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Dr. Wen Yu Li
Investigador del Departamento de
Control Automático
Presente.

Me es grato informar a usted que el proyecto de investigación No.50480, **"Neural adaptive control for nonlinear multiple time scale dynamic systems"**, que usted sometió al Conacyt en la **Convocatoria de Investigación Científica Básica 2005 del Fondo Sectorial de Investigación para la Educación**, fue evaluado positivamente, de acuerdo a la información emitida por el Conacyt el día 12 del presente mes.

A nombre de la Dra. Rosalinda Contreras Theurel, Directora General, le extiendo una sincera felicitación por este reconocimiento a su trabajo de investigación científica.

Atentamente,

Lic. Yolanda Hernández Muñiz
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Neural adaptive control for nonlinear multiple time scale dynamic systems

CONACyT-50480Y 2007-2010

1 Introduction

Adaptive control of nonlinear systems has been an active area in recent years, but it is difficult to control unknown plants. A common approach to deal with this problem is to utilize the simultaneous identification technique. Neural networks have been employed in the identification and control of unknown nonlinear systems owing to their massive parallelism, fast adaptation and learning capability. Neural networks based control naturally leads to problems in nonlinear control and nonlinear adaptive control. The past decade has witnessed great activity in the field, with increased awareness on the part of researchers that such problems can be addressed within the framework of mathematical control theory.

Adaptive neural networks control can be classified by the types of neural networks or by methods. By neural networks, we have continuous time [23], discrete-time [2], feedforward [21] and recurrent [16] neuro control. By methods, for examples, internal model neuro control used forward and inverse model are within the feedback loop [25]. Neural control can realize output regulation and tracking problems in nonlinear systems [2], decentralized control for large-scale systems was proposed in [6], backstepping technique can be applied for neural control [24]. Adaptive neural networks control has two kinds of structure: indirect and direct adaptive control. Direct neuro adaptive may realize the neuro control by neural network directly [21]. The indirect method is the combination of the neural network identifier and adaptive control, the controller is derived from the on-line identification [26]. Lyapunov synthesis approach is most popular tool for neural control [22]. Lyapunov–Krasovskii functions can be used for adaptive neural control with unknown time delays [5]. Passivity analysis can simplify the learning algorithms [29].

Some of neural networks applications, such as patterns storage and solving optimization problem, require that the equilibrium points of the designed network be stable [9]. So, it is important to study the stability of neural networks. Dynamic neural networks with different time-scales can model the dynamics of the short-term memory (neural activity levels) and the long-term memory (dynamics of unsupervised synaptic modifications). Their capability of storing patterns as stable equilibrium points requires stability criteria which includes the mutual interference between neuron and learning dynamics. The dynamics of dynamic neural networks with different time-scales are extremely complex, exhibiting convergence point attractors and periodic attractors [1]. Networks where both short-term and long-term memory are dynamic variables cannot be placed in the form of the Cohen-Grossberg equations [4]. However, a large class of competitive systems have been identified as being "generally" convergent to point attractors even though no Lyapunov functions have found for their flows.

There are not many results on the stability analysis of neural networks in spite of their successful applications. The global asymptotic stability (GAS) of dynamic neural networks has been developed during the last decade. Negative semi-definiteness of the interconnection matrix may make Hopfield-Tank neuro circuit GAS [5]; The stability of neuro circuits was established by the concept of diagonal stability [13]. By the frameworks of the Lur'e systems, the absolute stability of multilayer perceptrons (MLP) and recurrent neural networks were proposed in [28] and [19]. Input-to-state stability (ISS) analysis method [10] is an effective tool for dynamic neural networks, and in [**?**] it is stated that if the weights are small enough, neural networks are ISS and GAS with zero input. Stability of identification and tracking errors with neural networks was also investigated. [8] and [14] studied the stability conditions when multilayer perceptrons are used to identify and control a nonlinear system. Lyapunov-like analysis is a popular tool to prove the stability. [26] and [29] discussed the stability of signal-layer dynamic neural networks. For the case of high-order networks and multilayer networks the stability results may be found in [11] and [23].

Although many important results and discoveries have been made in neural adaptive control, a number of open problems for nonlinear dynamic systems remain unsolved.

1. Various physical problems are characterized by the presence of a small disturbance which because it is active over a long period of time, has a non-negligible cumulative effect. Perturbation methods can be used to obtain an approximate solution in the form of an expansion in a small parameter. A special method is called singular perturbation. It makes use of multiple time scales in initial value problems and coordinate stretching in regions of sharp change in boundary value problems. A basic requirement of perturbation methods is that the nonlinear system is complete known. If we use the universal approximation properties of neural networks [7], can we apply perturbation methods to *unknown* nonlinear systems?

2. Many large scale systems, such as power systems, can be decomposed into slowly coherent areas and fast subsystems in the Lure formation by time scale property [12].

Some mechanics systems can also be divided into fast and slow subsystems, for example the dynamic of flexible-link robot can be broken into two parts in a separate time scales [18]. Since the normal neural control uses unique time scale, some papers have used two neural networks to control the fast and slow subsystems independently [17]. Each controller is normal unique time scale. Can we design multi-time scale neural networks controller for multi-time scales plant directly?

3. Neural networks operate in two modes: computing and learning. For example, Hopfield type recurrent neural networks, the computing operation defined by the system equation is a "fast" synaptic event associated with a small time constant (RC), whereas the learning (synaptic weight change) can be thought as a "slow" process with a large time constant $\frac{1}{\lambda}$ (λ is learning rate). Almost all of analysis for neural control regard these two modes operate in the same time scale. If we use multi-time scales, can we design both learning and computational parts of a neural networks to ensure learning convergence and closed-loop stability?

4. Many practical systems involve sensors that provide signals at slow sample rates. The controller and output sensor have different time scales. Some control systems have different control periods, for example, in visual servoing system joint servoing is faster than image-based control [27]. To the best of our knowledge, multi-rate technique for neural control has not yet been established in the literature. Can we use neural networks to apply multi-rate control?

To the best of our knowledge, adaptive control and identification for multiple time scale dynamic systems via multiple time scales neural networks has not yet been established in the literature. The project objective is to develop a methodology for the analysis and design of nonlinear dynamic systems that have an underlying multiple time-scale structure via neural networks. The presence of two or more widely separated time-scales offers the opportunity for reduced-order analysis and design, yet at the present time there is no general methodology for uncovering and exploiting time-scale separation in nonlinear systems.

We are developing neural networks with multiple time scales for time-scale identification and reduced-order model development for high-order nonlinear systems that arise in the context of analyzing and designing machines, processes, structures, ground and aerospace vehicles, robots, and other mechanical systems. Since the neural networks with multiple time scales have learning abilities in multirate, we can do identification and adaptive control for multiple time scales systems. They have universal forms for a large class of multiple time scales nonlinear systems, we can develop an universal proof approach to overcome the validation difficulty in complete large scale systems. In order to show the effectiveness of adaptive neural networks with multiple time scales, we will use two typical multi-time scales nonlinear systems, flexible-link robot arm and multi tank system, to verify the theory results.

2 Objectives

We will study adaptive neural networks control with multiple time scales in both theory and application. Following objectives will be reached in this project.

1. *Give new neural networks models for multi-time scales systems*. For multi-time scales nonlinear systems, singular perturbation, large scales system theory and multirate theory are mostly used when the plants are known. The normal neural networks can model any nonlinear plant, but they are unique time scale. In order to model multi-time scales nonlinear systems, one approach is to use multiple neural networks, where a switch logic is applied to change time scales [30]. But multiple neural networks cannot take benefits from multi-time scales theory. In this project, we will use multi-time scales theory to construct new modelling frameworks, which are called Multi-Time Scales Neural Networks (MTSNN). These new neural networks will include four types: continuous time static networks, continuous time dynamic networks, discrete-time feedforward networks and discrete-time recurrent networks.

2. *Give new learning laws for Multi-Time Scales Neural Networks (MTSNN)*. The four neural networks models in Objective 1 are special nonlinear systems. We will show how to design learning algorithm by nonlinear multi-time scales theory instead of traditional gradient descent. These learning algorithms can guarantee convergence without the usual problems, such as local minima, slow convergence, etc. At least we will be able to develop sufficient conditions for such convergence. Because nonlinear multi-time scales theory can consider learning process and neural networks computing at same time, some better learning laws can be obtained which will ensure fast learning convergence and closed-loop stability.

3. *Modelling analysis*. Multi-time scale decompositions can reduce the model complexity [18]. Multi-time scales systems identification via neural networks is a very interesting

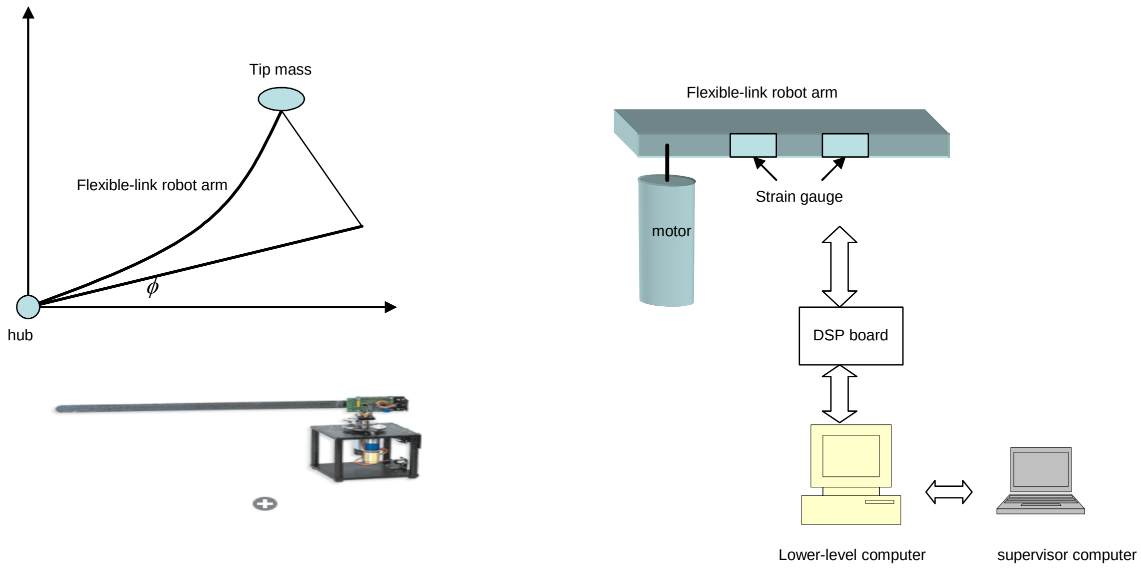

Figure 1: Flexibale-link robot arm control system

topic. This project will use perturbation methods and multirate technique in neural identification. Several theory problems will be solved, such as observability, stability, parameters identification, convergence for each subsystems and for whole multi-time scales system, etc.

4. *Robust adaptive control for uncertain multi-time scales nonlinear system*. Adaptive control via multi-time scales neural networks can follow the route of traditional approaches: singular perturbation method [18], large-scale systems theory [6] and multirate technique [27]. Nobody have ever used *multi-time scales* neural networks control for multi-time scales nonlinear system. We will solve following problems: controllability of uncertain multi-time scales nonlinear system, robust stability for uncertain nonlinear system, how to obtain continuous and discrete control commands, etc.

5. *Applications*. We will present one software package with MATLAB, with which we can do identification and synthesis automatically via multi-time scales neural networks. We will also present two prototypes: flexible-link robot arm (see Fig.1) and multi tank system (see Fig.2). Flexible-link robot arm is a benchmark problem for singular perturbation method. Multi tank system can be used for multirate control.

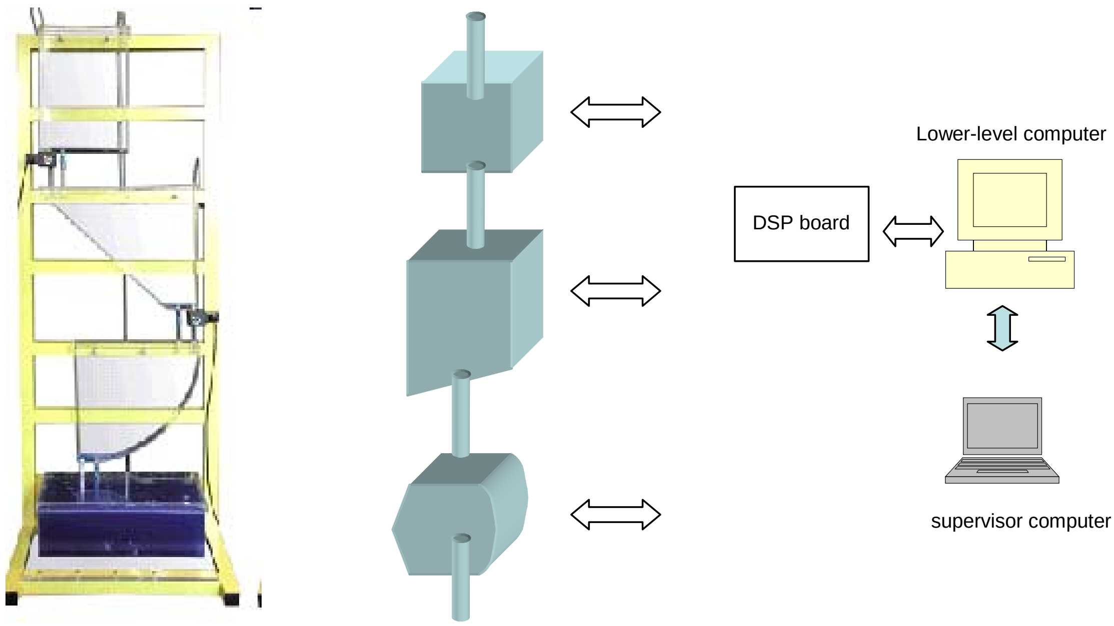

Figure 2: Multi-tank system

3 Methods

In order to finish the objectives proposed in this project. We will use following approaches.

1. Multi-Time Scales Neural Networks (MTSNN) are our new modeling tools. The theory base of singular perturbation methods is

$$\begin{aligned} \dot{x} &= f\left(x, z, u, \varepsilon\right) \\ \varepsilon \dot{z} &= g\left(x, z, u, \varepsilon\right) \end{aligned}$$

   As a "boundary" value problem, we have the conditions as $x(0) = x_0$, $z(t_f) = z_f$. We may construct four types of neural networks with two time scales (fast and slow)

   - Continuous time static MTSNN

$$\begin{aligned} \dot{\widehat{x}}_{1,t} &= f\left(x_{1,t}, x_{2,t}\right) \\ \varepsilon \dot{\widehat{x}}_{2,t} &= g\left(x_{2,t}, x_{2,t}\right) \\ \widehat{y}_t &= W_t \sigma([V_{1,t}, V_{2,t}] \left[\widehat{x}_{1,t}, \widehat{x}_{2,t}\right]^T) \end{aligned}$$

     where $\widehat{x}_{1,t} \in \Re^n$, $\widehat{x}_{2,t} \in \Re^n$ are the states of the neural network, f and g are nonlinear functions which we will design, W_t and $[V_{1,t}, V_{2,t}]$ are the weights of the neural networks

- Continuous time dynamic MTSNN. A general dynamic neural network with two time-scales can be expressed as

$$\begin{aligned} \dot{x} &= Ax + W_1\sigma_1(V_1\left[x,z\right]^T) + W_3\phi_1(V_3\left[x,z\right]^T)u \\ \epsilon\dot{z} &= Bz + W_2\sigma_2(V_2\left[x,z\right]^T) + W_4\phi_2(V_4\left[x,z\right]^T)u \end{aligned} \tag{1}$$

where $x \in R^n$ and $z \in R^n$ are slow and fast states, , $W_i \in R^{n\times 2n}$ ($i = 1\cdots 4$) are the weights in output layers, $V_i \in R^{2n\times 2n}$ ($i = 1\cdots 4$) are the weights in hidden layers, $\sigma_k = \left[\sigma_k(x_1)\cdots\sigma_k(x_n), \sigma_k(z_1)\cdots\sigma_k(z_n)\right]^T \in R^{2n}$ ($k = 1,2$), $\phi(\cdot) \in R^{2n\times 2n}$ is diagonal matrix,$\phi_k(x,z) = diag\left[\phi_k(x_1)\cdots\phi_k(x_n), \phi_k(z_1)\cdots\phi_k(z_n)\right]$ ($k = 1,2$), $u(k) = \left[u_1, u_2\cdots u_m, 0, \cdots 0\right]^T \in R^{2n}$. $A \in R^{n\times n}, B \in R^{n\times n}$ are stable matrices (Hurwitz). ϵ is a small positive constant. The structure of the dynamic neural networks (2) is shown in Fig.3. When $\epsilon = 0,$ the dynamic neural networks (1) have been discussed by many authors, for example [26], [23] and [29]. One may see that Hopfield model is a special case of this kind of neural networks with $A = diag\{a_i\}$, $a_i := -1/R_iC_i$, $R_i > 0$ and $C_i > 0$. R_i and C_i are the resistance and capacitance at the ith node of the network respectively. The sub-structure $W_1\sigma_1(V_1\left[x,z\right]^T) + W_3\phi_1(V_3\left[x,z\right]^T)u$ is a multilayer perceptron structure. In order or simplify the theory analysis, we let the hidden layers $V_i = I$. We discuss a single layer neural network

$$\begin{aligned} \dot{x} &= Ax + W_1\sigma_1(x,z) + W_3\phi_1(x,z)u \\ \epsilon\dot{z} &= Bz + W_2\sigma_2(x,z) + W_4\phi_2(x,z)u \end{aligned} \tag{2}$$

- Discrete-time feedforward MTSNN. We consider multilayer neural network(or multilayer perceptrons, MLP) which is represented as

$$\begin{aligned} \widehat{x}_1(k+1) &= f\left(\widehat{x}_1(k), \widehat{x}_2(k)\right) \\ \varepsilon\widehat{x}_2(k+1) &= g\left(\widehat{x}_1(k), \widehat{x}_2(k)\right) \\ \widehat{y}_t &= V_t\sigma(\left[W_{1,t}, W_{2,t}\right]\left[\widehat{x}_1(k), \widehat{x}_1(k)\right]^T) \end{aligned}$$

where the scalar output $y(k)$ and vector input $X(k) \in R^{n\times 1}$ is defined in (**??**), the weights in output layer are $V_k \in R^{1\times m}$, the weights in hidden layer are $W_k \in R^{m\times n}$, ϕ is $m-$dimension vector function. The typical presentation of the element $\phi_i(.)$ is sigmoid function.

- Discrete-time recurrent MTSNN

$$\begin{aligned} \widehat{x}(k+1) &= A\widehat{x}_t + V_{1,k}\sigma\left[W_1(k)x(k)\right] + V_{2,k}\phi\left[W_2(k)x(k)\right]U(k) \\ \varepsilon\widehat{z}(k+1) &= B\widehat{z}(k) + V_{3,k}\sigma\left[W_3(k)x(k)\right] + V_{4,k}\phi\left[W_4(k)x(k)\right]U(k) \end{aligned}$$

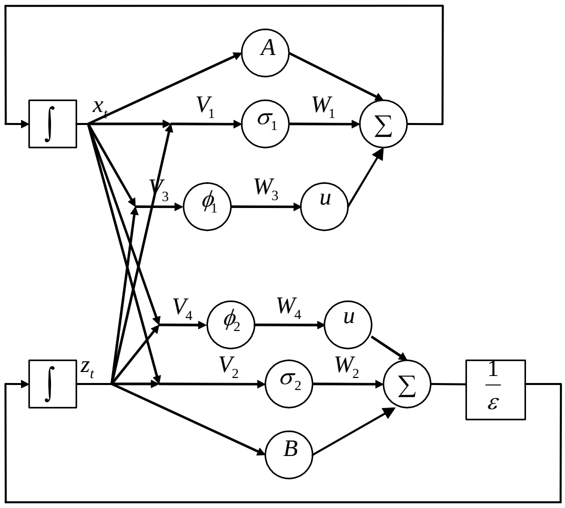

Figure 3: Dynamic neural network with two time-scales

where $\widehat{x}(k) \in \Re^n$ represents the internal state of the neural network . The matrix $A \in \Re^{n\times n}$ is a stable matrix which will be specified after. The matrices $W_i(k) \in \Re^{m\times n}$ are the weights of the neural network, the weights in output layer are $V_{i,k} \in R^{1\times m}$, σ and ϕ are $m-$dimension vector function $\sigma = [\sigma_1 \cdots \sigma_n]^T$. The typical presentation of the element $\sigma_i(.)$ is sigmoid function.

The stability of neural networks can be discussed using Tikhonov's theorem. There are other interesting problems for these new types of neural networks, such as how to choose ε, time scale analysis for neural networks, stability radius of the neural networks by Popov-Yakubovich theory, etc.

2. New learning laws for Multi-Time Scales Neural Networks (MTSNN). The typical adjustment algorithm for the weights of neural networks are gradient descent. In continuous time, learning law is

$$\dot{W}_{1,t} = -\lambda P\sigma(V_{1,t}\widehat{x}_t)\Delta_t^T$$
$$\dot{V}_{1,t} = -\lambda PW_{1,t}D_\sigma\Delta_t\widehat{x}_t^T$$

In discrete-time, the learning algorithm

$$W_{k+1} = W_k - \lambda e(k)\,\phi' V^{0T} X^T(k)$$
$$V_{k+1} = V_k - \lambda e(k)\,\phi^T$$

In order to ensure stable learning, λ should be very small. Combine these algorithms and the normal neural networks

$$\dot{\widehat{x}}_t = A\widehat{x}_t + W_{1,t}\sigma(V_{1,t}\widehat{x}_t)$$
$$\tfrac{1}{\lambda}\dot{W}_{1,t} = -P\sigma(V_{1,t}\widehat{x}_t)\Delta_t^T$$

It is in the form of singular perturbation. Here the neuro states and neuro weights are redefined as fast and slow variables. It exhibit all the characteristic feature of singularly perturbed systems. We may use singular perturbation theory to obtain better learning laws.

3. Modeling via Multi-Time Scales Neural Networks (MTSNN) in this project can be divided into two types: singular perturbation method and multirate identification.

   - Neural networks identification is in the sense of black-box. If we know the black-box can be divided into fast and slow subsystems, it becomes gray box, now MTSNN is more suitable, because the model (MTSNN) and plant have the same structure. For example, modelling for flexible link robot, the dynamic of a robot with n_r flexible links and n_e elements for each link is

     $$D(q)\ddot{q} + C\left(q,\dot{q}\right)\dot{q} + F\left(q,\dot{q}\right) + G(q) + Kq = B(q)u$$

     By singular perturbation method it can be rewritten as

     $$\ddot{q}_r = -M_{rr}H_r - M_{rf}H_f - M_{rf}K_{ffs}z + M_{rr}u$$
     $$\varepsilon^2\ddot{z}_r = -M_{fr}H_r - M_{ff}H_f - M_{ff}K_{ffs}z + M_{fr}u$$

     The following neural networks have the same form as above

     $$\dot{\widehat{x}}_t = A\widehat{x}_t + W_{1,t}\sigma(V_{1,t}\widehat{x}_t) + W_{2,t}\phi(V_{2,t}\widehat{x}_t)\pi(u_t)$$
     $$\varepsilon\dot{\widehat{z}}_t = B\widehat{z}_t + W_{3,t}\sigma(V_{3,t}\widehat{x}_t) + W_{4,t}\phi(V_{4,t}\widehat{x}_t)\pi(u_t)$$

   - Multirate identification. When the output y is measured J times slower than the secondary process output v and the input u, an output estimate y_e should be produced at each sampling interval of v and u, this is multirate inferential theory. We can apply this theory to neural identification, where the outputs of neural networks are also in multirate.

4. Adaptive control with multi-time scales neural networks (MTSNN) is absolute new controller. Several theory problems should be discussed, such as stability, robust modification (for example, dead-zone, $\sigma-$modification), indirect and direct adaptive control, can be applied to MTSNN. The following techniques can be used

- Normal neuro control theory [23] can be used to analyze each subsystems.
- For the whole system singular perturbation, multirate control and K-monotone theory can be used to analyze the closed-loop system. For multirate neuro control, inter sample responses are estimated and used as compensation for the missing measurements of the controlled output. This scheme can therefore operate at the desired fast rate. We can also update the control action at the slow rate that the output is sampled, it is different from conventional techniques.
- Some traditional controller can be combined with neuro control, for example optimal control, LQG, etc. Large scale systems can be decomposed hierarchically. For example, adaptive optimization problem can be solved by decoupling the performance index. For MTSNN, the object can be decoupled by the hierarchical structure, and multirate control technique may be applied.

5. Flexible-link robot arm is an economic multi-time scales prototype. The two subsystem have their own inner-loop control system (PD control). We are interesting in multi-time scales neural networks control. There are some results on classical control (PD, LQG, optimal) combined with neural networks control [18]. It is very interesting to check if this multi-time scales system can be stabilized a multi-time scales neural networks.

6. Control of the multi tank system is to maintain the water levels in the three tanks at some desired values. Three control loops are needed, theory analysis shows that Zone appears if these control algorithms are simple switch. We will check our multirate neuro adaptive control algorithm to model and avoid Zone.

4 Members of this project:

- Responsible:

Dr. Wen Yu Liu (SNI – II, investigador titular del CINVESTAV nivel 3C)

- Participants:

Dr. Ieroham Barouch (SNI – I, investigador titular CINVESTAV nivel 3A)
Dr. Manuel de la Sen (collaborative researcher from Facultad de Ciencias de Universidad del País Vasco, Spain)

Dr. QuanMin Zhu (collaborative researcher from Faculty of Engineering and Mathematical Sciences, University of the West of England, UK)

Dr. Yuhong Zhang (collaborative researcher from University of Delaware, USA)

M. en C. Alejandro Cruz Sandova (CINVESTAV Doctor Degree student, generation 2004)

M. en C. Rubio Avilla Jose de Jesus (CINVESTAV Doctor Degree student, generation 2003)

M. en C. Rigoberto Toxqui Toxqui(CINVESTAV Doctor Degree student, generation 2004)

5 Feasibility

Human resource:

- The responsible Dr.Wen Yu Liu has worked on neural network control and nonlinear system theory for 8 years, he has published 30 international journal papers and about 70 international conference papers on these two areas. Especially, in recent three years she has paid more attention on multi-time scales system via neural networks. Dr Wen Yu Liu had been the responsible of a CONACyT project (ref. 38505A) during the period 2002-2004, and the project was finished successfully. Dr.Wen Yu Liu has ability to combine neural networks and nonlinear system theory together and develop a new modeling tool: Multi-Time Scales Neural Networks (MTSNN). This project will be done in the Department of Automatic Control of CINVESTAV. There are several professors working on neural networks and nonlinear system. We have already got some results on neural networks [29], multi-model [30], and nonlinear control [31]. These are great help for this project.

- One of participants Dr.Ieroham Barouch is an expert on neural networks. He has been the responsible of the development of neural networks algorithms. So, he has enough experience to assure the completion of simulation and learning algorithm.

- Dr. Manuel de la Sen is a world-wide known expert in the area of nonlinear system control. We knew each other 8 years ago, and we have intended to cooperate since 3 years before. We tried to apply a bilateral project in the last year. Although it was not approved, the cooperation relation has been established. We believe his participation will be very helpful.

- Dr. QuanMin Zhu and Dr. Yuhong Zhang are the pioneers in the area of neural control, also they are the first researchers who proposed the concept of neural multi-time scales control. We have some communication with them. And they gave us a lot of valuable advice. We believe that their participations will be significant on improving research quality.
- The three Ph.D. students, Alejandro Cruz Sandova, Rubio Avilla Jose de Jesus and Rigoberto Toxqui Toxqui, have a lot of programming and software design experience. On the other hand, our doctoral students have basic theoretical research capability. By the direction of their advisors they are able to finish their activities.

Laboratories and Equipment:

- This project will be executed in the Department of Automatic Control of CINVESTAV, where three laboratories and various types of computers, workstations, operation systems, software and networks may be utilized freely.

6 Expected Results

- 4-6 international journal publications (each year will publish 2 international journal papers)
- 6-9 international conference publications (each year will publish 2-3 international conference papers)
- Multi-Time Scales Neural Networks (MTSNN) software package
- Two prototypes: flexible-link robot arm and multi tank system for the lab of our department
- 3 doctoral thesis (now 5 doctor students already started their works)
- 2 master thesis

7 Plan of the Project

- The first year will realize Objective 1 and Objective 2:

- Cuatrimestre 1: collect publications about multi-time scales system, and proposed a survey on adaptive control of multi-time scales nonlinear system
- Cuatrimestre 2: study Multi-Time Scales Neural Networks. We will propose a basic framework which can model and control uncertain multi-time scales nonlinear system. Finish Objective 1
- Cuatrimestre 3: propose new learning laws for MTSNN. Finish Objective 2

- The second year will realize Objective 3 and Objective 4
  - Cuatrimestre 1: Theory analysis and simulation for nonlinear systems identification via MTSNN, finish Objective 3
  - Cuatrimestre 2: Theory analysis and simulation for nonlinear systems adaptive control via MTSNN, finish Objective 4
  - Cuatrimestre 3: Prepare some paper for international journals.

- The third year will realize Objective 5
  - Cuatrimestre 1: do the experiment on flexible-link robot arm and multi tank systems.
  - Cuatrimestre 2: finish software package, with which we can do identification and synthesis automatically via multi-time scales neural networks
  - Cuatrimestre 3: prepare the final document and some papers for publication.

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8 Recent five publications:

1. Wen Yu, Xiaoou Li, Discrete-Time Neuro Identification without Robust Modification, *IEE Proceedings on Control Theory and Applications*, Vol.150, No.3, 311-316, 2003.

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