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Active mode detection for hybrid systems using feed- forward neural networks

***Abstract**. In this paper, we present a new strategy that allows detecting the active mode in Hybrid Automaton (HA) which a behaviour description of Hybrid Systems. The proposed approach is based on using two Feed-Forward Neural Networks (FFNN). The first FFNN has two sets of inputs: the current modes' state of the HA and the jump conditions for switching between modes. The output is a sequence of boolean values that indicate the new state of the modes. The second FFNN converts the sequence of boolean values to an integer number that indicates the current mode' index of the HA. The procedure is tested on the thermostat problem*

***Streszczenie.** W tym artykule prezentujemy nową strategię, która umożliwia wykrycie aktywnego trybu w Hybrydowym Automacie (HA), który stanowi opis zachowania Systemów Hybrydowych. Zaproponowane podejście opiera się na wykorzystaniu dwóch sieci neuronowych typu Feed-Forward (FFNN). Pierwsza sieć FFNN posiada dwie grupy wejść: stan obecnych trybów HA oraz warunki skokowe do przełączania się między trybami. Rezultatem jest sekwencja wartości logicznych wskazujących nowy stan trybów. Druga sieć FFNN przekształca sekwencję wartości logicznych na liczbę całkowitą wskazującą indeks aktualnego trybu HA. Procedura jest testowana na problemie termostatu. (**Wykrywanie trybu aktywnego w systemach hybrydowych wykorzystujących sieci neuronowe ze sprzężeniem zwrotnym**)*

Keywords: Active mode, Hybrid Automaton, Hybrid Systems, Feed-Forward Neural Networks, thermostat problem
.**Słowa kluczowe:** Tryb aktywny, Hybrydowy Automat, Systemy Hybrydowe, Sieci neuronowe typu Feed-Forward, Problem termostatu

Introduction

A dynamical system explains how a state changes over time. Dynamical systems can be divided into two groups based on the nature of their states: continuous and discrete. [1]. There is another type of systems that combining the two aspects cited above: Hybrid Systems. Due to the intriguing theoretical issues raised by the design of these last systems, the academic community has been conducting extensive research on them.

Due to the intriguing theoretical issues raised by the design of these last systems, the academic community has been conducting extensive research on them. A closed system called a hybrid automaton has discrete decision logic that controls when and how it switches between its different discrete modes, with a vector field controlling the continuous behavior in each of the discrete modes [2].

There are several approaches that are involved into model hybrid automaton. We cite for example: its implementation under Scicos toolbox of Scilab [3], in [4] a library of components for modelling hybrid automata in a natural fashion has been implemented in Modelica and in [5] the Stateflow/Simulink tool of Matlab is used combining finite state machine concepts, Statecharts formalisms and flow diagram notations.

Understanding the active mode, which describes how the HS evolves at any given instant, is an essential piece of knowledge that makes it easier to apply the numerous findings from the domains of identification, control, stability analysis, and state estimates [6].

Many works have been done about the studied active mode determination. The first work carried out in this context was done in [7] by stating the problem in the form of a state estimation problem in a noisy environment. In [8], the recognition of the active mode is carried out by the means of model-based diagnosis techniques. A method based on using the input/output data on a time horizon is applied in [9]. And recently a study has been done in [10] using a Petri net for the discrete part of the system and differential equations for the continuous part.

In this paper we propose a new method based on using two Feed-Forward Neural Networks. The first FFNN has two sets of inputs: the current modes' state of the HA and the jump conditions for switching between modes. The output of this first network is a sequence of boolean values which indicate the new state of the modes. The second FFNN converts the sequence of boolean values to an integer number that indicates the current mode' index of the HA.

The remainder of this paper is organized as follows: the Feed-Forward Neural Network approach is described in section 2. Application of our methodology is applied on the thermostat problem which is the subject of the section 3. Finally, some conclusions are given in section 4.

The FFNN mode detection approach

Hybrid systems are modelled by hybrid automaton which has many discrete modes (represented by the ellipses). Each discrete mode has a corresponding differential equation that controls how the system's continuous state changes over time. Arrows between the distinct modes also show potential mode change. Along with each mode switch there is a jump condition that determines the occurrence of the switching mode. The latter is governed by continuous or discrete variables.

In the rest of the paper we use the expression N-mode HA to denote a hybrid automaton with N modes. Figure 1 represents an example of a 3-mode HA.

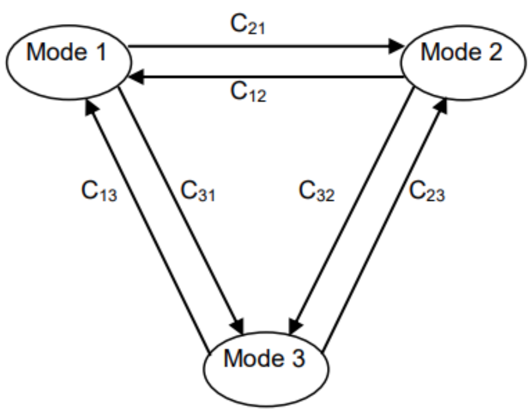

Fig.1. Model of a 3- mode HA

The C_{ij} denotes the jump condition from mode 'j' to mode 'i'. The basic idea of our work is using two FFNNs. The first FFNN1 has two sets of inputs boolean values: the current modes' state of the HA (Mi) and the jump conditions for switching between modes (C_{ij}) hence:

Mi = 1 if the ith mode is active else Mi = 0.

C_{ij} = 1 if the jump condition occurs C_{ij} = 0.

The FFNN1's output is a sequence of boolean values that indicate the new state of the modes. The second FFNN2 converts the FFNN1's output to an integer number that indicates the current mode' index of the HA. Figure 2 shows a representation of our approach for a 3-mode HA where:

M_1, M_2, M_3 : current modes' state.

C_{12}, C_{21}, C_{13}, C_{31}, C_{23}, C_{32}: jump conditions.

O_1, O_2, O_3: new state of the modes.

AM: active mode' index (integer number).

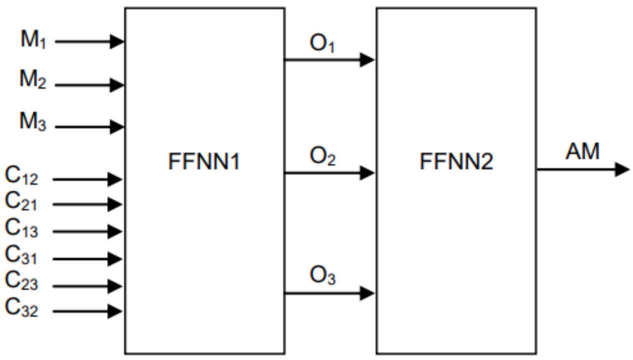

Fig.2. The proposed approach for a 3-mode HA

Simulation and results

In order to demonstrate the effectiveness of the proposed approach, we have tested it on an example of hybrid system: the thermostat plant. Let's consider a room being heated by a radiator controlled by a thermostat. The temperature *x* is controlled by switching the heater on and off [11]. According to the differential equation (1), it is assumed that while the heater is on, the room's temperature rises toward 100 degrees.

(1) $$\dot{x} = -x + 100$$

On the other hand, when the heater is off, the temperature decreases towards 0 degrees according to the following differential equation

(2) $$\dot{x} = -x$$

By turning on the radiator when the temperature is between 68° and 70° and shutting it off when the temperature is between 80° and 82°, the thermostat maintains a constant x of 75°.

There are discrete and continuous states in this hybrid system, as you can see.

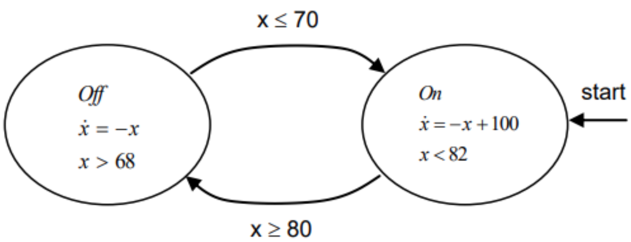

Fig.3. The hybrid automaton model of the thermostat

The room's temperature is represented by the continuous state, x, while the radiator's status is represented by the discrete state, q ∈{ON, OFF}.

The evolution of *x* is governed by a differential equation while the evolution of q is done through jumps. The evolution of the two types of state is coupled. When q = ON, x rises according to (1), while q = OFF, *x* decays according to (2). The system starts with a temperature equal to 60°.

We can represent this system as a 2-mode HA model that is shown in Figure 3.

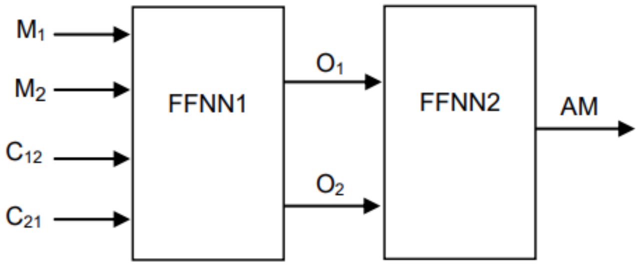

Fig.4. The FFNN strategy for the thermostat problem

In this hybrid automaton we have two modes: the mode 1 for the mode 'Off ' and mode 2 for the mode 'On '.

Figures (5) and (6) show, respectively, the temperature signal obtained by solving the two equations and the obtained active mode evolution.

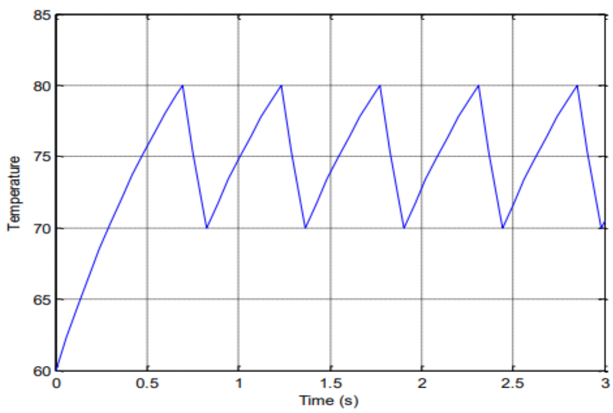

Fig.5. Evolution of the temperature

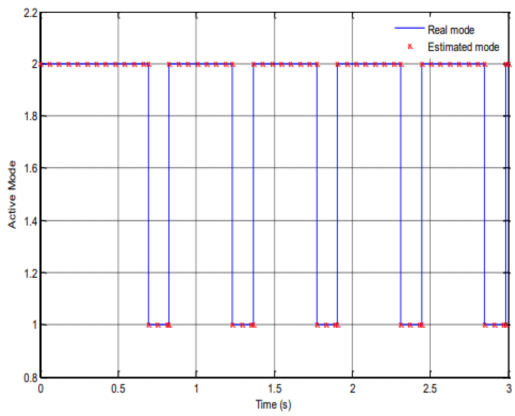

Fig.*6*. Evolution of the active mode

Figure 4 shows the scheme strategy with the two FFNNs for the thermostat problem with the following notations: C_{21} for the condition '$x \leq 70$', C_{12} for the condition '$x \geq 80$', M_1 for the mode 1 and M_2 for the mode 2.

The two FFNNs used in simulation have both three layers: an input layer (with 04 inputs for the first FFNN and 02 inputs for the second), a unique hidden layer with 08 neurons and an output layer (with 02 neurons for the first FFNN and one neuron for the second). The training algorithm used is the Levenberg-Marquardt and the learning sequence for the first FFNN is taken in the set $\{[0,1]^T, [1,0]^T\}$ for C_{12} and C_{21}.

For the set of inputs $\{M_1, M_2\}$ we choose for training the following values {1, 0} because the initial condition starts with the mode 2. For the second FFNN the training sequence for the second set of inputs is taken also in the set {1, 0}.

After training our networks we have tested them but before this we have used the Runge-Kutta algorithm for solving the two equations (1) and (2), and then we have simulated the system under the Stateflow/Simulink tool of the Matlab environment in order to compare the obtained results.

From the results, we note that the active mode obtained by the Stateflow/Simulink tool and the estimated active mode obtained by our approach are similar.

Conclusion

We have proposed in this paper a new methodology for the active mode detection in hybrid systems. This new approach consists on using two neural networks which gives the new state of the system (in boolean values) and converts the latter in an integer number that indicates the active mode' index. The performances of this approach were shown on a simulation example and the obtained results provide strong evidence of the good performance.

Our main objective in this article is the contribution of neural networks in hybrid systems theory which was done by modeling the evolution between the different modes of the system. Our future works are to propose an approach using different neural networks architectures in order to use them in different properties of the hybrid systems like: reachability, verification and others.

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