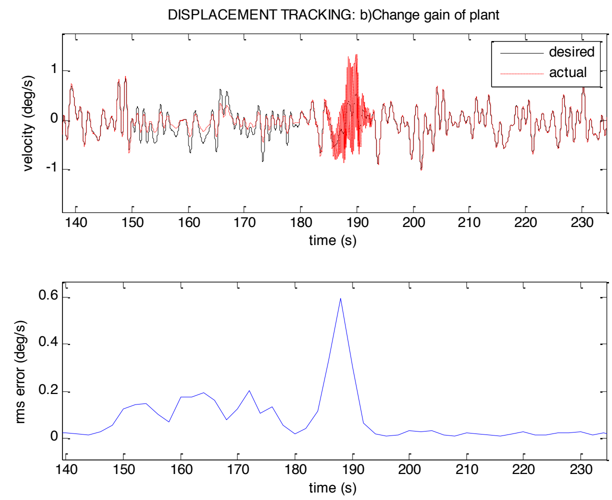

Fig 8. Gain of plant changed at 150s

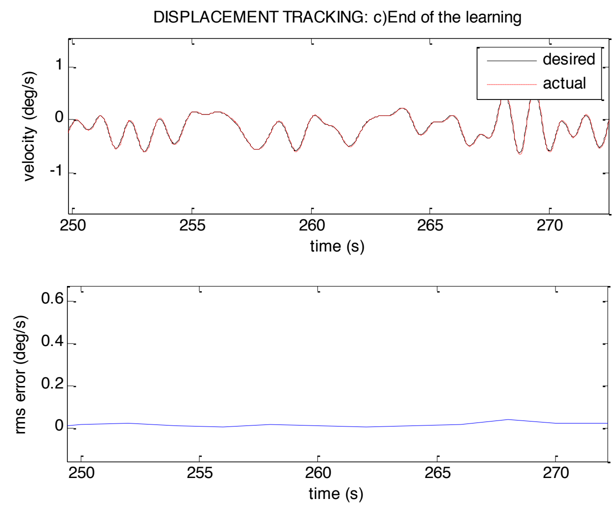

Fig 9. End of learning

Learning rate is increased to learn the plant change. The code learns for 150 s then plant model is changed by halving the gain. Then there is no learning for about 30 s and the effect of changing the plant model and after that time the learning can be seen again. A high learning rate results in oscillations due to overlearning.

4. Conclusions

In this paper pre-training and post-training investigation was done. An analysis of the RMS error after training revealed satisfactory performance. System performance with different learning rates was done. It is concluded that bigger learning rates result in smaller RMS error. However higher learning rates ($\beta \gg 1$) results in instability hence complete loss of tracking.

Investigation of tracking on the dynamic model reveals that the adaptive controller is able to track even when changes occur in the plant model.

References

1. LenzA., AndersonS. R., PipeA. G., MelhuishC., Dean P.andPorrillJ., "Cerebellar-Inspired Adaptive Control of a Robot Eye Actuated by Pneumatic Artificial Muscles," in IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 39, no. 6, 2009, pp. 1420-1433.
2. AndersonS. R., PearsonM. J., PipeA., PrescottT., Dean P.andPorrillJ., "Adaptive Cancelation of Self-Generated Sensory Signals in a Whisking Robot," in IEEE Transactions on Robotics, vol. 26, no. 6, 2010, pp. 1065-1076.
3. Dean, P., Porrill, J. & Stone, J. V.,"Decorrelation control by the cerebellum achieves oculomotor plant compensation in simulated vestibulo-ocular reflex". Proceedings. Biological sciences / The Royal Society, 269(1503), pp.1895–904. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1691115&tool=pmcentrez&rendertype=abstract [Accessed May 23, 2014].
4. Shibata, T. andSchaal, S., "Biomimetic gaze stabilization based on feedback-error-learning with nonparametric regression networks". Neural networks : the official journal of the International Neural Network Society, 14(2), pp.201–16. Available at: http://www.ncbi.nlm.nih.gov/pubmed/11316234.
5. Dean, P. Porrill J, Ekerot CF, Jörntell H., "The cerebellar microcircuit as an adaptive filter: experimental and computational evidence". Nature reviews. Neuroscience, 11(1), 2010, pp.30–43. Available at: http://www.ncbi.nlm.nih.gov/pubmed/19997115 [Accessed May 23, 2014].
6. Mussina, A.,Ceccarelli M., Balbayev G.,Neurorobotic investigation into the control of artificial eye movements. Mechanisms and Machine Science. vol. 57, 2018, pp. 211–221.
7. Nussibaliyeva A., Carbone G., Mussina A., Balbayev G., Study of 'Artificial Vision on the Adaptive Filter Basis for Implementation in Robotic Systems". Mechanisms and Machine Science,volume 73, 2019, pp.2319-2328.
8. Anderson, S.R. and Wilson, E.,Simulink Adaptive Filter Code_TDLs, 2011, [Simulink block and Matlab scripts].