An introduction to data-driven discovery of cyber-physical systems

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Cyber-physical systems (CPS) embed software into the physical world, which are often encountered in a great variety of applications, in particular medical monitoring, robotics, smart grids, intelligence manufacture, and unmanned systems. CPSs have been demonstrated resistant to modeling for the inherent complexities originated from the incorporation of cyber and physical components together with their interactions. The study introduces a general framework facilitating pure data-driven reverse engineering cyber-physical systems, which involves physical system identification as well as transition logic inference. It has been substantiated by abundant real-world examples varying from electrical and mechanical systems to applications in medicine. This present work sheds some light on the underlying mechanism of CPSs while making predictions of the trajectory of CPSs with the assistance of the proposed model. Such information has been proven decisive for performance evaluation of CPSs. Significantly, it has application potential on debugging in the implement and guiding the redesign to guarantee the demanding performance.

The proposed Identification of HYbrid Dynamical Systems (IHYDE) Algorithm applied to a thermostat.

We now introduce the key principle of IHYDE with a room temperature control system: one of the most ubiquitous and simplest hybrid dynamical systems composed of a heater and a thermostat. By switching the heater on or off at any given time, a thermostat could maintain y(t), the real temperature approximate to user's satisfying temperature. The room temperature increases by a rate of 30a Celsius degree per hour (see Fig. 1A) once turning on the heater. Correspondingly, it drops at a rate of $-ay(t)$ ($a > 0$) Celsius degree per hour once the heater is off, the parameter is relevant to room's insulation.

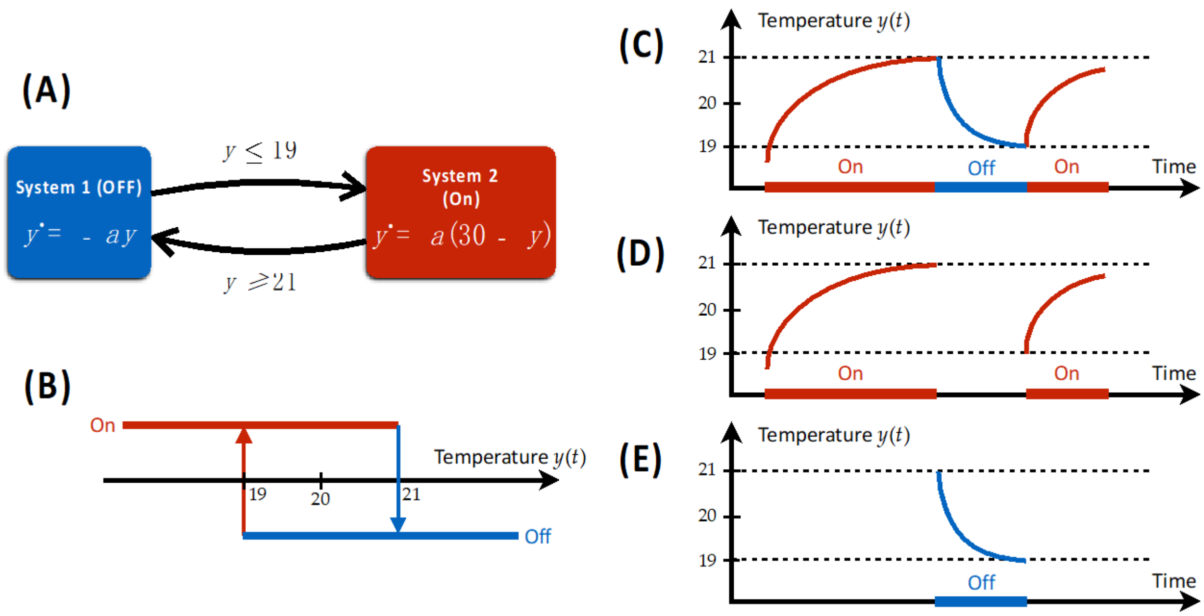

FIG. 1. An illustrative toy example of a thermostat. (A) Hybrid dynamical system's physical dynamic equations and switching logics. The present switching logic is to turn on the heater once the temperature is lower than 19 Celsius degrees, and off when it exceeds 21 degrees. Temperature y dissipates to the exterior at the rate of $-ay(t)$ ($a>0$) Celsius degree per hour when the heater is off, parameter depends on the room insulation. And the temperature raises by the rate of 30a Celsius degree per hour when the heater is on. (B) Transition logics of the relay hysteresis based on the room temperature. (C) Time series temperature data of a simulation of the thermostat system. Red (resp. blue) line illustrates the situation when the heater is on (resp. off). (D)-(E) Divided temperature data when the heater is on (off) from the original time series. (Reproduced from the original paper)

Suppose 20 Celsius degree is the expected temperature, and hysteresis prevents thermostats form rapid on-off switching, i.e., chattering. A practical transition logic (Fig. 1B) is setting the lower (resp. upper) limit, such as 19 (resp. 21) degrees, and turn on (resp. off) the heater once the temperature exceeds the boundary. IHYDE algorithm is designed to identify both thermostat subsystems together with the switching rules based on merely the recorded time series temperature data (see Fig. 1C). We would then elaborate on the core concept of IHYDE with this simple case.

Inferring subsystems. To begin with, IHYDE identifies the corresponding thermostat subsystem responsible to the time series temperature data iteratively. Therein the subsystem 2 that explain the majority of the acquired data (when the heater is on) is revealed by the algorithm (Fig. 1C). After which the dynamics of subsystem 2 is discovered using this part of data (see Fig. 1D). Same procedure is also conducted on the rest of the time series temperature data (Fig. 1E). Since the subsystem 1's dynamics (as the heater is off) shall be identified by the IHYDE using the remaining data.

Inferring transition logics. The next and ultimate step is to recognize the switching rules of both the subsystems, i.e., the principles following which switch the states between on and off. For subsystem 2 and its corresponding data in Fig. 1D (when the heater is on), the status quo maintains as the temperature varies within slightly lower than 19 degrees and approaching 21 degrees. Here the upper limit switching point between on and off is set when $y(t) = 21$, according to the software. In the practical application the switching happens once $y(t) \geq 21$ degrees. Likewise, the software learns that lower limit switching prerequisite between off and on is when $y(t) \leq 19$ (as in Fig. 1E).

In general, IHYDE verifies the dynamics of both subsystems and the switching logics from one subsystem to another automatically. Simple and isolated example as it is, IHYDE manage to acquire decent results while applied in more sophisticated scenarios with multiple subsystems, even with nonlinear dynamics and switching logics. More details refer to the original paper.

While the approach has its superiorities, some unsolved questions remains nonetheless. For instance, a new theory is demanded in order to interpret when the datasets in hand are informative enough to identify every (real) hybrid dynamical systems respectively. As a focal point in system identification, identifiability excludes the existence of abundant systems that may generate same data. Different hybrid dynamical systems may produce identical data, as illustrated in the original paper, which cannot be discriminated simply by datasets. The second issue consists in revealed models' linear parameterization. With regard to models with parameters entering nonlinearly, local minimizer could be acquired with gradient descent, yet it does not necessarily globally optimized. Lastly, the dictionary functions for certain systems depend on their fields. Relevant insight and domain knowledge help constructing dictionary function for hybrid dynamical system, thereby improving model accuracy while reducing computational cost. Canonical dictionary functions can be used to approximate the real dynamics once the critical domain knowledge is unclear or lacking, such as kernels, polynomials and Fourier series. A polynomial series successfully approximates a sinusoid as shown as an example. Despite all this, under such circumstances the very original real functions may be hard to obtain or lost. Hence, IHYDE reveals different dynamics depending on the selection of the canonical dictionary functions, while still detecting the of switching points. Notwithstanding, these identified dynamics still suffice predictions due to their approximation capability for the main dynamics of each subsystem.