

Artificial Adaptive Filter for Robotic Systems

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Received 22 September 2019; Accepted 22 February 2020

Abstract

Several neurobotic 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 plant on Matlab/Simulink. Main task of the VOR is to convert the vestibular signal to motor commands to the oculomotor plant, in other words head velocity to 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 shows significant 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 neurobotic 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 the horizontal VOR is

presented in the Fig1. Result of the moving of image extremely fast across retina is the vision degradation. The retinal slip would be produced by movements of the head, as it happens in locomotion. The VOR operates to counter-rotate the eyes to prevent retinal slip for maintaining the stable gaze [1].

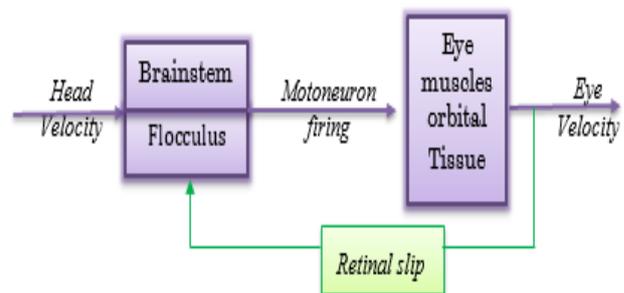


Fig 1. Bio-control circuit.

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 2 training 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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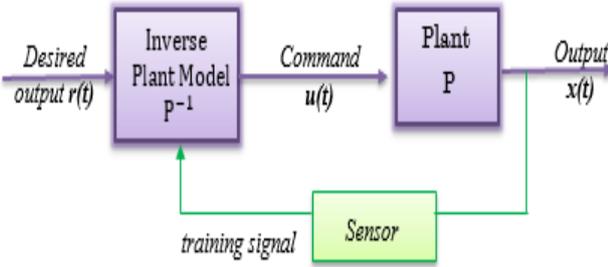


Fig 2. Control circuit

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

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

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].

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

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.

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.

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

where input $u(t)$ to the adaptive filter C, which was splitted 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 component p_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.

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

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

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.

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

where δw_j is the change in the j th 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 j th filter signal at time t

$\langle \rangle$ – 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.

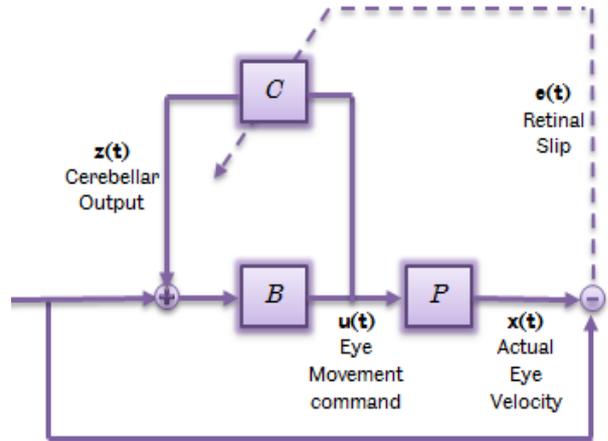


Fig 3. The basic VOR system.

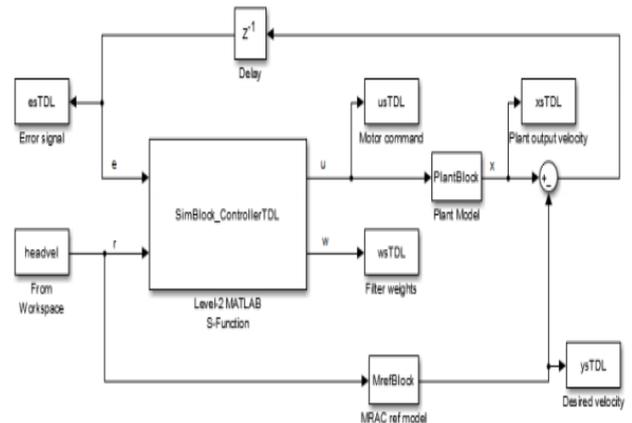


Fig 4. Block-diagram in Simulink software

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 how adaptive component reduces error (Fig5).

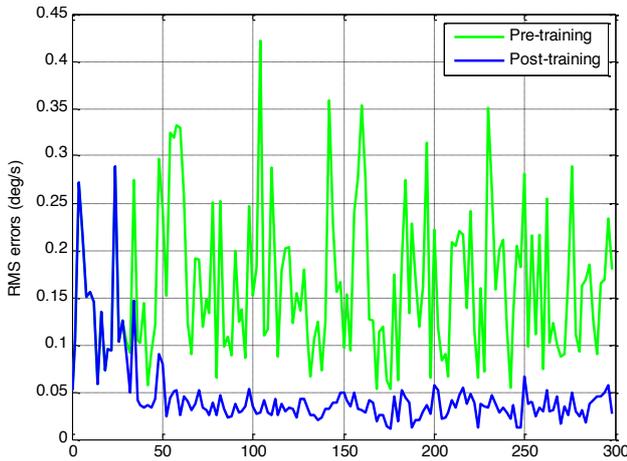


Fig 5. Retinal slip before and after training (learning began at 30 s).

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.

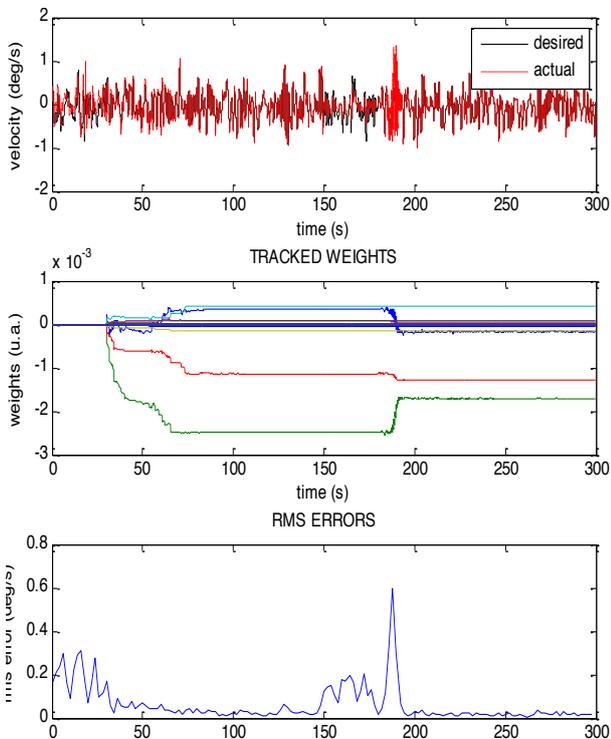


Fig 6. Performance of the system with dynamic plant

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

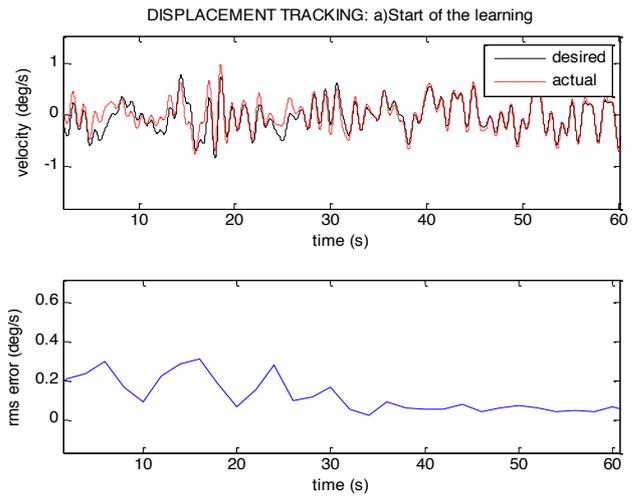


Fig 7. Start of the learning

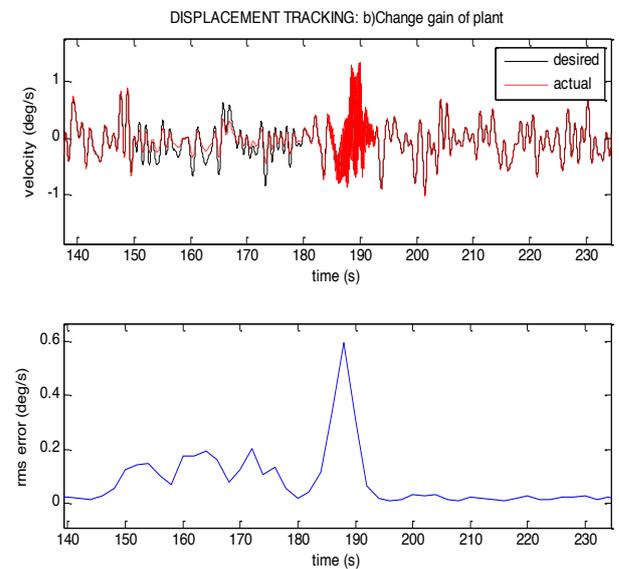


Fig 8. Gain of plant changed at 150s

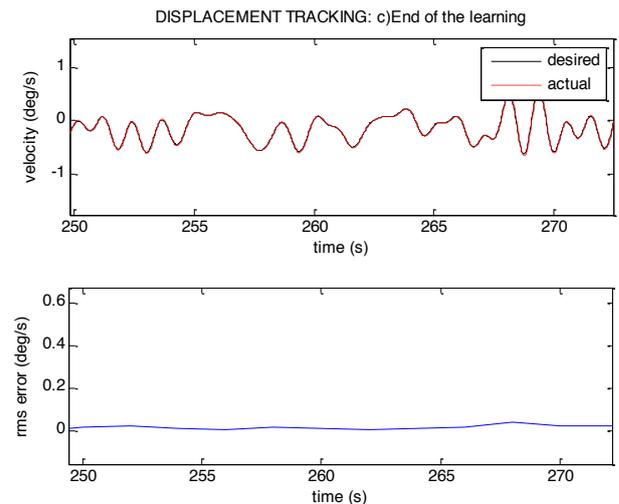


Fig 9. End of learning.

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.

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