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Consejo Nacional de Ciencia y Tecnología

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**DR. WEN YU LIU**
**CENTRO DE INVESTIGACIÓN Y DE ESTUDIOS AVANZADOS DEL IPN**
**PRESENTE**

**Ref. : 38505-A** **MODELING AND CONTROL OF UNCERTAIN HYBRID SYSTEMS VIA HYBRID NEURAL NETWORKS**

Por el presente hago de su conocimiento que por dictamen del Comité de Evaluación del área correspondiente, el proyecto de referencia ha sido aprobado académicamente para recibir apoyo de este Consejo, con la siguiente cantidad:

**Monto Total Aprobado: $163,207.00**

Asimismo, le informo que el procedimiento para otorgar fondos a proyectos de investigación es a través de depósitos bancarios en una cuenta de cheques, de la cual usted será el titular. El seguimiento administrativo de las ministraciones y gastos corresponderá al administrador del proyecto y quedarán a cargo de auditores externos las visitas periódicas de vigilancia a la administración de los fondos.

Anexo al presente encontrará el convenio específico correspondiente donde se establecen los derechos y obligaciones de ambas partes durante el desarrollo del proyecto. Le recuerdo que el documento **"Lineamientos para la Administración de Proyectos de Investigación"**, que contiene la información necesaria para el buen desarrollo del proyecto, se encuentra disponible en el sitio web del CONACYT, en la sección de proyectos. En caso de alguna duda, le solicito sea tan amable de comunicarse a la brevedad posible a la Dirección de Apoyo a la Investigación, a los teléfonos (5)327-7400 ext. 3830 y 3824, y al 01800-2361004.

Estoy seguro que nuestro compromiso de colaboración institucional será positivo para el desarrollo cientifico nacional.

Atentamente

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# Modeling and Control of Uncertain Hybrid Systems via Hybrid Neural Networks

CONACyT-38505A 2002-2004

## 1 Introduction

Hybrid systems are characterized by combinations of discrete and continuous features. Many modern computer-based control systems appear to be well modeled by hybrid systems, for example, chemical bath process, flexible manufacturing system, transportation systems, communication networks and switching system. There are significant advantages using hybrid system, one may represent time and event-based behaviors more accurately. If we convert the discrete part into continuous model, for example pistons in gasoline engine have four operation modes which is a discrete event process, only the average values of the physical quantities are modeled [2]. Hybrid systems also provide a basic framework and methodology for analysis and synthesis of intelligent systems [14], supervisory control for continuous systems is a good example [13]. Reducing complexity is another important reason for using hybrid systems, because hybrid models may model dynamic processes at different levels [9].

Hybrid systems have been developed for a long time. The recent efforts in hybrid systems research concentrate on designing controllers with guaranteed stability [19] and performance [2], the analysis of their dynamic behaviors [10], developing unified and systematic theory for them [3] and extending their application in more areas [1]. Hybrid systems have been studied by both computer scientists and system scientists. Computer scientists have been interested in the behavior of multiprocessor program. The models are usually based on Petri nets and automatons. Hybrid Petri nets are mostly used by them [5]. System scientists, on the other hand, have used some set of equations and cared about their solutions. Switch systems are typical model for studying [20]. Each approach has its strengths and weaknesses. Integrating both ideas in a complementary way is a new direction in hybrid systems [14] [12]. Discrete event model (automaton), continuous model (differential equation) and an interface (actuator/generator) are organized together to create a more general framework for hybrid systems.

Although many important results and discoveries have been made in hybrid system, a number of open questions remain unsolved[13].

- Computational complexity: Finite state automaton suffers from state explosion problems when dealing with high concurrent systems.
- Identification: Little attention has been paid on the issues of identification and event detection [22], because there no exists a suitable framework for the hybrid system identification .
- Automatic synthesis method: It is well known that an adaptive controller may automatically adjust its control parameter in order to cope with a uncertain continuous plant. Since hybrid system has event driven model, it is difficult to extend this adaptive mechanism to hybrid systems.
- Validation: Lyapunov-like method is currently used, but the automatic computation of such piecewise continuous function is just beginning to be studied.
- Applications: There have recently been significant applications in traffic control, automotive systems and chemical processes, etc. Few results can be found in robotic systems.

In this project, we will use a new framework, *Hybrid Neural Networks,* for hybrid systems. Hybrid neural networks take benefits from both neural networks and Petri nets. It has learning and event-representation abilities, so we can do identification and adaptive control for hybrid systems easily. Since it has universal form for a large class of hybrid systems, we may develope an universal proof approach to overcome the validation difficulty in hybrid systems. In order to show the effectiveness of the Hybrid Neural Networks, we will use two typical hybrid systems, two tanks system and two-robots cooperation, to verify the theory results.

## 2 Objectives

We will study hybrid systems in both theory and application via hybrid neural networks . Following objectives will be reached in this project.

1. *Give a new model for uncertain hybrid systems.* We call the framework as Hybrid Neural Networks. For hybrid systems modeling, Petri nets and automaton are mostly used for discrete event part; differential equation is usually used for continuous part. But neither hybrid Petri nets (Petri nets+differential equation)[5] nor supervisory hybrid system (automaton+differential equation+interface)[12] has learning ability. They cannot model

uncertain hybrid systems. We will propose a framework which is a combination of neural networks [23] and adaptive Petri nets [15]. This hybrid neural networks can model both discrete event parts (Petri nets) and continuous-time parts (neural networks). The learning abilities of neural networks and adaptive Petri nets make it possible to model uncertain hybrid systems.

2. *Give an object oriented hybrid neural networks.* The model in Objective 1 may model the three kinds of uncertainties: parameters uncertainties in continuous-time parts and discrete event parts and structure uncertainty in continuous-time parts. If there exists structure uncertainty in discrete events parts, Petri nets cannot cope with it. Object oriented idea provide us a formal group-modeling method [16]. We will propose an object-oriented hybrid neural networks which can model all kinds of uncertainties in hybrid systems.

3. *Identification analysis.* Hybrid systems identification in this project includes two parts: continuous-time subsystem identification via neural networks; discrete event subsystem identification via adaptive Petri nets. To the best of our knowledge, there are not published results on hybrid system identification with respect to both continuous-time part and discrete event part. Several theory problems will be solved, such as observability, continuous states observation, discrete event detection, parameters identification of continuous and discrete systems, convergence for each subsystems and for whole hybrid system, etc.

4. *Robust adaptive control for uncertain hybrid system.* Hybrid systems synthesis are still following the route of traditional approaches: computer scientists usually used controlled Petri nets [8] and supervisory control theory [21]; system scientists preferred to use optimal control [9], PID control [7], predictive control [3], robust control [6]. Nobody have ever cared about robust control for uncertain hybrid system and used adaptive control. We will solve following problems: controllability of uncertain hybrid systems, robust stability for uncertain hybrid system, how to obtain continuous control commands and discrete event commands, how to avoid Zone (switch infinitely), etc.

5. *Applications.* We will present one software package with MATLAB, with which we can do hybrid system identification and synthesis automatically. We will also present two prototypes: two-tanks system (see Fig.1) and vision-based assembly system (see Fig.2).

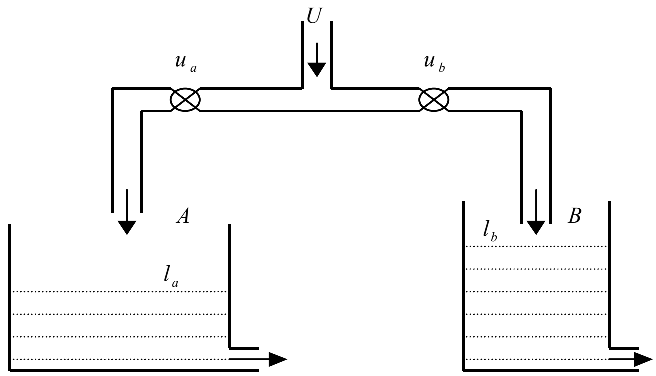


Figure 1: Two-tanks system

Two-tanks system and two-robots vision-based assembly system are typical hybrid systems.

# 3 Methods

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

1. Hybrid Neural Networks is our new modeling tool for uncertain hybrid system. It has ability of modeling continuous-time systems and discrete event system. We may put neural networks into the places of Petri nets (see Fig.3). This structure is similar as hybrid Petri nets, hybrid Petri nets put continuous property in tokens or transitions [5]. Hybrid neural networks put continuous property in places. This difference make hybrid neural networks have hierarchical modeling ability: Petri nets models upper level systems (for example, logic, condition, supervisory commands, etc.), neural networks model lower level systems (continuous time processes). In Fig.1 the upper level system is logically driven: (1) if $l_a > 10$ then $u_a = 0$ and $u_b = 85\%U$; (2) if $l_b > 12$ then $u_b = 0$ and $u_a = 70\%U$. These rules can be modeled as in Fig.3 where the conditions are in the transitions. The lower lever system is two tanks continuous-time plants which can be represented as

$$\dot{l}_a = -0.2l_a + 0.026u_a, \quad \dot{l}_b = -0.3l_b + 0.03u_b$$

It is easy to model them by two neural networks. At the input of neural networks there is a token receiver which can transfer token signal to commands for neural networks; At the output of neural networks there is a token creator which can transfer the value of

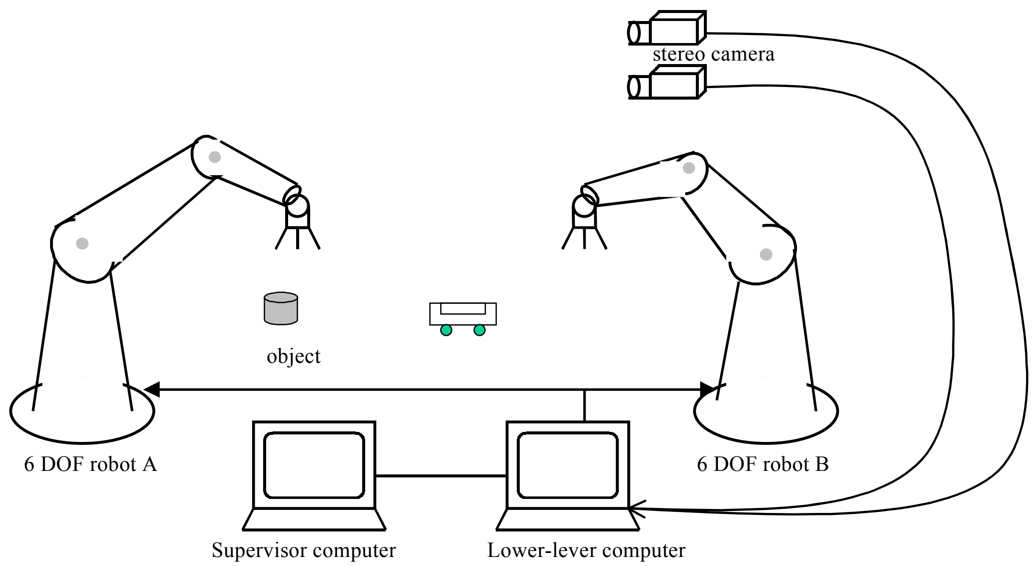


Figure 2: Two-robots vision-based assembly system

neural networks into tokens. Since neural networks have learning ability, uncertainties in the two tanks can be modeled. Uncertainties in upper lever can be modeled by adaptive fuzzy Petri nets. If fuzzy production rule is

$$\text{If } a \text{ Then } c \ (\mu, \ Th, \ w)$$

where $a$ is antecedent portion, $c$ is the consequent proposition, $\mu$ is the certainty factor of the rule, $Th$ is the threshold, $w$ is the weight, it can be represented as adaptive fuzzy Petri nets. For example, the rule [ If $a_1(\lambda_1, w_1)$ AND $a_2(\lambda_2, w_2)$ Then $c(\mu)$] can be represented as in Fig.4. First, it is expressed as adaptive fuzzy Petri nets (a), than it is transformed into a neural networks (b). We can use neural networks learning technique to update the weights of the logic rules. This is only a simple example, for more general case we will study in this project.

2. In order to model the structure uncertainty in the upper level system (for example, in Fig.1 one more tanks is added in this hybrid system), we may use object oriented idea to model this system. The hybrid system is divided by its category, not by its physical position. Each group has one unique property. For example, two-tanks system is changed into three-tanks systems, we can model it as in Fig.5. Tanks and valves are two subsystems, when we add a tank, we only need to add a neural networks in tank systems and a color token in valve system. The whole hybrid system model is not changed.

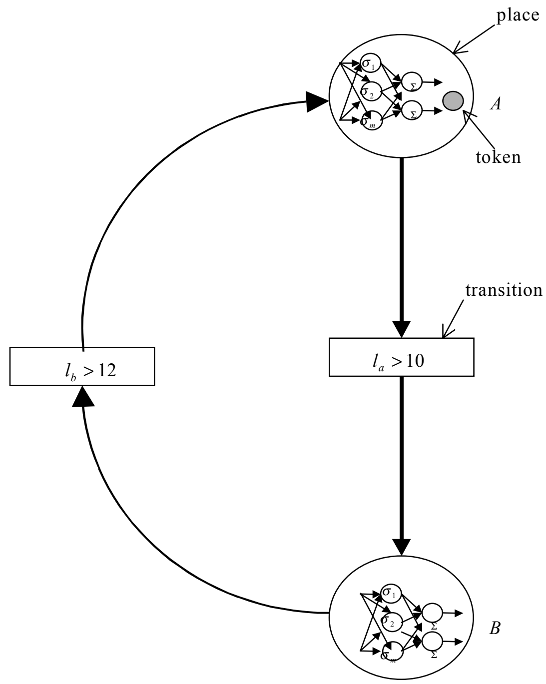


Figure 3: Hybrid neural networks

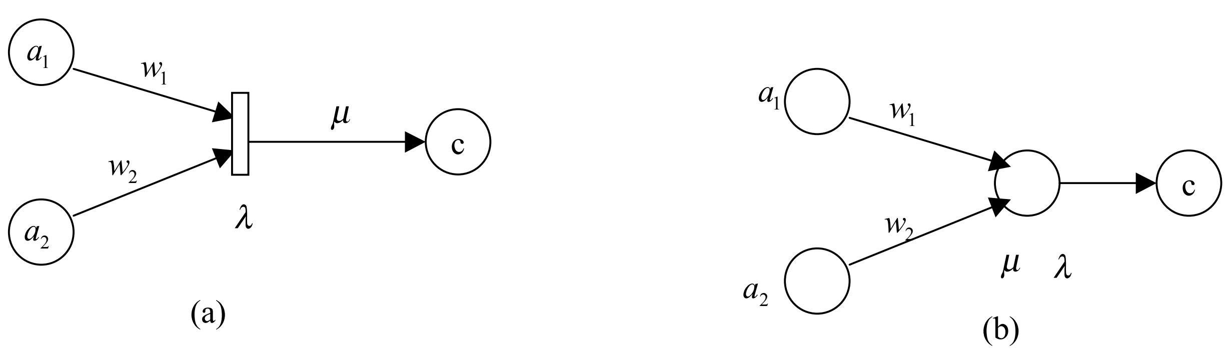


Figure 4: Adaptive fuzzy Petri nets

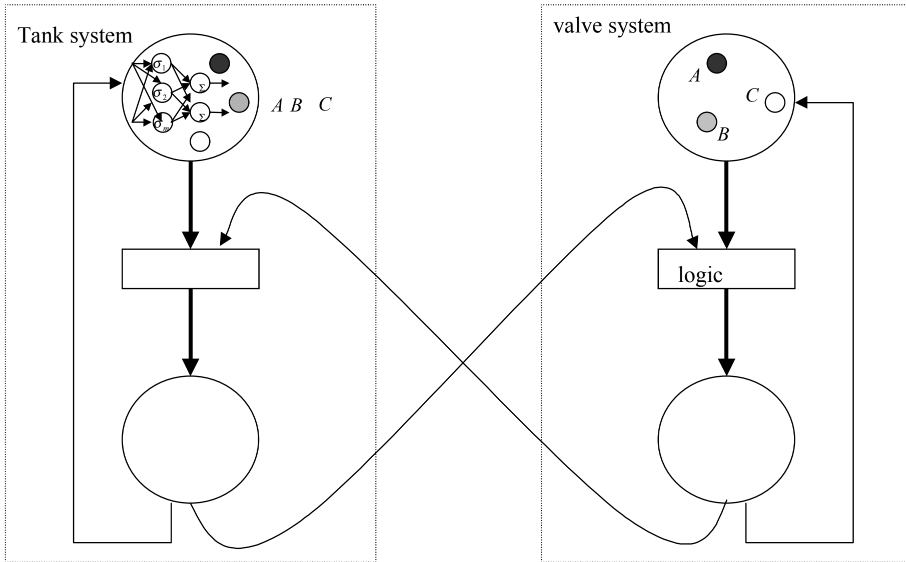


Figure 5: Object oriented hybrid neural networks

3. Hybrid systems identification in this project can be divided into two levels: discrete event subsystems identification and continuous-time subsystems identification. We may use following approaches.

   - Observability for only continuous-time part may be found in [25]. The normal discrete event observability (event-detectable) was discussed by [22]. We may use the similar technique as in [22] to study adaptive fuzzy Petri nets and object oriented Petri nets. By combining with neuro observer, we may obtain the observability of hybrid systems.
   - Also there are many results on discrete event estimation and continuous-time observer, hybrid system observer cab be a combination of these two. Since the separation principle cannot be used, we cannot design two observer independently. A possible way is to design neuro observer [25] in the Petri nets framework, or design Petri nets observer considering continuous-time state estimation.
   - Parameters in the continuous-time subsystem can be identified directly by neural networks. Parameters in the discrete event subsystem can be obtained by the transformation as in Fig.4. More detail should be discussed.
   - Identification convergence includes identification stability and convergence velocity. There exits some results on identification stability for discrete event [18] and neural

networks [23]. Our job is to join these two parts together effectively. Convergence velocity analysis of hybrid systems can use the idea of [10] and classical exponential convergence theory.

4. Stability issue in hybrid systems control have been studied by many researchers [1]. The difference in this project is the Petri nets is extended as adaptive fuzzy Petri nets and continuous-time model is neural networks. We may use their basic ideas and our results on neural networks [24] to analyze the stability. The other difficulty in our project is the uncertainties in hybrid systems, robust adaptive technique [11], such as dead-zone, $\sigma-$modification, can be applied to hybrid systems control.

   - We will extend the *supervisory control* into a general form: the supervisor is an expert systems, it may be described by production rules. Certainty factors of fuzzy production rules are correspond the weights of output arcs in Petri nets. They may be updated directly like a neural network. Many neural networks' learning algorithms may be applied for adaptive Petri nets, such as Widrow-Hoff and back-propagation learning laws. So we may learn experts' knowledge automatically. The continuous-time subsystems can be controlled by standard neuro control.
   - *Adaptive control* for hybrid systems can be decomposed hierarchically. For example, adaptive optimization problem can be solved by decoupling the performance index. We will consider neuro control problem, the object can be decoupled by the hierarchical structure, and multistages control technique may be applied.
   - Zone-avoiding can be realized by introducing time-delay in switch, we call it hysteresis switch. We can use our multiple neural networks results [26] in hybrid systems control to construct multiple hybrid controller.
   - Control of the two-tanks system is to maintain the water levels in the two tanks at some desired values. Theory analysis shows that Zone appears if the control algorithm is a simple switch. We will check our adaptive control algorithm has Zone or not, we will also check some Zone-avoiding approaches, such as hysteresis switch, Petri nets supervisory, etc.
   - Two-robots vision-based assembly system is an economic manufacture prototype. The two robots have their own inner-loop control system (PD control), we are interesting in their final position. So our feedback signals can be from stereo camera.

These signals will be used for two robots. The supervisor will finish discrete event subsystem control (logic command, cooperation, etc.), lower-level computer will realize visual servoing for two robots. Another option is to use LEGO programmable robot vehicle to make up a simple manufacture system. LEGO vehicle will be programed off-line, with the stereo camera we can realize automatic control for the hybrid system.

# 4 Feasibility

- Dr.Wen Yu has worked on neural network and Petri nets for more than 5 years, he has published more than 40 international journal and conference papers on these two areas. He has ability to combine these two modeling tools together and develop a new modeling tool: hybrid neural networks.

- Dr.Wen Yu now has two master students and three Ph.D. students. One master student, Sergio Perez, is working on hybrid systems modeling. The other master student, Gerardo Loreto, is working on visual servoing. One of his Ph.D. students, Marco A.Moreno, has been working on stereo vision theory for two years, he will continue his work and apply hybrid system control in the two-robots vision-based assembly experiment system. One of his Ph.D. students, Francisco J. Pineda, is just beginning to study on hybrid systems, he will work in the project for 3 years. The other one, Juan Reyes-Reyes, is working on dynamic neural networks, he will finish by the end of this year. His students will help him a lot in this project and this project will provide a good opportunity for postgraduate education.

- This project will be done in the Department of Automatic Control of CINVESTAV. There are many professors working on neural networks and visual servoing. We have already got some results on neural networks [23], Petri nets [27], and visual servoing [17]. These are great help for this project.

- We will establish a two-robots vision-based assembly experiment system. Because the visual servo control does not require precise robots, we may construct it as Fig.2. We will use two powerful computers, two good cameras, two special experimental robots, one LEGO robot vehicle and a video capture card . The price for it is less than $10,000 US dollar. It is well known that with this money we even cannot buy a good experiment robot. But we will built a simple manufacture prototype experiment. Our department already has the two-tanks experiment system. We can do our Zeno-avoiding experiment directly.

# 5 Plan of the Project

- The first year will realize Objective 1 and Objective 2:
  - Cuatrimestre 1: collect publications about the hybrid systems, and proposed a survey on hybrid systems
  - Cuatrimestre 2: study hybrid neural networks. We will propose a basic framework which can model and control uncertain hybrid systems. Finish Objective 1
  - Cuatrimestre 3: study object oriented hybrid neural networks. Finish Objective 2
- The second year will realize Objective 3 and Objective 4
  - Cuatrimestre 1: Theory analysis and simulation for hybrid systems identification, finish Objective 3
  - Cuatrimestre 2: Theory analysis and simulation for hybrid systems adaptive control, finish Objective 4
  - Cuatrimestre 3: Prepare some paper for international journals, establish the two-robots vision-based assembly experiment system. Finish the MATLAB package which we can identify and synthesize hybrid systems.
- The third year will realize Objective 5:
  - Cuatrimestre 1: do the experiment on the two-robots vision-based assembly system and two-tanks systems.
  - Cuatrimestre 2: Apply each new control algorithm on the real systems, if the experiment results are not satisfied, we may modify the control laws
  - Cuatrimestre 3: prepare the final document and some papers for publication.

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