



# CPS: Synergy: Collaborative Research: Collaborative Vehicular Systems

THE OHIO STATE UNIVERSITY

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## Introduction

The ongoing research aims to develop rules to study and methods to coordinate a network of fully and partially self-driving vehicles, interacting with conventional vehicles driven by people on a complex road grid, so that overall safety and efficiency of the traffic system can be improved. The potential outcomes of the research can add to the collective understanding of more general systems with hierarchical structures; help create designs with minimal computation and communication delay; and provide mathematical proofs for safety and reliability of a class of systems that combine physical, mechanical, and biological components with purely computational ones.

Researchers at the Control and Intelligent Transportation Research (CITR) Laboratory at The Ohio State University and Cyber-Physical Systems Laboratory (CPSLab) at Arizona State University are collaborating to address a series of vehicular-CPS problems, with applications in the entire range of Cyber-Physical Systems.

## CONTACT

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CITR Control and Intelligent Transportation Research Lab



## Mission and Focus

Motivated by our earlier efforts:

- “Autonomous Driving in Dense, Mixed Traffic Environments” (OSU, NSF Supported)

Three main concerns:

### 1. Collaboration:

- Autonomous (semi-autonomous) and totally “human-driven” in mixed-mode traffic.
- Subsets of vehicles making decision and exchanging information securely.
- Objective: Safe and reliable traffic flow.

### 2. Scalability:

- Scalability through hierarchies
- Grouping CPS entities as teams, convoys, regions, etc.

### 3. Testability and Verifiability:

- CPS calculus as a modeling and verification tool to prove safety conditions.
- Automated selection of test parameters and initial conditions through optimization methods

## Real-time Traffic Scene Perception via Deep Learning

### System Setup

### Dataset

4883 total training images from both cameras  
376 total test images from both cameras  
5 types of intersections:  
1. Four-way stop sign controlled.  
2. Traffic light signal controlled.  
3. Cross walks without stop signs.  
4. Roundabout-type.  
5. Three-way intersections.

### Training

Sampling from model distribution → Alternating Gibbs Sampling, updating all hidden units in parallel followed by updating all visible units in parallel

Sample hidden layer given input training vector in parallel using  $p(h_i = 1 | v) = \sigma(c_i + \sum_j v_j w_{ij})$ , then using  $p(v_j = 1 | h) = \sigma(b_j + \sum_i h_i w_{ji})$ , compute probability of each visible unit = 1 i.e. reconstruct the visible layer.

Learning is then done using this reconstruction instead  $\Delta w_{ij} = \text{learning\_rate}(c_i v_j h_{j+1} - P(c_i v_j h_{j+1}))$

### Inference

1. Compute hidden variables (features) given visible pixels  
 $p(h_i = 1 | v) = \sigma(c_i + \sum_j v_j w_{ij})$

2. Compute new inferred visible layer pixels using the computed hidden features  
 $p(v_j = 1 | h) = \sigma(b_j + \sum_i h_i w_{ji})$

## Development of a Pipeline for Creating Realistic Vehicle Simulator

### A Proposed Pipeline

- Design and implement a **work pipeline** that allows to **import** real **map** information, **customize environment** with realistic graphics and **import** it into a 3D **driving simulator**.

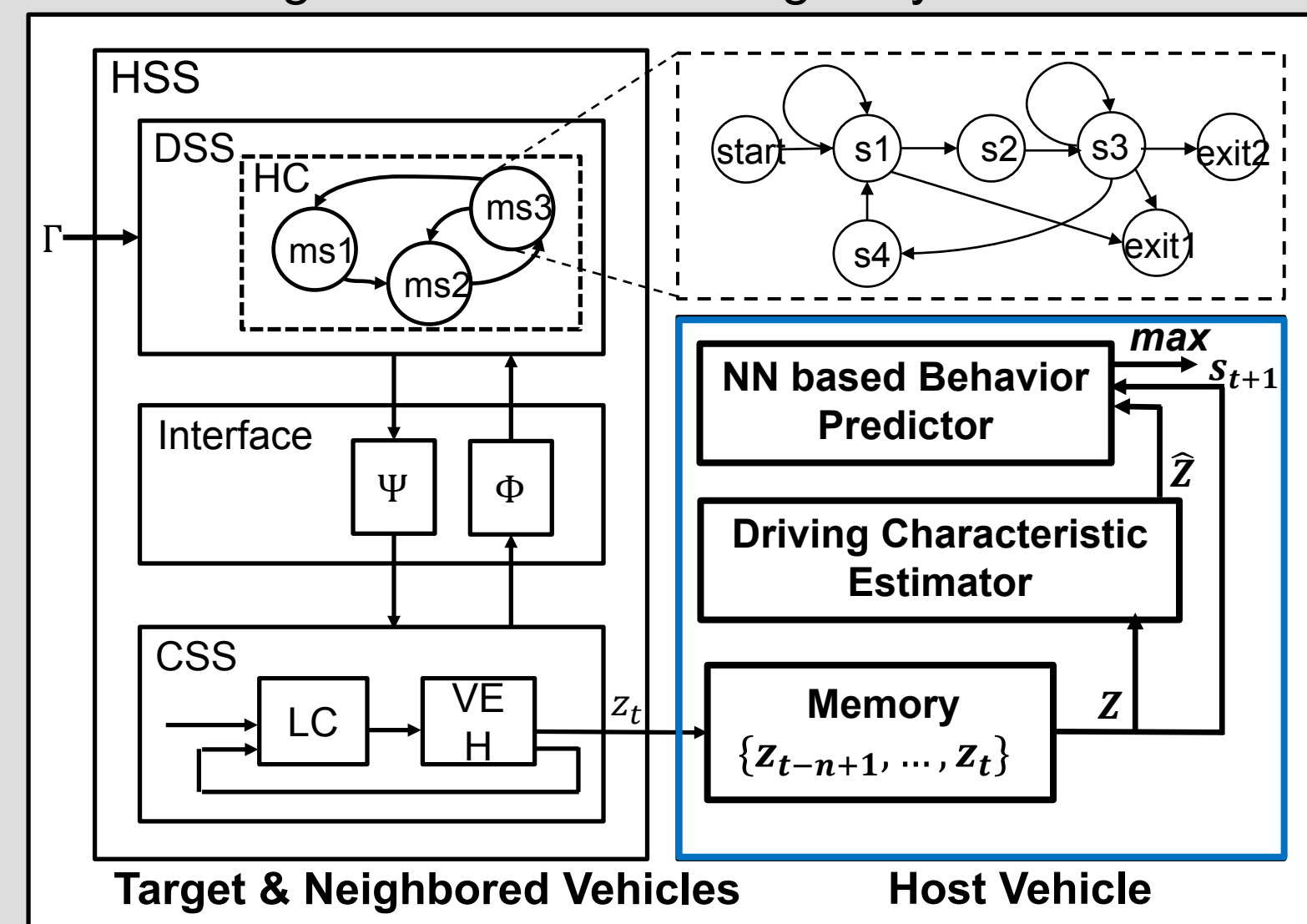
[ US I-80 Highway ]

[ Nagoya University ]  
(Higashiyama campus)

## Recognition and Prediction Framework for Autonomous Driving in Mixed-mode Traffic

### The Proposed Framework

- A framework is proposed for recognition of driving intentions and prediction of lane-change behavior on the highway.

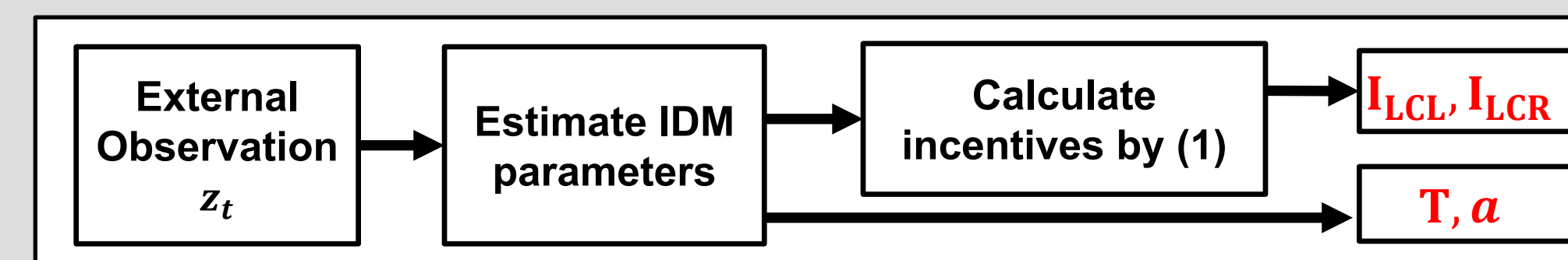


- The hybrid state system represent control systems of human-driven vehicles.
- Driving Characteristic is Uniquely determined.
- The driving characteristic estimation and behavior prediction methods are proposed.
- $z_t$ : Observation - Position, velocity, and acceleration of vehicles
- $Z$ : Set of observations
- $\hat{Z}$ : Set of estimated driving characteristics
- $s_{t+1}$ : Predicted the future lane-change behavior

### Determination of Driving Characteristic

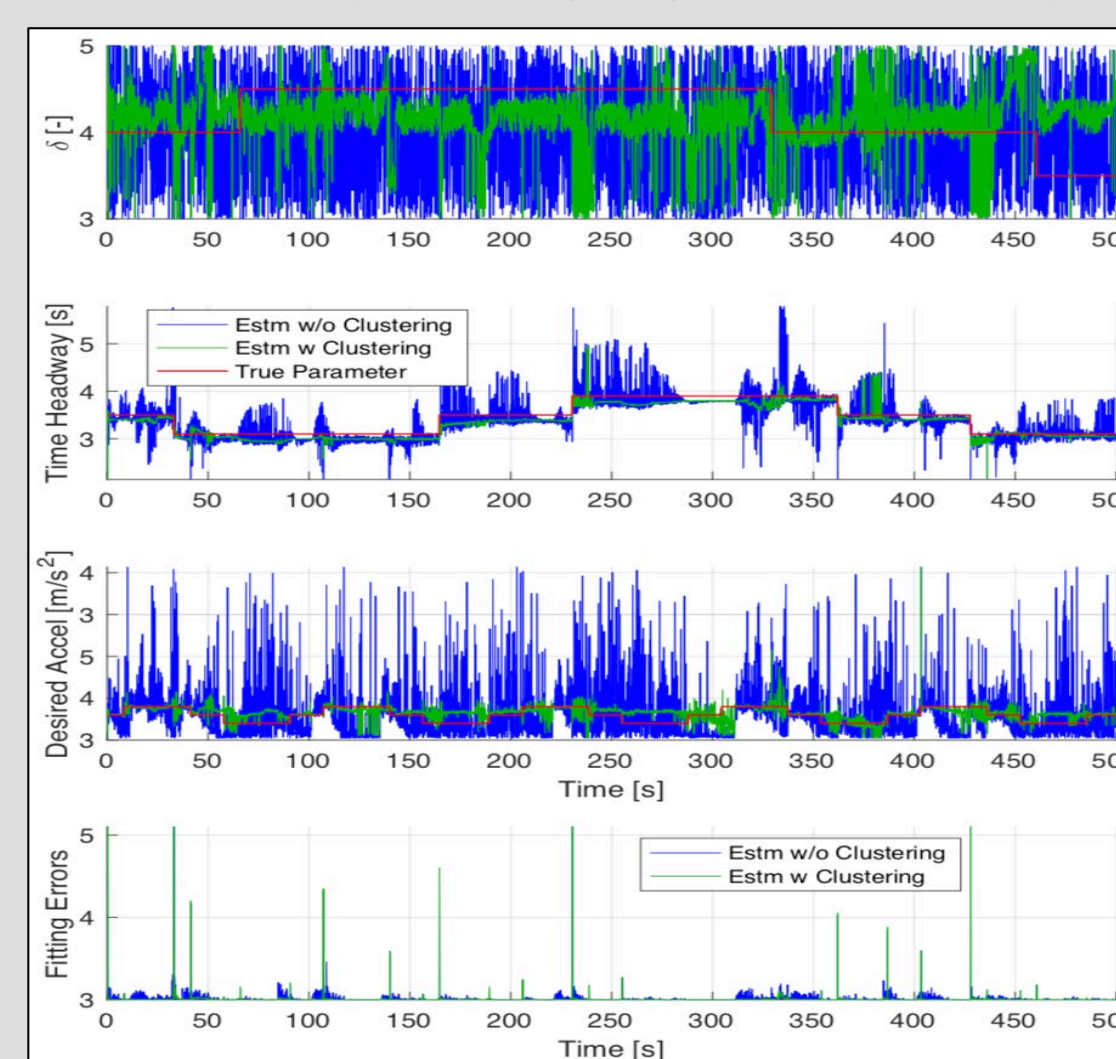
- General driving features are implemented to determine parameters of the driving characteristic (D-Char):  $\hat{z} = \{T, a, I_{LCL}, I_{LCR}\}$
- Parameters of IDM and MOBIL are independent to traffic conditions
- Four parameters are chosen from the Intelligent Driver Model (IDM) and the Minimize Overall Braking Induced by Lane change (MOBIL).

$$I_a = \tilde{a}_T - a_T + 0.35(\tilde{a}_n - a_n + \tilde{a}_0 - a_0), d = \{LCL, LCR\} \quad (1)$$



### Estimation of Driving Characteristic

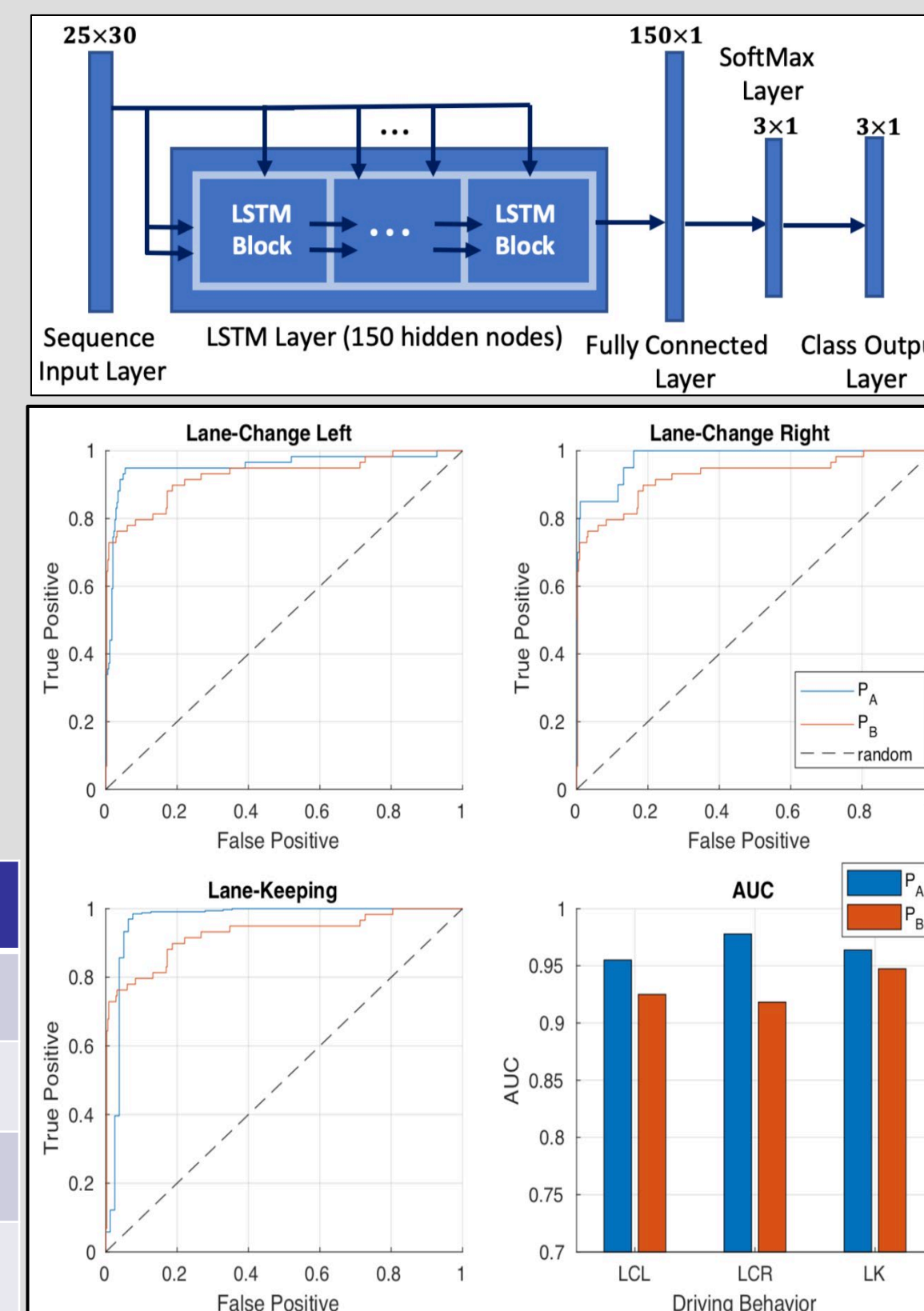
- Genetic Algorithm (GA) with evolving Takagi-Sugeno (eTS) online clustering method is implemented.
- The eTS is implemented to update constraints of parameters of IDM.
- Parameter estimation performance comparison via GA w/ and w/o eTS.
- Car-following is simulated by using IDM with **arbitrary set parameters**.
- Fitting errors (MAE) of w/ and w/o eTS estimations are 0.0015 and 0.0032.
- **Estimation GA w/ eTS outperforms the one w/o eTS.**



### Neural Network based Behavior Predictor

- Five layered (single LSTM layer) neural-network is proposed.
- 238, 80, and 1312 sets for LCL, LCR, and LK were extracted from NGSIM US-80 highway data.
- 75% and 25% of data are used for training and validation.
- Prediction performances comparison between training the predictor by using observations (DNN2) and observations + estimated D-Char (DNN1) to show **worthiness of D-Char implementation**.

	DNN1	LCL	LCR	LK	DNN2	LCL	LCR	LK
Accu.	0.953	0.980	0.963	0.963	0.835	0.943	0.842	
Preci.	0.794	0.875	0.984	0.984	0.462	0.400	0.975	
Recall	0.915	0.700	0.969	0.969	0.830	0.300	0.820	
F1	0.850	0.777	0.977	0.977	0.835	0.943	0.862	

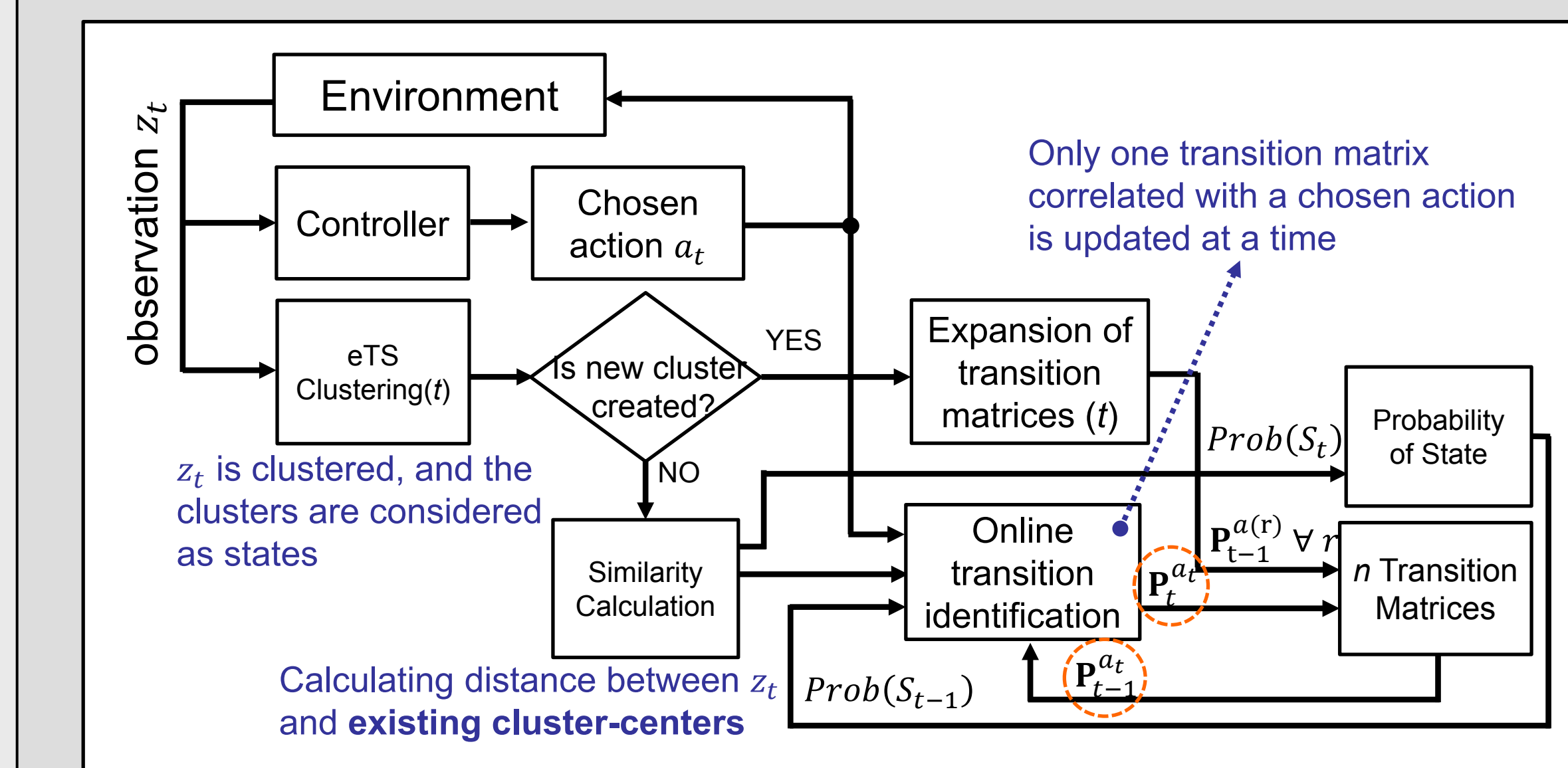


## Evolving Control System Design

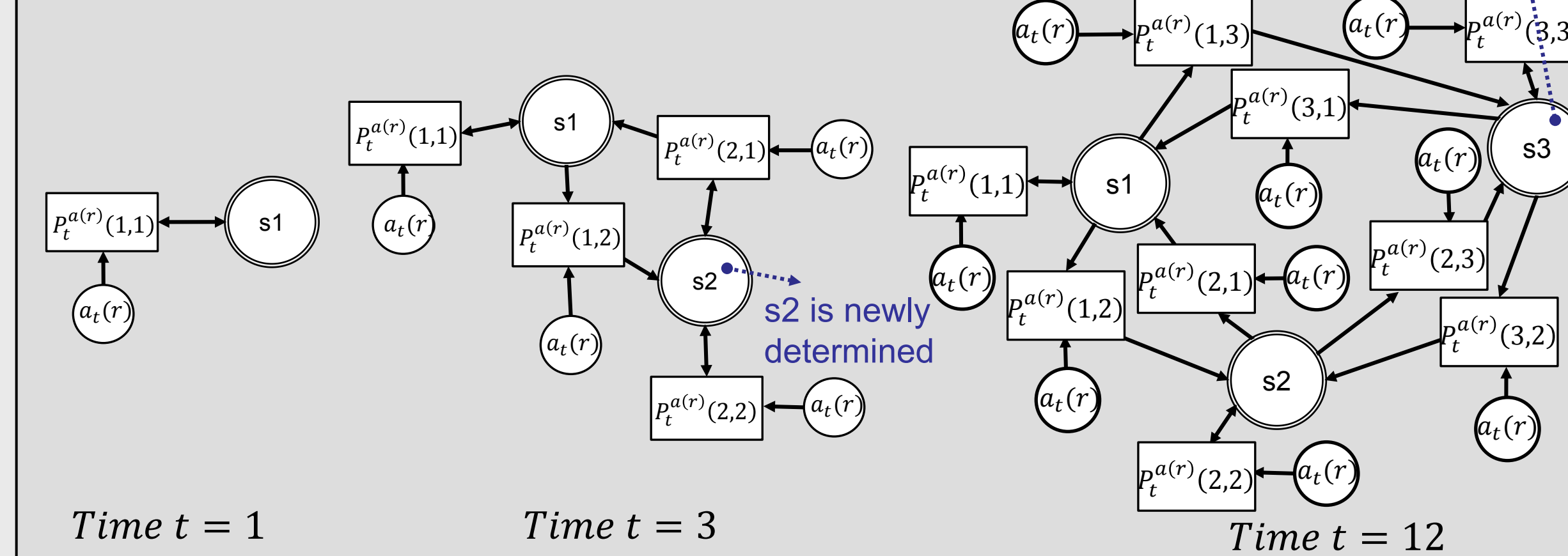
### An evolving method for autonomous driving vehicle control

- An evolving Finite State Machine is proposed to provide probability distributions of future states for controllers to choose an optimal action.
- The rule-based and supervised-learning controllers cannot react under unexpected situations due to no existing rules.
- Reinforcement-learning controller can learn an optimal action under unexpected situations, but its performance is susceptible to a given reward function.

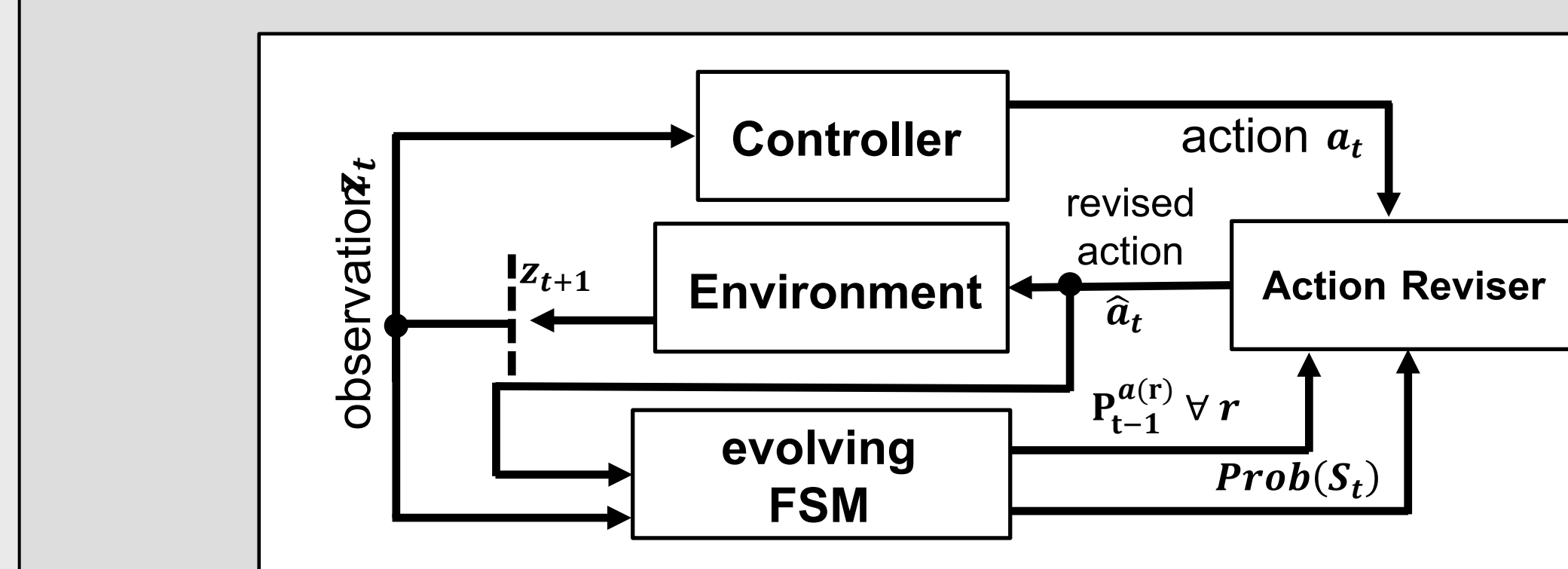
### An evolving Finite State Machine (e-FSM) Framework



- States are determined as needed.
- An online clustering method, evolving Takagi-Sugeno (eTS) is implemented to determine states that represent unique situations.
- State-set at time  $t$  is defined as  $S_t = \{s_t(1), s_t(2), \dots, s_t(n_t)\}$  where  $n_t$  is the total number of states determined by time  $t$  (vary).
- Discrete action-set is implemented  $A_d = \{a(1), a(2), \dots, a(q)\}$  where  $q$  is the total number of actions (fixed).
- State-Transitions are identified and expanded by a stochastic method.
- Example of evolving sequence:



### An Online Evolving Framework for Controller



## References

For a list of references, please contact the PIs using the contact information on the left.