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Implementation of Recurrent Neural Network to Control Rotational Inverted Pendulum using IMC Scheme

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Abstract: Problem statement: This paper presents an overview of a controller for a Rotational Inverted Pendulum (RIP) based on a New Recurrent Neural Network (NRNN) using Internal Model control (IMC). The RIP consists of a DC servo motor, arm and pendulum. The RIP is modelled in MATLAB/Simulink and the simulation results are shown besides the experimental results. The proposed experiment shows intelligent method for stabilizing the RIP, which can recommend the control designers of nonlinear systems. The outcome exposed that the NRNN controller competent of controlling the RIP system productively, as exposed in the simulation results.

Key words: Non liner modelling, Rotational Inverted Pendulum system, Recurrent Neural Network, Adaptive Control.

INTRODUCTION

Neural Network (NN) was in the beginning advanced to retrieve data on the purely experimental basis and emulate the human brains. Here are a lots of applications built employing the rule owing to its exciting characteristics, i.e.: the facility to find out, universal approximation and the capability. Intelligent controller is improved or adaptive controller that routinely learns via communicating by means of their surroundings (C.kambhampati et al, 2000; J.C. Atuonwu et al, unpublished). This paper presents the completion of the strategy NRNN control to dampen or control the vibration of the RIP system.

A recurrent neural network (RNN) based control technology for the RIP is a dynamic system. RIP system is a dynamic which the system is activated, in which the freedom and flexibility of the system are more than other actuators. These properties of RIP are a suitable for control and robotic applications, since this system has a great numeral of beneath actuated subsystems (Cazzolato *et al*, 2008; Krohling *et al.,* 2002; Yun Du1 *et al*, 2009). RIP normally has a, rotates on a horizontal plane, pendulum and an arm. The NRNN approaching non linear system of the plan be able to run the guiding and stability the belief to abridge of controller. These results are a significant solution for the new controller proposed. Fig 1 is a schematic of pendulum (RIP) system.

Linearize of RIP including open loops poles with two variable degrees of freedom that put on the right hand side of a plane. So suggest the NRNN controller be effective in the direction of control of system.

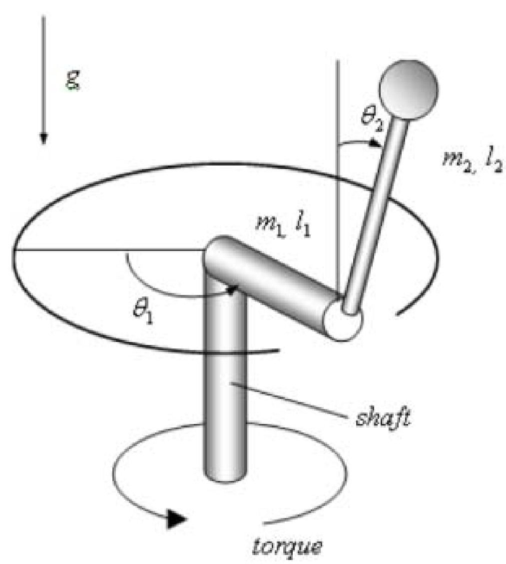

Fig. 1: Schematic of pendulum (RIP).

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Modeling and of Description of Rip Based on New Rnn:

The NRNN controller is needed as the regulating procedure for arm and pendulum are immoderately composite. Consequently, intelligent identifiers are leading to regulate the control system parameters. (A. A. Shojaei *et al*, 2011; A. A. Shojaei *et al.,* 2012). A greater part of the researchers focused on new RNN for aim optimization. This paper researches the presentation of a NRNN with controller mean and detector mean, for stabilizing the RIP in the RNN tuning problem.

Fig 2 illustrate of NRNN based control plan.

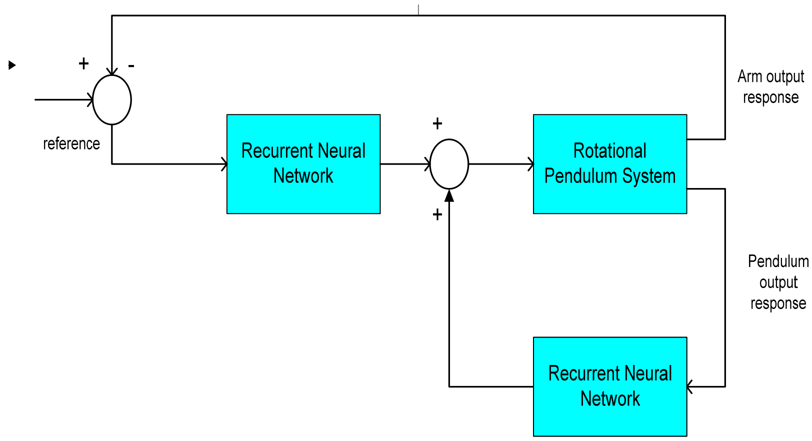

Fig. 2: Strategy of NRNN control.

Overview of NRNN:

The NRNN is a type of neural network, where the relationship between the units forming a cycle. Therefore, the open-loop controls point, not able to maintain the information at the target value. Can still reach them is the basis for the development of strategy to control total control. It is necessary to recommend the appropriate classification of the controller in order to design a stable system. For this reason, it wants an adaptive control system with online value to achieve the favourable control for every operating condition.

Methodology:

A recurrent NN is with regard to the shape of the loop, where it feedback loops dissimilar, in contrast to the other NN that just a feed-forward loop has (K.Arai *et al,* 2000). This type of NN will be controlled as RNNC controller G_C (s) and a type of plant is, $\tilde{G}_p(s)$ that the identifier RNNI is called, are used as shown in Fig 3.

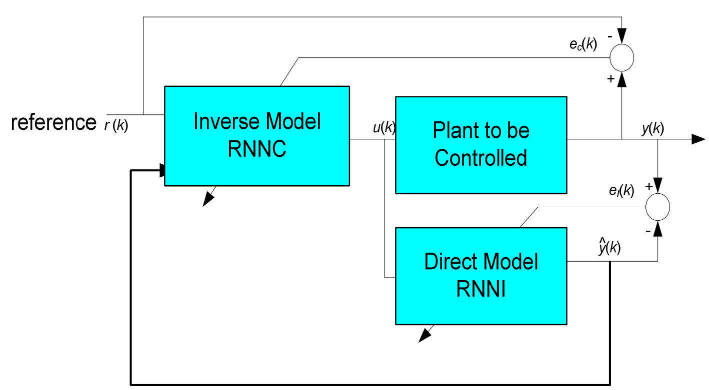

Fig. 3: RNNI and RNNC using IMC.

RNN Identifier (RNNI):

Fig 4 displays the structure of the RNNI contains several layer form called the output and input layers. It is identifier for detective work variable output through a feedback system of the power system plan. Consequently, The input step signals of the RNNI are $I_2(t)$, $I_3(t)$, $I_4(t)$, $I_5(t)$ and $U(t)$; apiece neuron is related through repetitive weights $W_{ji}^{R}(t)$. The neuron is matched with weights $W_{kj}^{O}(t)$ to the input and output layers (Chen *et al*, 2006).

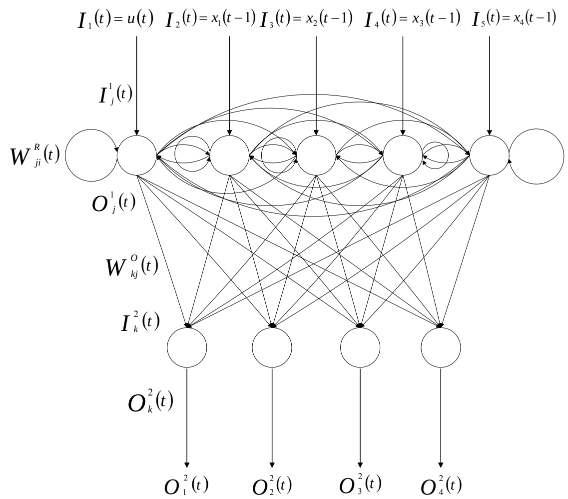

Fig. 4: The RNNI construction.

The RNNI form is as follows:
Input- output layer of the jth neuron:

$$I_j^1(t) = I_j(t) + \sum_{i=1}^{m_1} W_{ji}^R(t) O_j^1(t-1), j = 1, \dots, m_1 \quad (1)$$

$$O_j^1(t) = f\left(I_j^1(t)\right) = \frac{e^{I_j^1(t)} - e^{-I_j^1(t)}}{e^{I_j^1(t)} + e^{-I_j^1(t)}}, j = 1, \dots, m_1 \quad (2)$$

Input-output layers of the kth neuron:

$$O_k^2(t) = I_k^2(t) = \sum_{j=1}^{m_1} W_{kj}^O(t) O_j^1(t), k = 1, \dots, n_1 \quad (3)$$

Error function:

$$E_I(t) = \frac{1}{2} \sum_{k=1}^{n_1} (x_k(t) - O_k^2(t))^2, \quad (4)$$

$x_k(t), k = 1, \dots, n_1$, are the outputs.
The weights $W_{kj}^O(t)$ and $W_{ji}^R(t)$ use the steepest decline algorithms which equalize are to:

$$W_{kj}^O(t+1) = W_{kj}^O(t) + \Delta W_{kj}^O(t) = W_{kj}^O(t) - \eta_I^O \frac{\partial E_I(t)}{\partial W_{kj}^O(t)} \quad (5)$$

$$W_{ji}^R(t+1) = W_{ji}^R(t) + \Delta W_{ji}^R(t) = W_{ji}^R(t) - \eta_I^R \frac{\partial E_I(t)}{\partial W_{ji}^R(t)} \quad (6)$$

$E_I(t)$ is expressed since:

$$\frac{\partial E_I(t)}{\partial W_{kj}^O(t)} = -\left(x_k(t) - O_k^2(t)\right) O_j^1(t) \quad (7)$$

$$\frac{\partial E_1(t)}{\partial w_{ji}^{R}(t)} = -\sum_{k=1}^{n_1}\left[\left(x_k(t) - O_k^2(t)\right) w_{kj}^{O}(t)\left(1 - \left(O_j^1(t)\right)^2\right)\right] O_j^1(t-1) \quad (8)$$

RNN Controller (RNNC):

Fig 5 displays the essential formation of the practical new RNN manager. RNNC regulates and joystick the power source output through an input voltage, So RNNC involves output and input layers. The output layer has one neuron only where as the input layer has mc neurons. The output and input layers are $T_j^1(t)$ and $S_j^1(t)$ in that order. There are several signals, which are come in into the input layer; $u(t-1)$, $x_1(t-1)$, $x_2(t-1)$, $x_3(t-1)$. Each input layer neuron is coupled with all by means of repetitive weights $V_{ji}^{R}(t)$. The output weights $V_j^{O}(t)$ are coupled amid the output and input neurons (Abiyev *et al*, 2003).

The output and input layers of the jth neuron are:

$$S_j^1(t) = S_j(t) + \sum_{i=1}^{m_c} V_{ji}^{R}(t) T_i^1(t-1), j = 1, \dots, m_c \quad (9)$$

$$T_j^1(t) = f\left(S_j^1(t)\right) = \frac{e^{S_j^1(t)} - e^{-S_j^1(t)}}{e^{S_j^1(t)} + e^{-S_j^1(t)}}, j = 1, \dots, m_1 \quad (10)$$

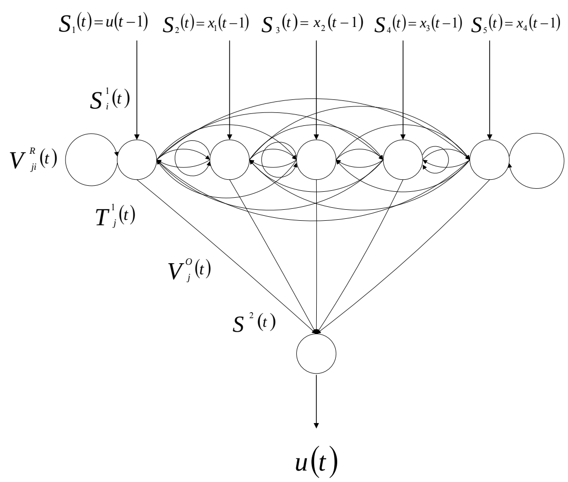

Fig. 5: The RNNC arrangement.

Output single is indicated follows:

$$u(t) = S^2(t) = \sum_{j=1}^{m_c} V_j^{O}(t) T_j^1(t) \quad (11)$$

Error function:

$$E_c(t) = \frac{1}{2}\sum_{k=1}^{m_c}(r_k(t) - x_k(t))^2 \quad (12)$$

The position are $r_k(t)$, $k = 1, \dots, m_c$.

$V_{ji}^{R}(t)$ and $V_{kj}^{R}(t)$ resolute by:

$$V_j^{O}(t+1) = V_j^{O}(t) + \Delta V_j^{O}(t) = V_{kj}^{O}(t) - \frac{\partial E_c(t)}{\partial V_j^{O}(t)} \quad (13)$$

$$V_{jj}^{R}(t+1) = V_{jj}^{R}(t) + \Delta V_{jj}^{R}(t) = V_{jj}^{R}(t) - \eta_{C}^{R} \frac{\partial E_C(t)}{\partial v_{jj}^{R}(t)} \tag{14}$$

So, η_C^R and η_C^O are gradient error and L_r with respect to the weights $V_j^O(t)$ and $V_{jj}^R(t)$ are:

$$\frac{\partial E_C(t)}{\partial v_j^O(t)} = -\sum_{k=1}^{n_C} \left[\left(r_k(t) - x_k(t) \right) W_{k1}^{O}(t) \left(1 - \left(O_1^1(t) \right)^2 \right) \right] T_j^1(t) \tag{15}$$

$$\frac{\partial E_C(t)}{\partial v_{jj}^R(t)} = -\sum_{k=1}^{m_C} \left[\left(r_k(t) - x_k(t) \right) W_{k1}^{O}(t) \left(1 - \left(O_j^1(t) \right)^2 \right) \right] \tag{16}$$

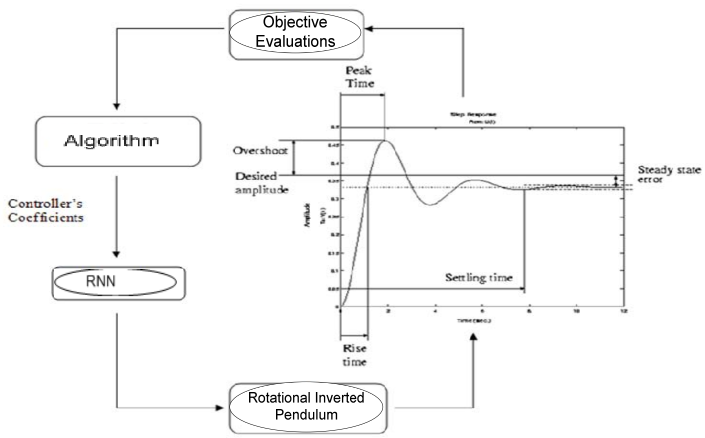

Fig. 6: Essential suggestion for stabilizing the RIP of RNN optimization.

Simulation Results:

In this section, the simulation of the expressed is explained, so nonlinear system for the RIP, used for equations and (A. A. Shojaei *et al*, 2011).

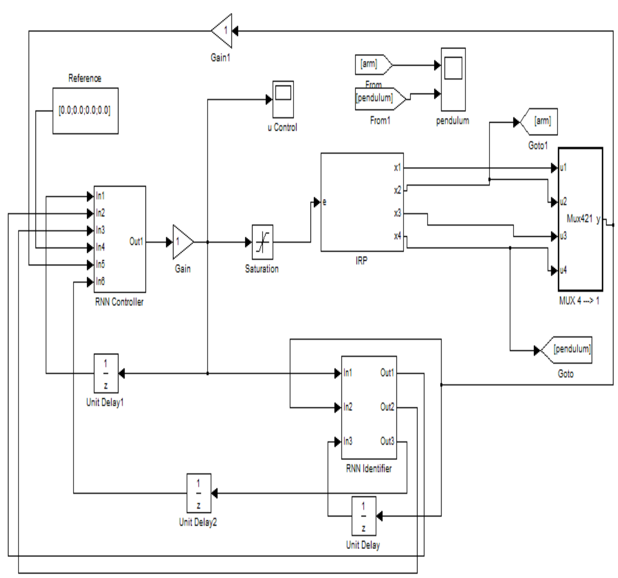

Fig. 7: Block diagram of the designed NRNN system in MATLAB/Simulink environment.

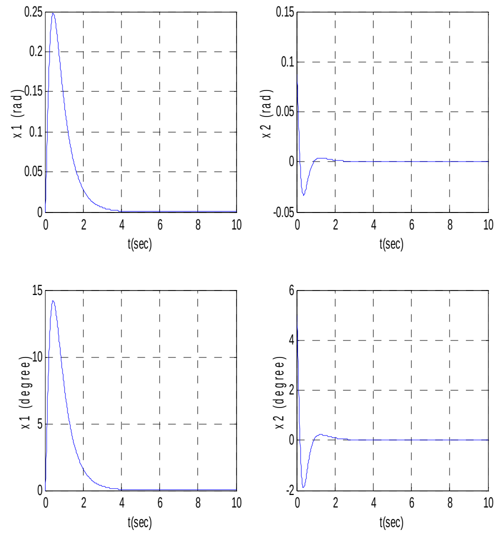

Fig. 8: Result simulation of NRNN including radian & degree for arm and pendulum.

In this place, the RIP nonlinear model is sculptured by MATLAB/Simulink™. The simulation is in progress to bring the pendulum with the swing up approach. Fig 8 displays a total plan of the simulated RIP nonlinear system in MATLAB/Simulink™. The results simulation of the NRNN controller is proposes in Figures 8 which demonstrate the response of pendulum and arm correspondingly according to radian /degree.

Experimental Setup:

A prototype of the control system was implemented to validate the functionality of the proposed method. Hardware requirement including Micro-box 2000C with proper support of I/O board (ADC/DAC/Encoder/GPIO), Electro Mechanical Engineering Control system (EMECS) is a set of electro mechanical device for control engineering (Inverted/Double-link Pendulum Speed, Position & Force feedback control), DAC driver circuit, Switching power supply and RJ-45crossover Ethernet cable. Simulink environment, xPC Target provides a high performance to physical systems and in real time on Micro-Box.

Table 1: Mechanical and Electrical System Parameters.

Physical quantity	Symbol	Numerical value
mass of arm	m_1	0.056 kg
length of arm	l_1	0.16 m
distance to arm center of mass	C_1	0.08 m
inertia of arm	J_1	0.00215058 kg-m^2
mass of pendulum	m_2	0.022 kg
length of pendulum	l_2	0.16 m
distance to pendulum center of mass	C_2	0.08 m
inertia of pendulum	J_2	0.00018773 kg-m^2
armature resistance	R_m	2.5604 Ω
back-emf constant	K_b	0.01826 V-s/rad
torque constant	K_t	0.01826 N-m/A

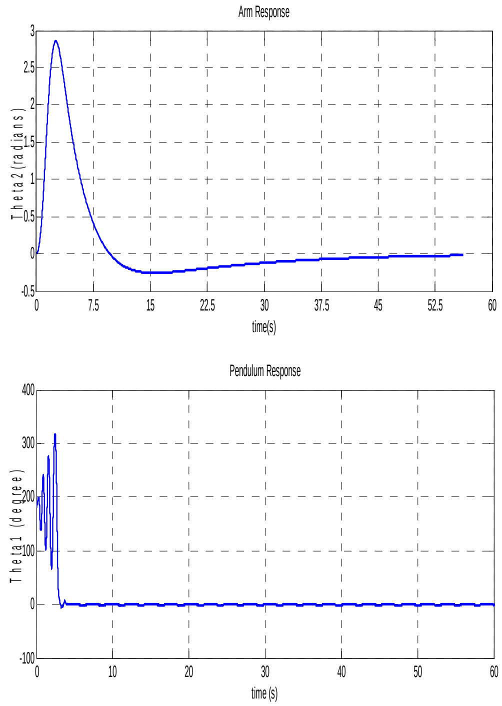

Fig. 9: The response of arm (in radians) and response of pendulum (in degrees) using NRNN.

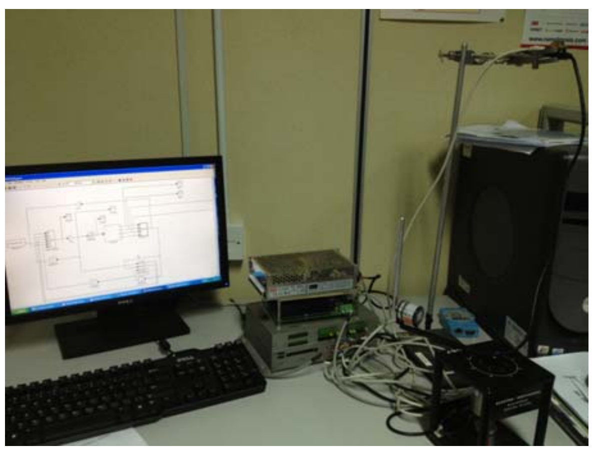

Fig. 10: Hardware circuit prototype.

The experimental result of the NRNN controller is proposes in Figures 9 which demonstrate the response of pendulum and arm likewise. Therefore the results of simulation is not exactly of real-time model, but the results are suitable for extend of the stability of RIP control system.

Conclusion:

This paper introduces a perfect controller for pendulum and arm (θ_1,θ_2) of a RIP by means of a new RNN controller for system stabilizing. The proposed controller and detector means are capable of stabilizing the Rotational Inverted Pendulum based on RNN method. The simulation and experiment of the control system are performed and the results show the feasibility of the model.

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