Detecting State Changes of Indoor Everyday Objects using Wi-Fi Channel State Information

Sep. 12th, 2017

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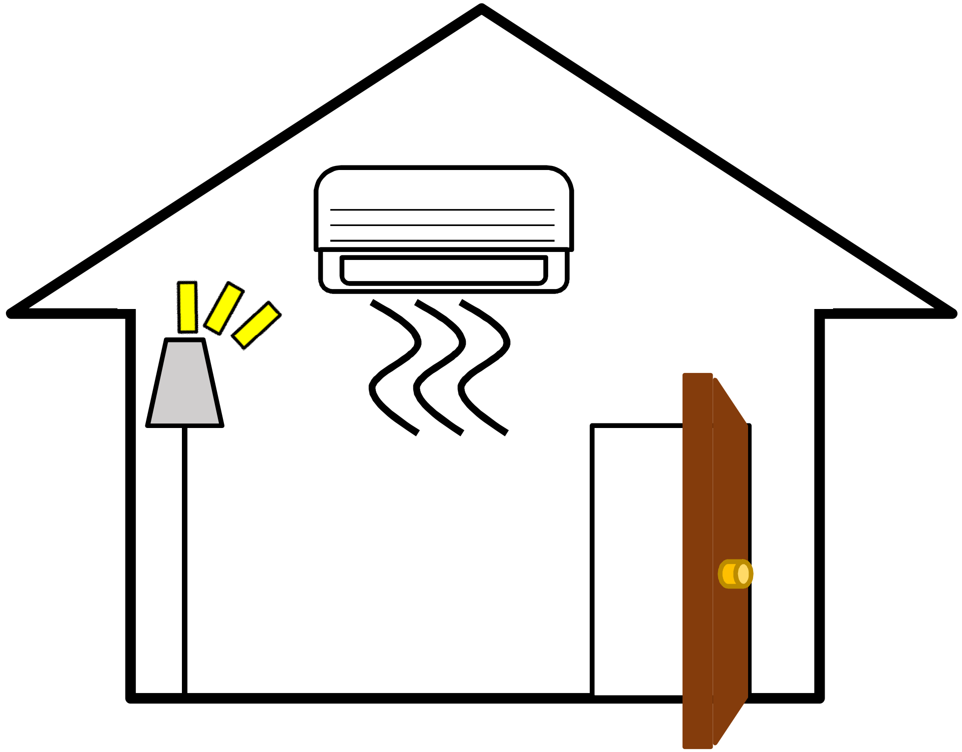
Background

Detecting State Changes of Indoor Everyday Objects
(e.g. Open/Close door or window)

Application

- Home automation (adaptive HVAC control)
- Monitoring an independently living elderly person



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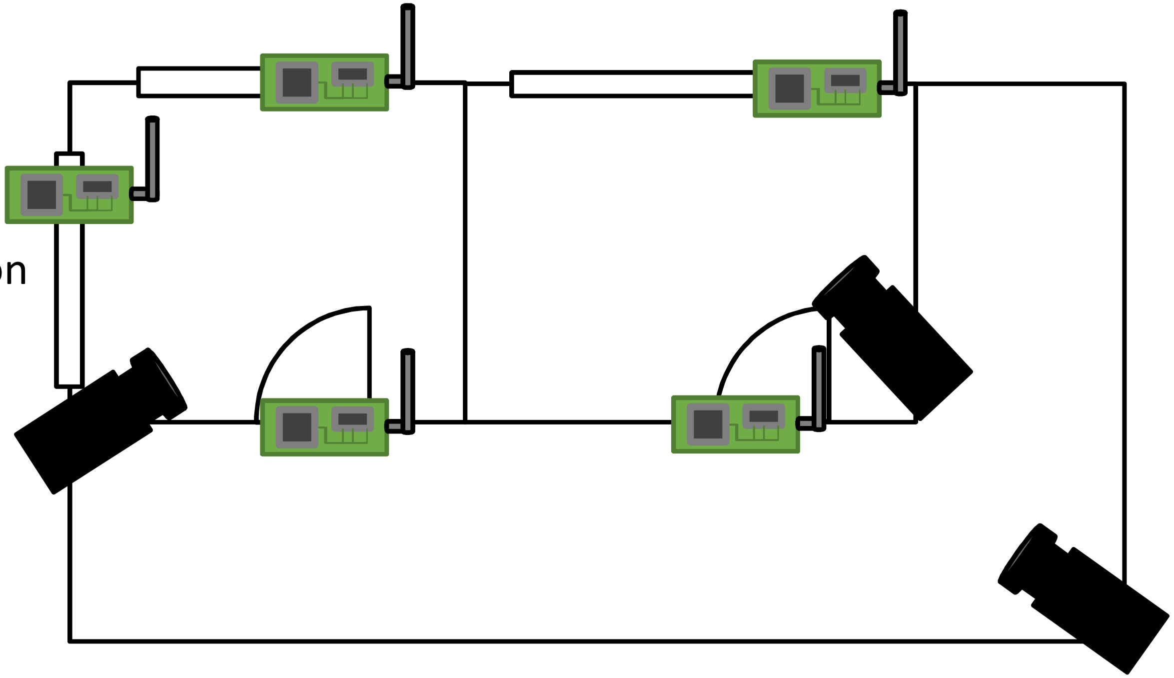

—Usual Method—

- ✓ Attach sensors to each object
  - ◆ High deployment and maintenance costs
- ✓ Use camera images
  - ◆ Invasion of privacy

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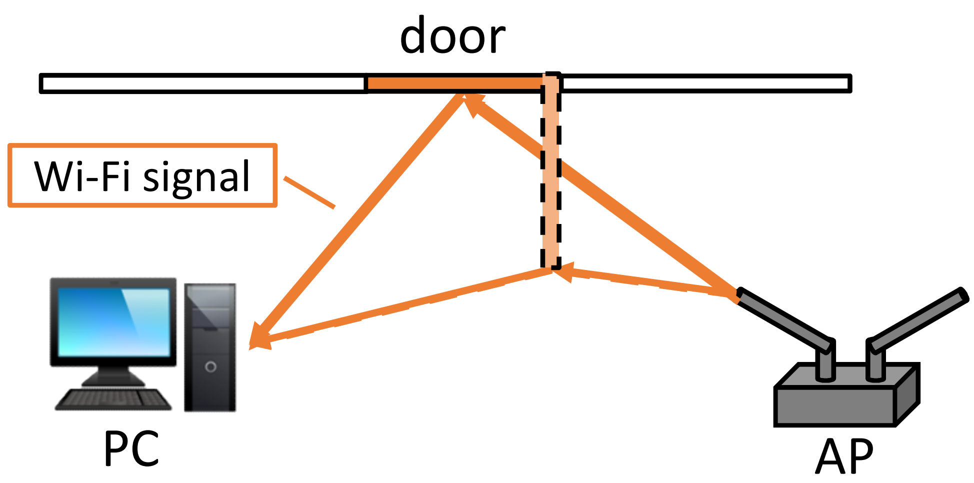

<u>Wi-Fi signal</u>

- The path of Wi-Fi signal is greatly affected by state changes of the indoor everyday objects.
- Wi-Fi communications are used widely in indoor environments.

Purpose

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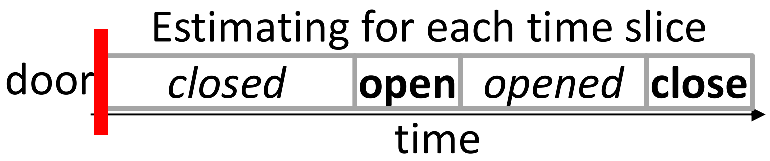
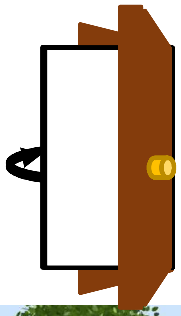
- Estimate states of indoor everyday objects from <u>propagation information of Wi-Fi signals</u> based on machine learning techniques.





- **open**
- **close**

} **event**

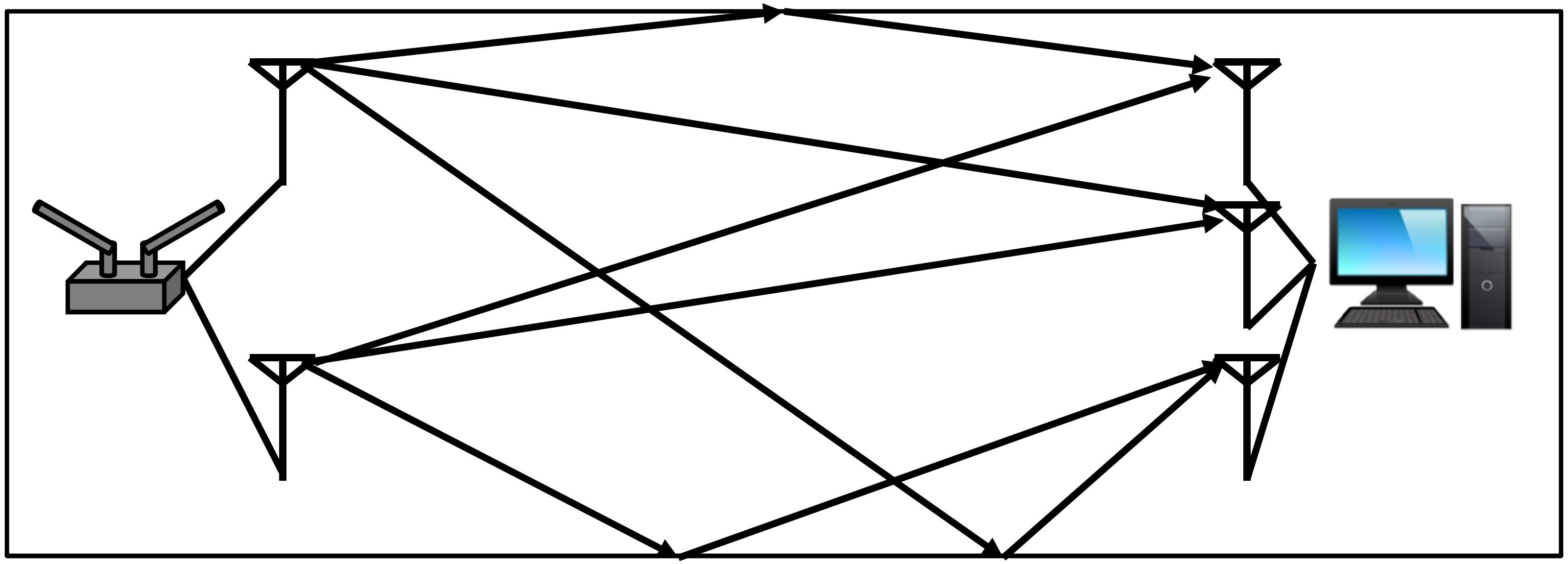
- *opened*
- *closed*

} *state*

Propagation Information

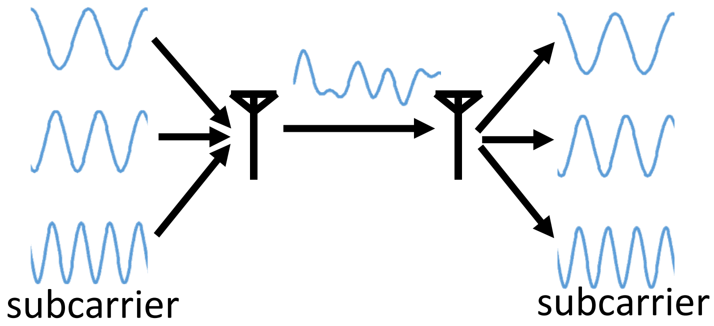
- Channel State Information (CSI)
  - including the various effects such as reflection and path loss of signals
  - high dimensional complex matrix

Channel State Information

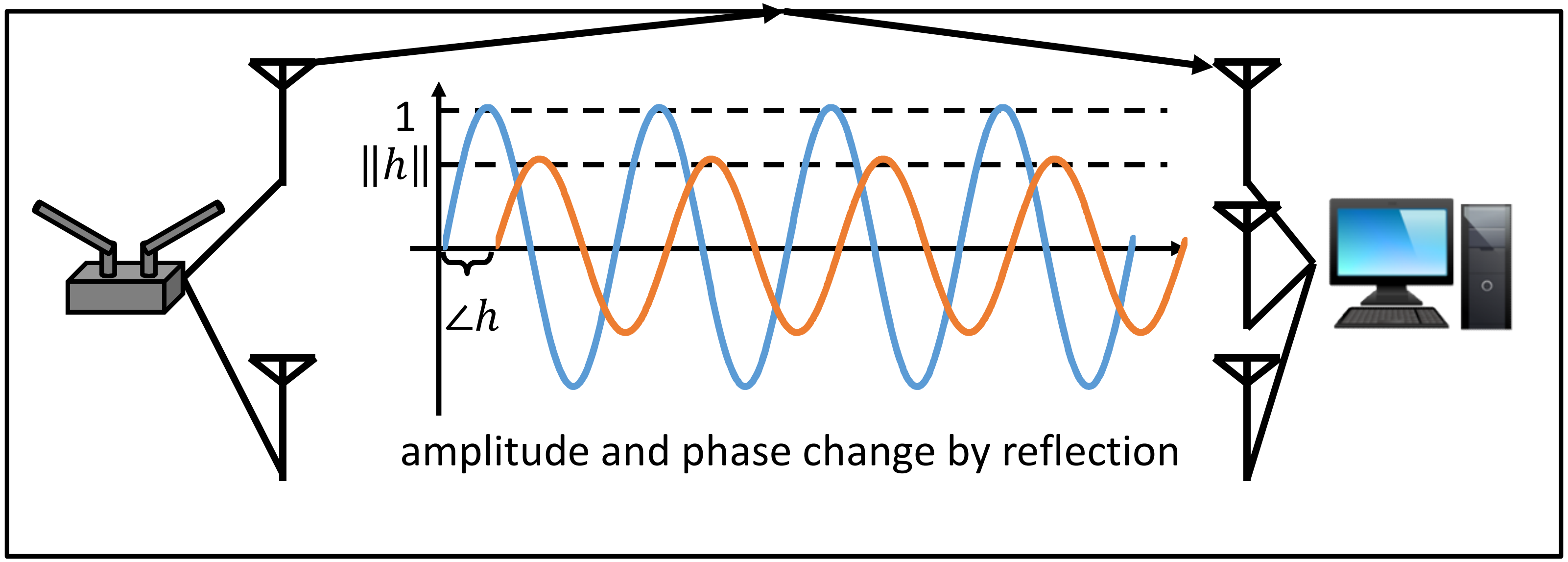


- MIMO (Multiple Input Multiple Output)
  using multiple antennas for transmitting and receiving signals

- OFDM (Orthogonal Frequency Division Multiplexing)
  using subcarriers whose frequencies are different from each other

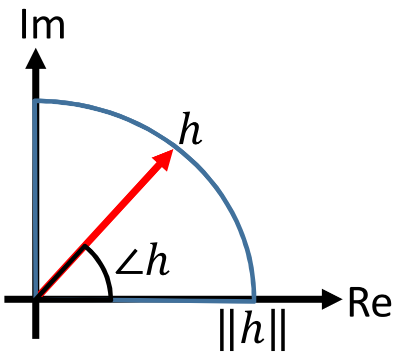


Channel State Information

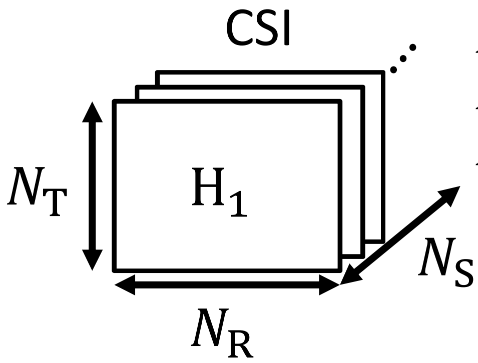


h: complex value
$\|h\|$: amplitude change
$\angle h$: phase change

$$h = \|h\| e^{j\angle h}$$



h is obtained at each antenna and subcarrier



N_{T}: # of transmit antennas
N_{R}: # of receive antennas
N_{S}: # of subcarriers

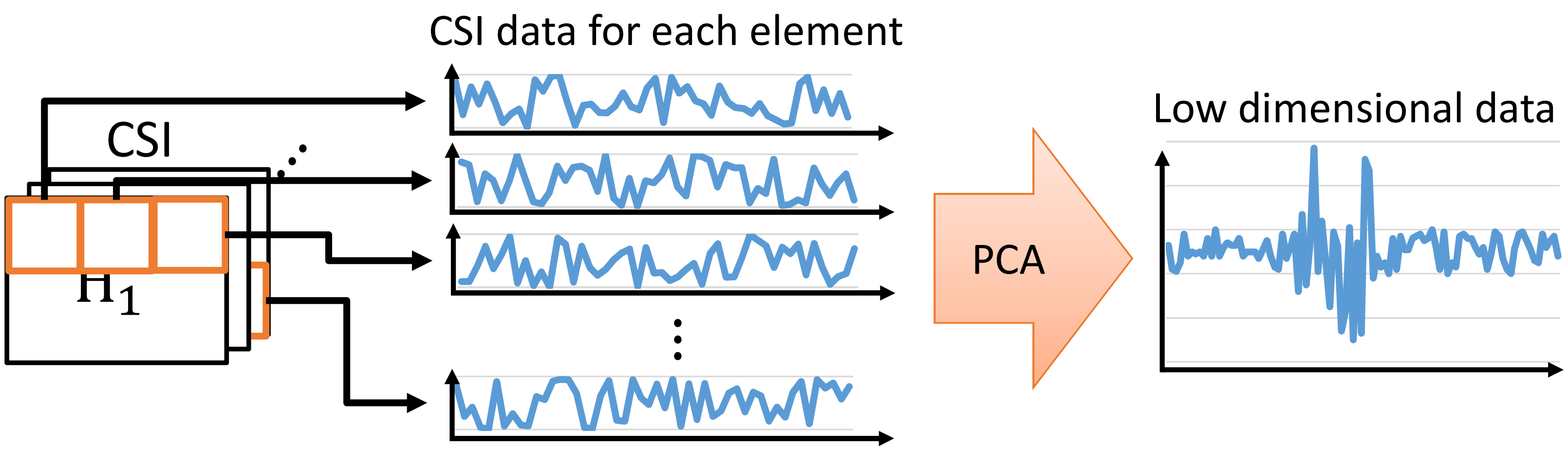
Problem

- Wi-Fi signals are very noisy ⇨ Noise reduction
- CSI is complex information including reflection ⇨ Difficult to design feature

Existing approach

Noise reduction: Aggregate CSI data and reduce the dimensionality using PCA

Feature design: Researchers design manually (waveform, frequency of data)



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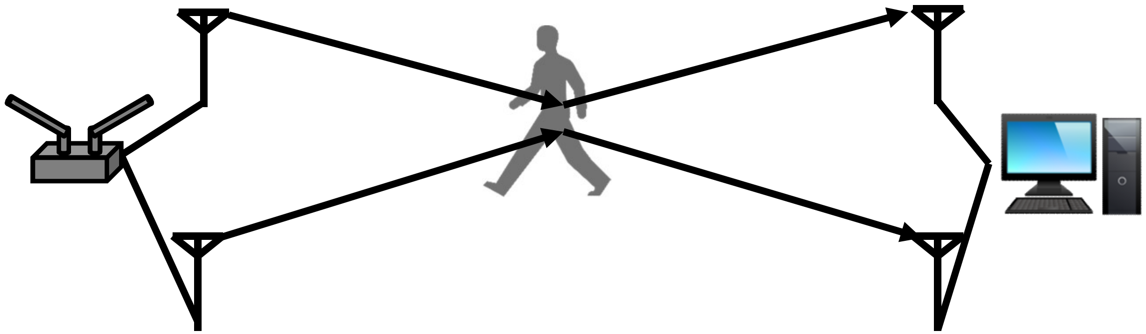
Activity of one person
(e.g. walking, falling)



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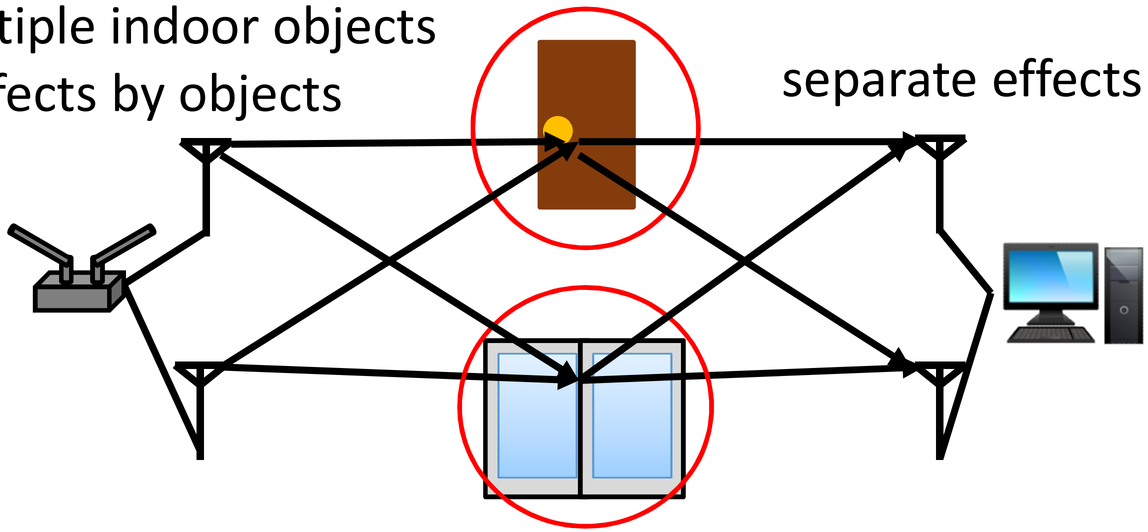
States of multiple indoor objects

Mixed effects by objects

separate effects caused by objects



Approach

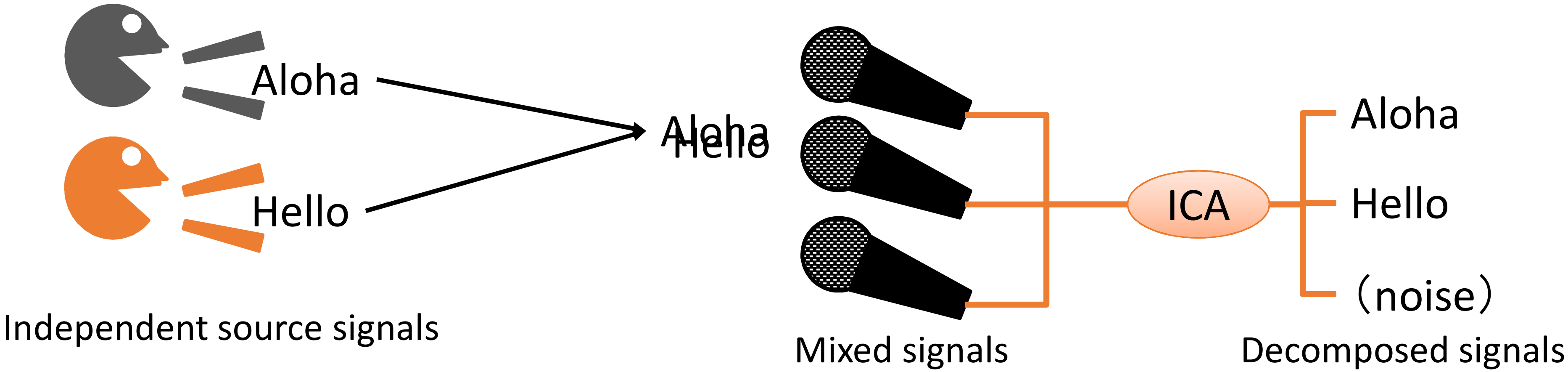
- Noise reduction & Separation: Independent Component Analysis (ICA)

- Feature design: extracted automatically using Convolutional Neural Network (CNN)

Approach

- Noise reduction & Separation: Independent Component Analysis (ICA)

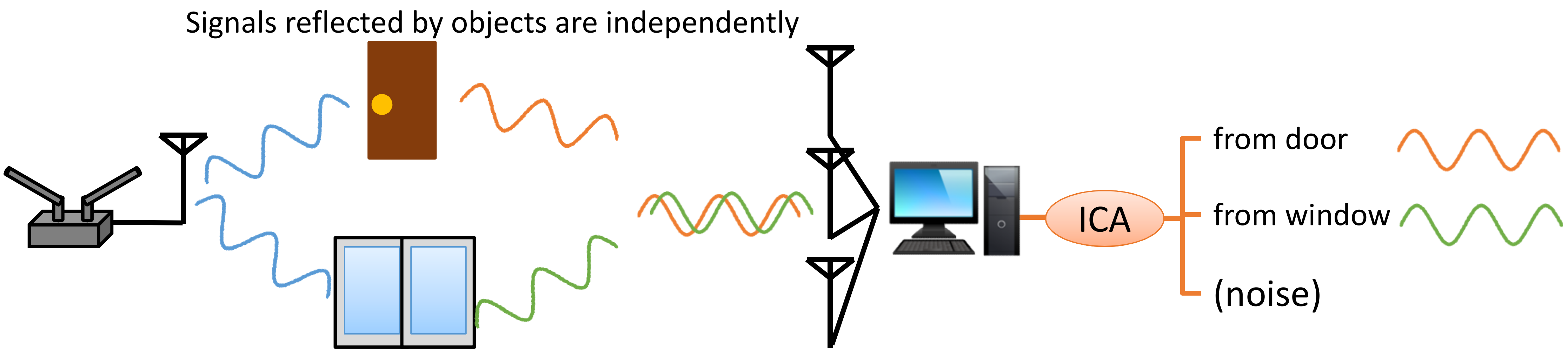
Blind source separation



- Feature design: extracted automatically using Convolutional Neural Network (CNN)

Approach

- Noise reduction & Separation: Independent Component Analysis (ICA)

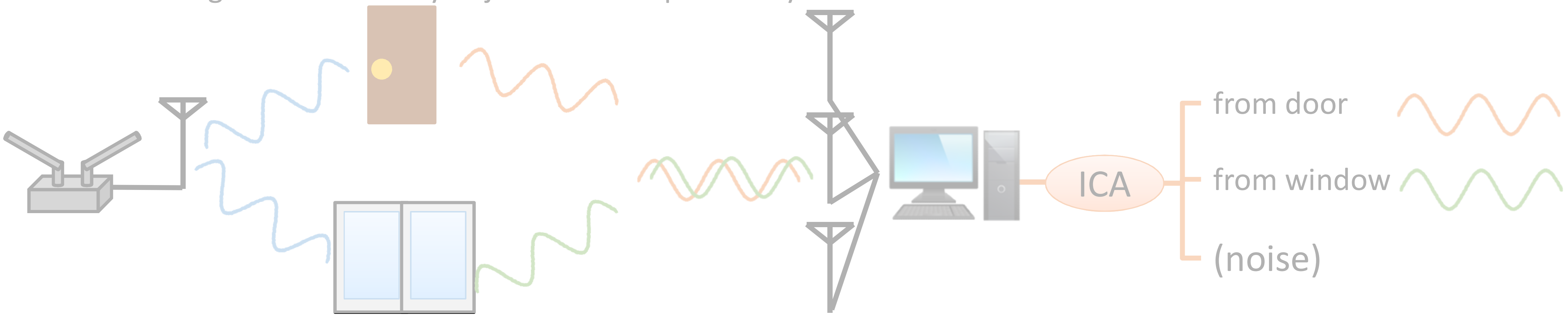


- Feature design: extracted automatically using Convolutional Neural Network (CNN)

Approach

- Noise reduction & Separation: Independent Component Analysis (ICA)

  Signals reflected by objects are independently



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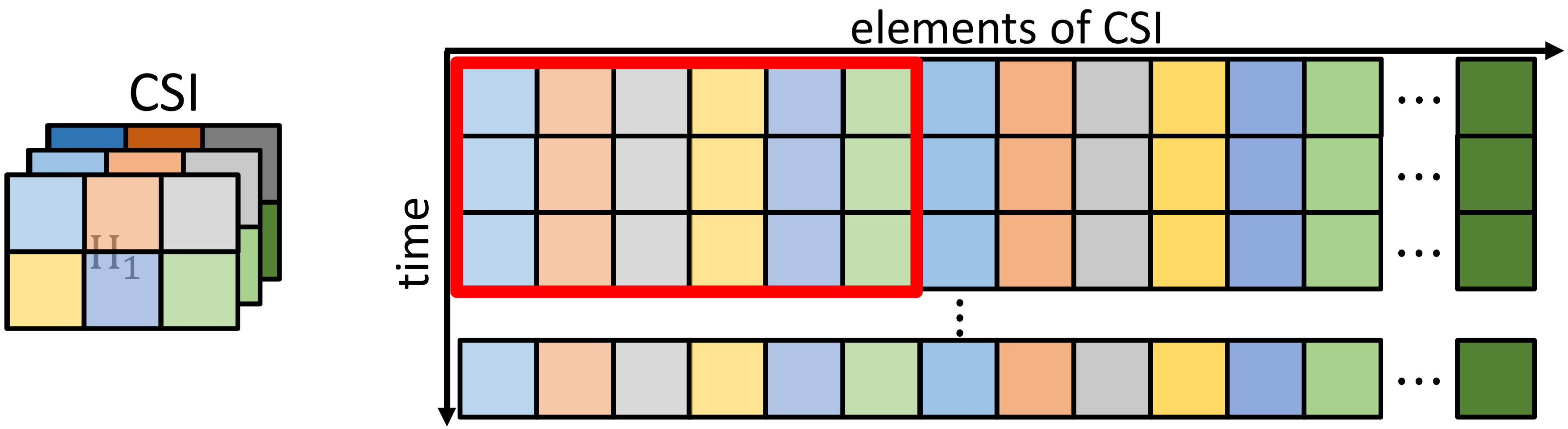
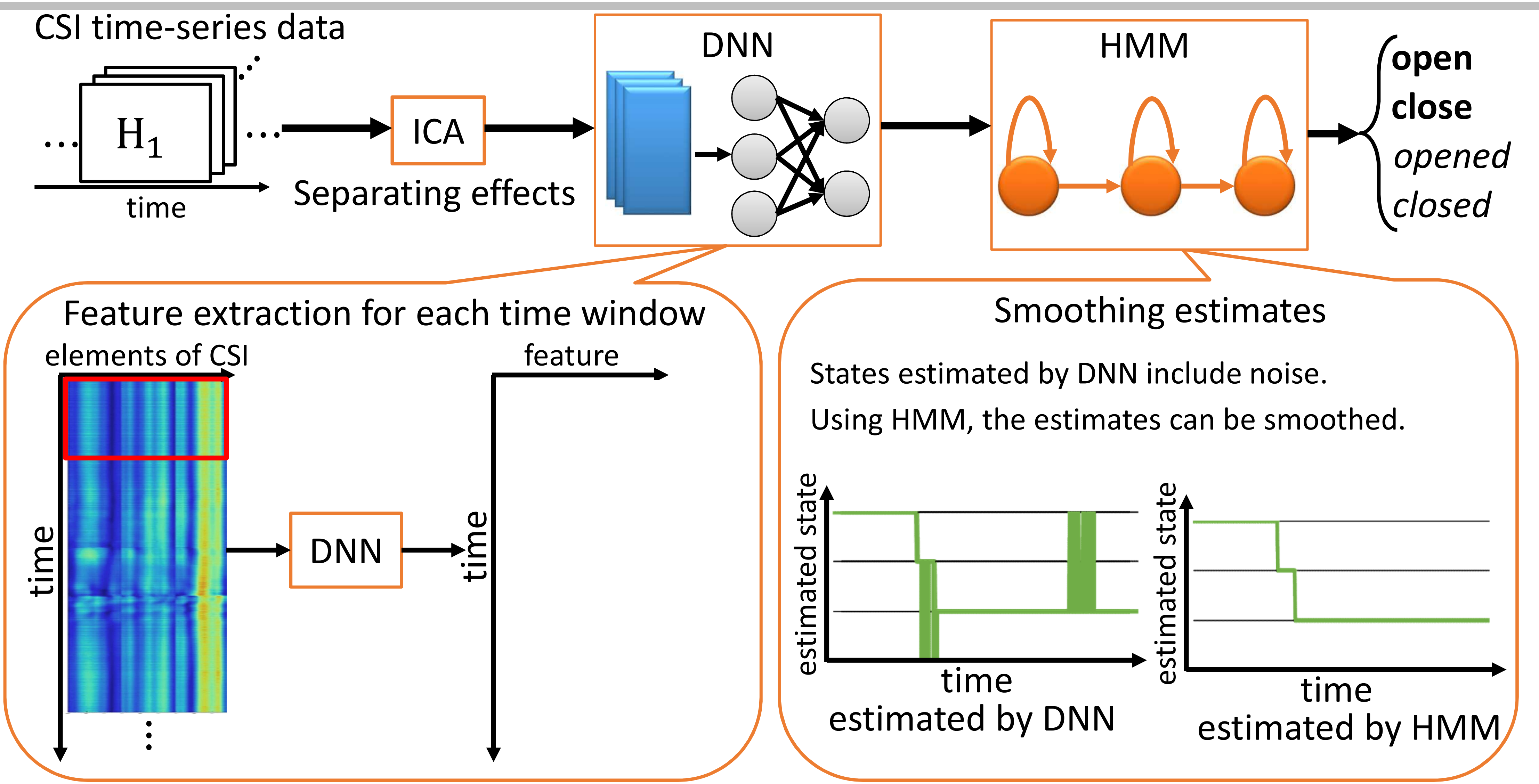


Overview of Proposed Method



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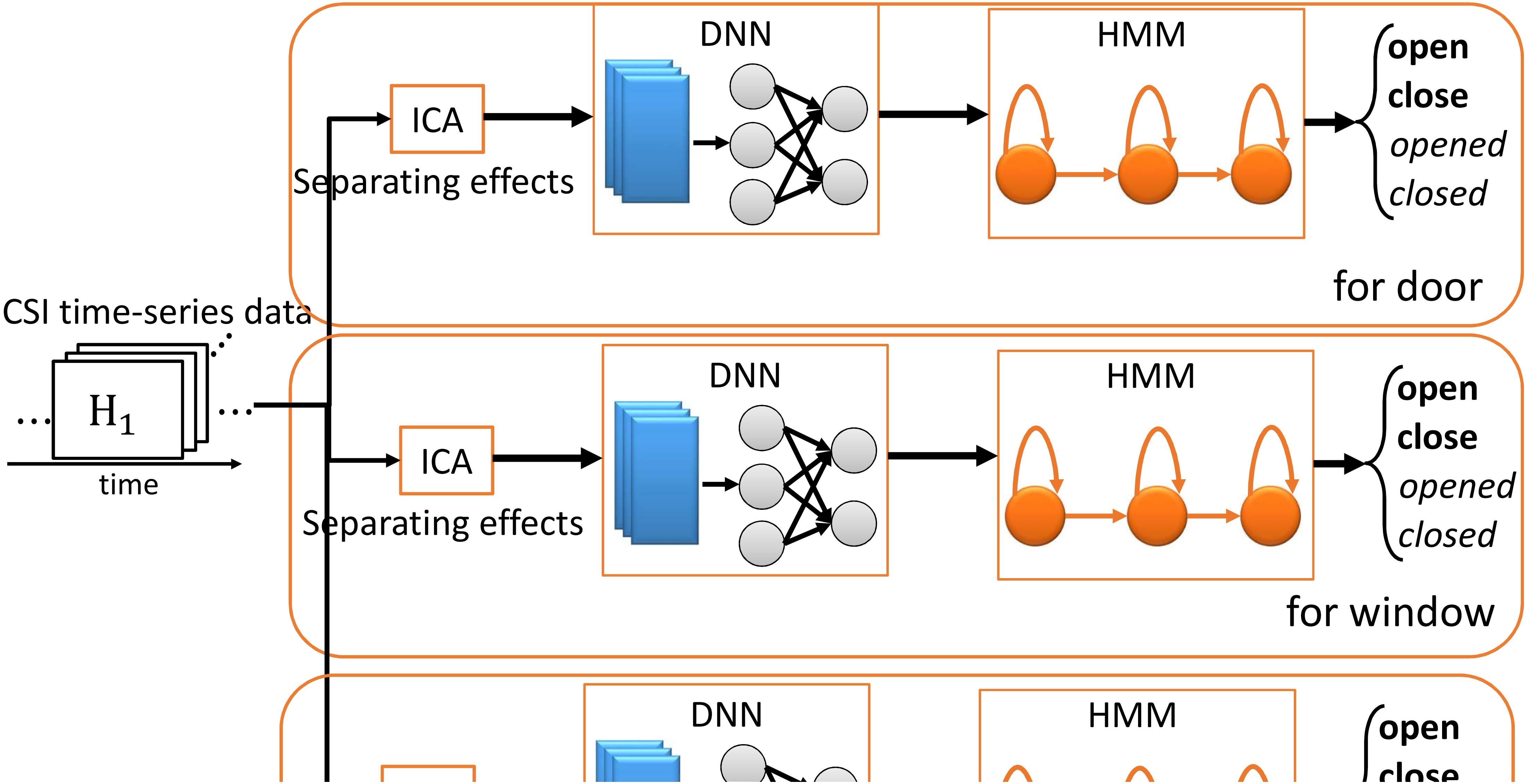
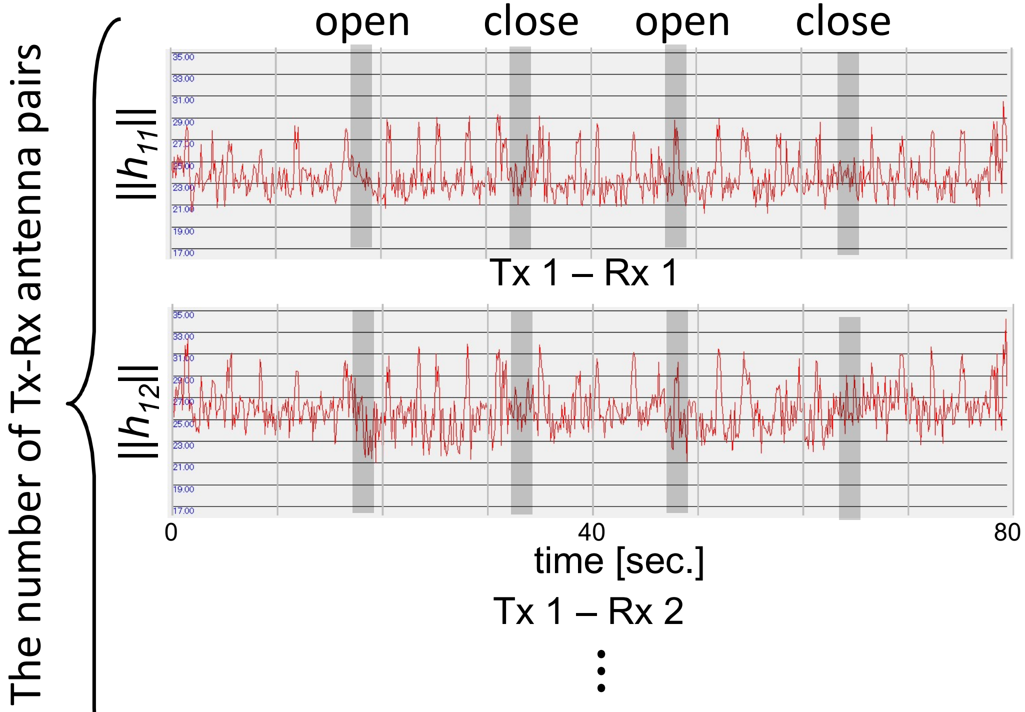


ICA

ICA decomposes amplitude and phase of CSI for each subcarrier.

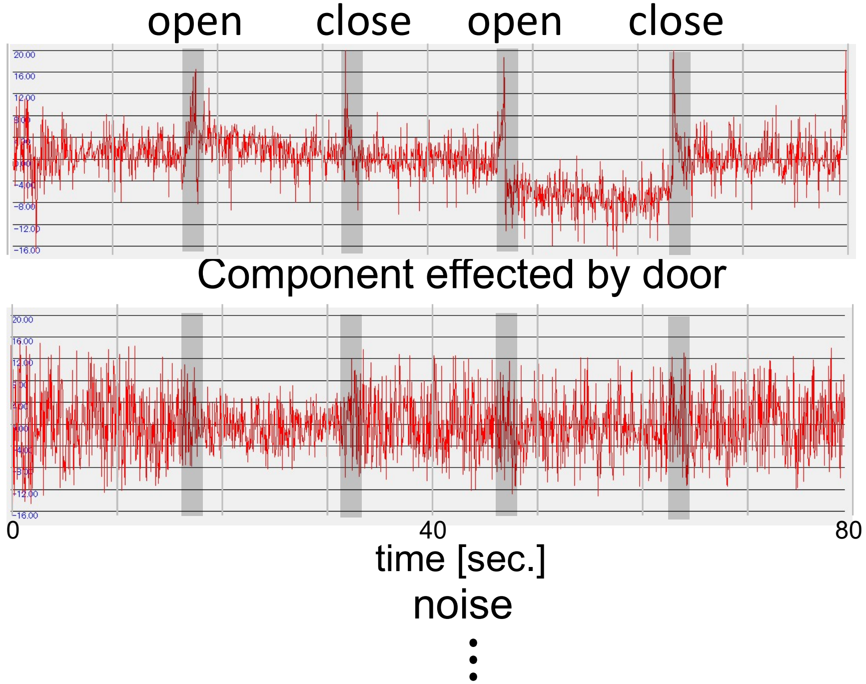
Amplitude of CSI when door open/close



Can not find apparent changes in the signals when events occurred

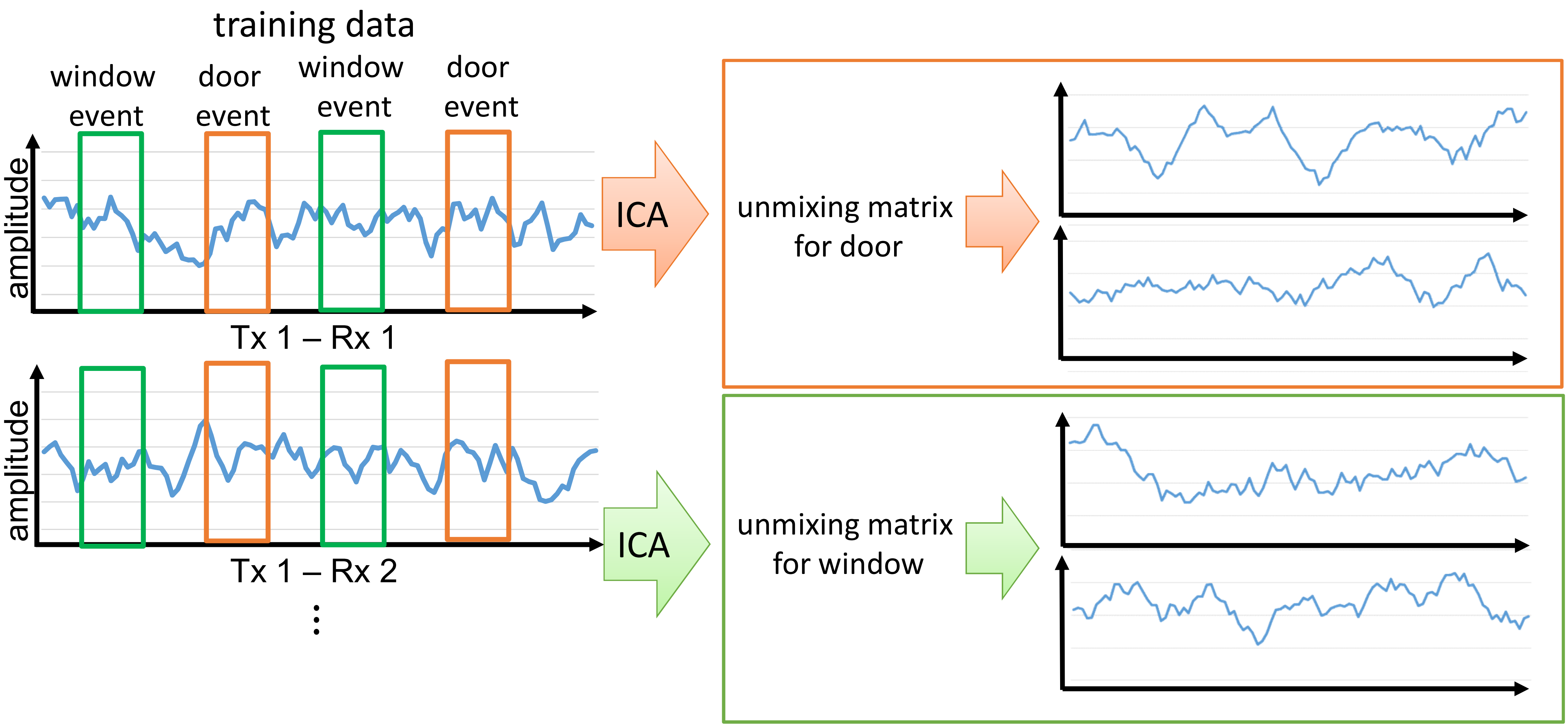
ICA

Decomposed signals

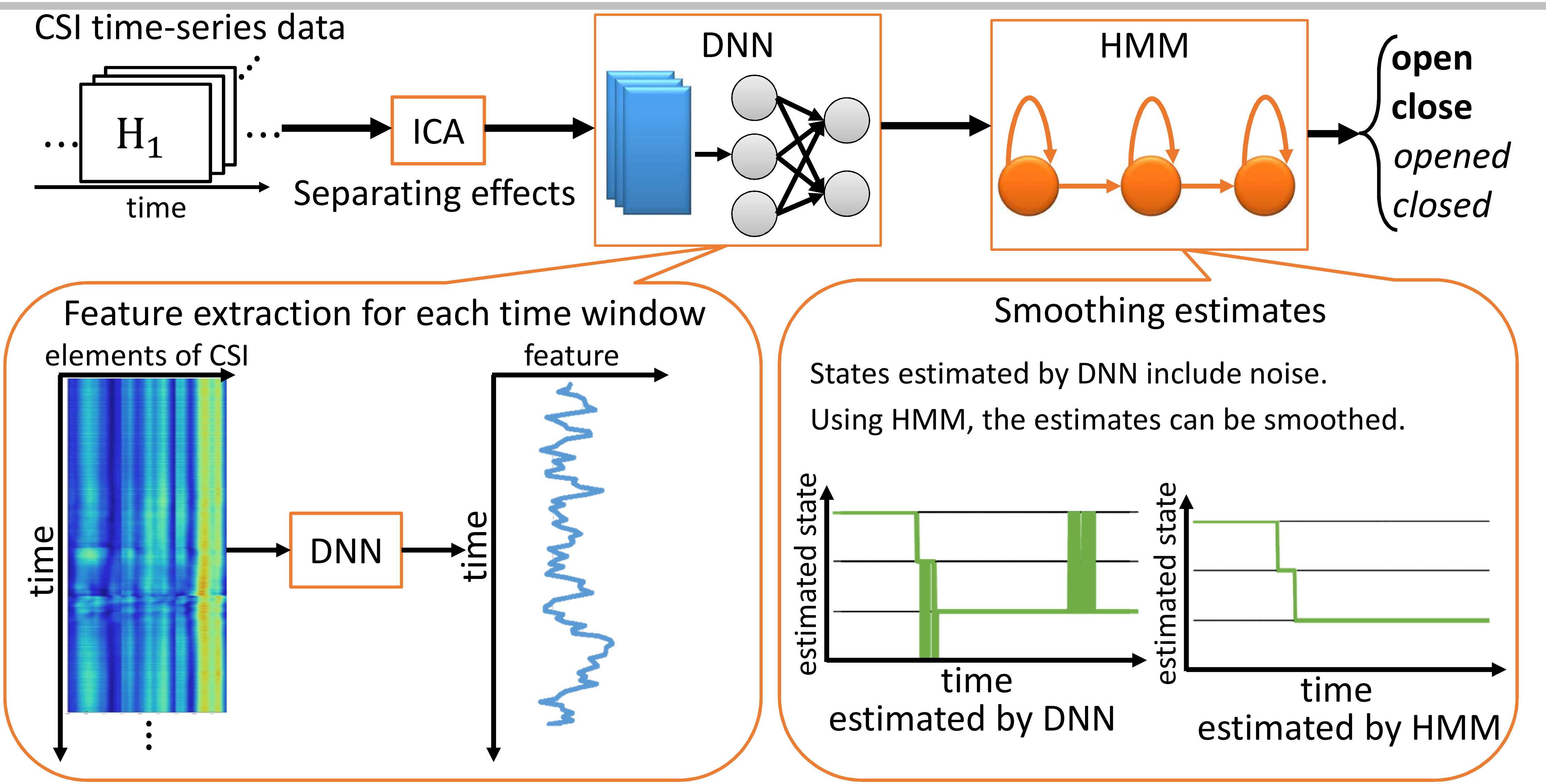


First component captures signal changes when events occurred

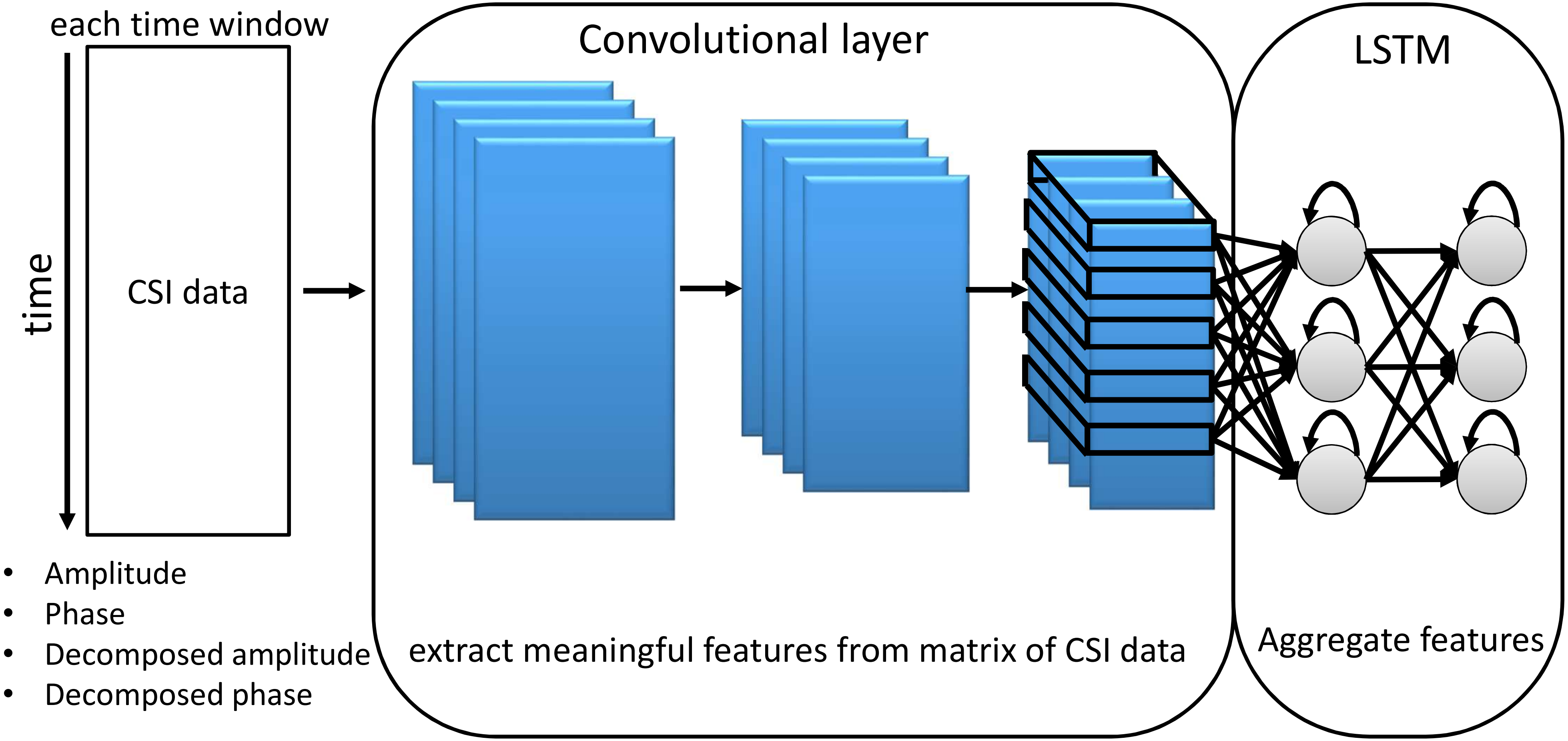
ICA


training data
window event
door event
window event
door event
amplitude
Tx 1 – Rx 1
amplitude
Tx 1 – Rx 2
⋮
ICA
ICA
unmixing matrix for door
unmixing matrix for window

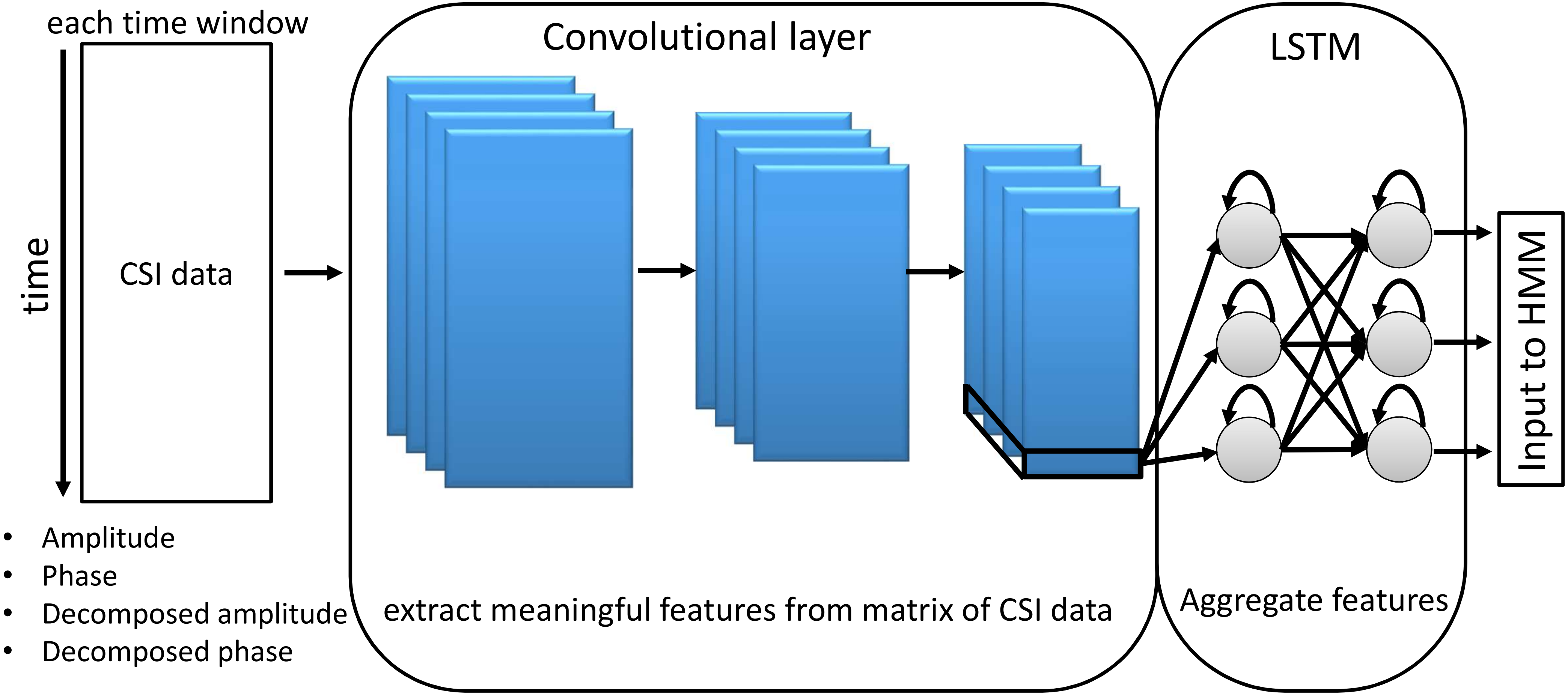
Overview of Proposed Method



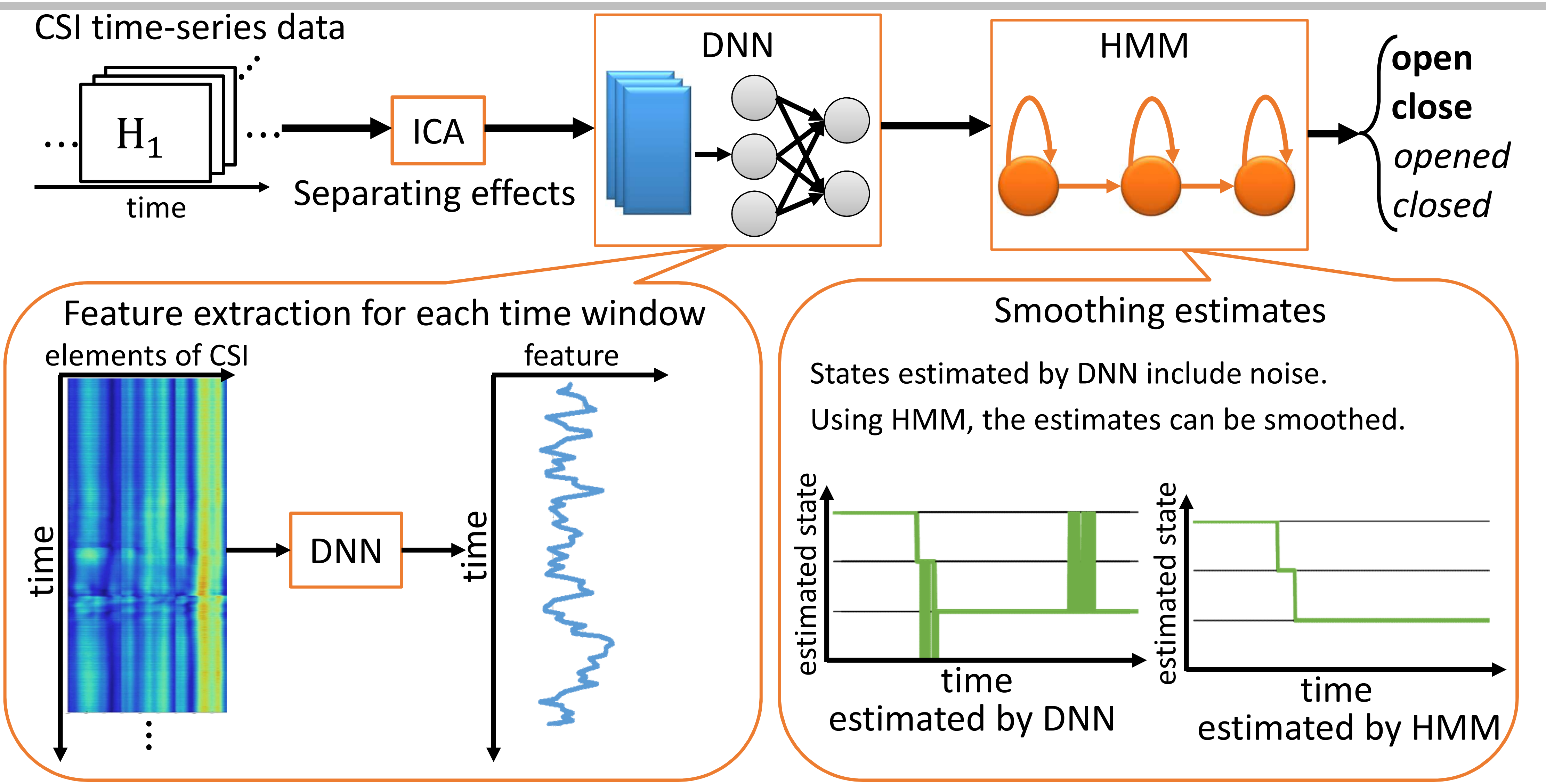
DNN


each time window
time
CSI data
• Amplitude
• Phase
• Decomposed amplitude
• Decomposed phase
Convolutional layer
extract meaningful features from matrix of CSI data
LSTM
Aggregate features

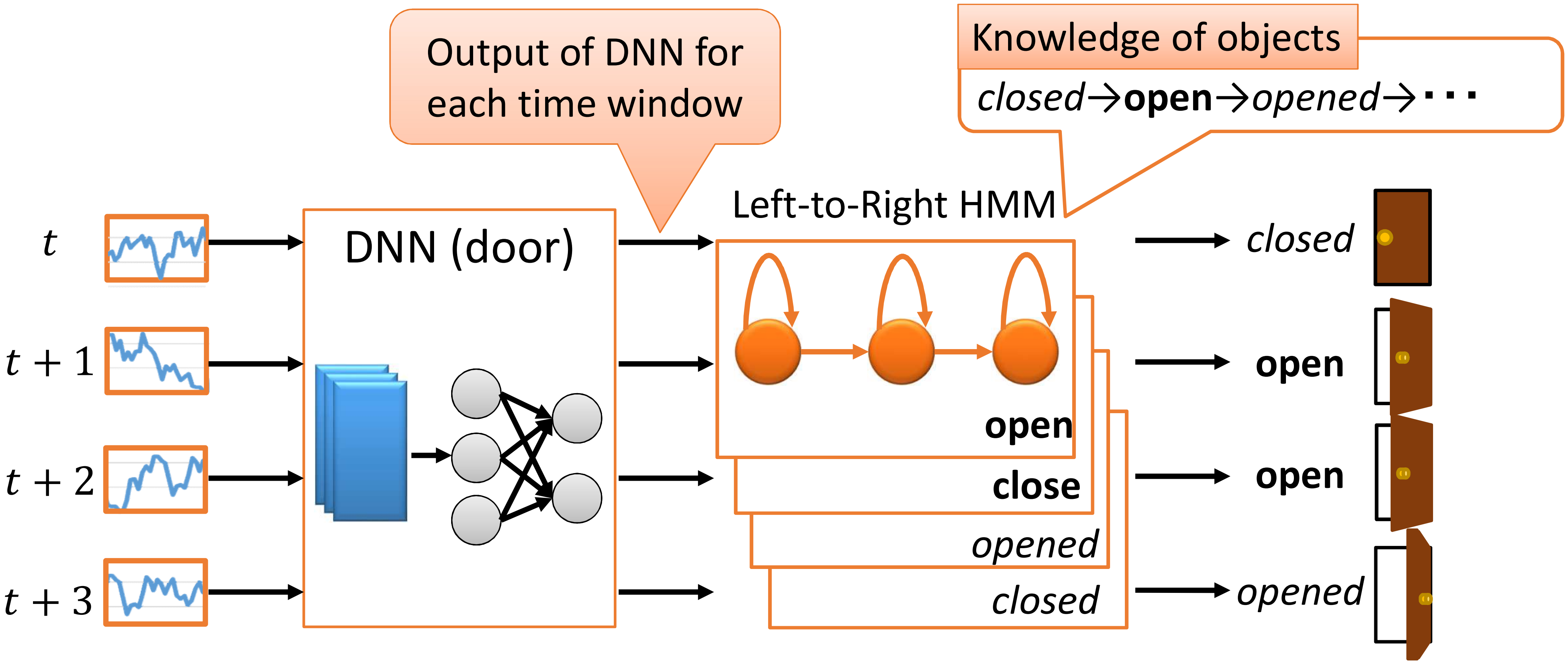
DNN


each time window
time
CSI data
Convolutional layer
extract meaningful features from matrix of CSI data
LSTM
Aggregate features
Input to HMM
• Amplitude
• Phase
• Decomposed amplitude
• Decomposed phase

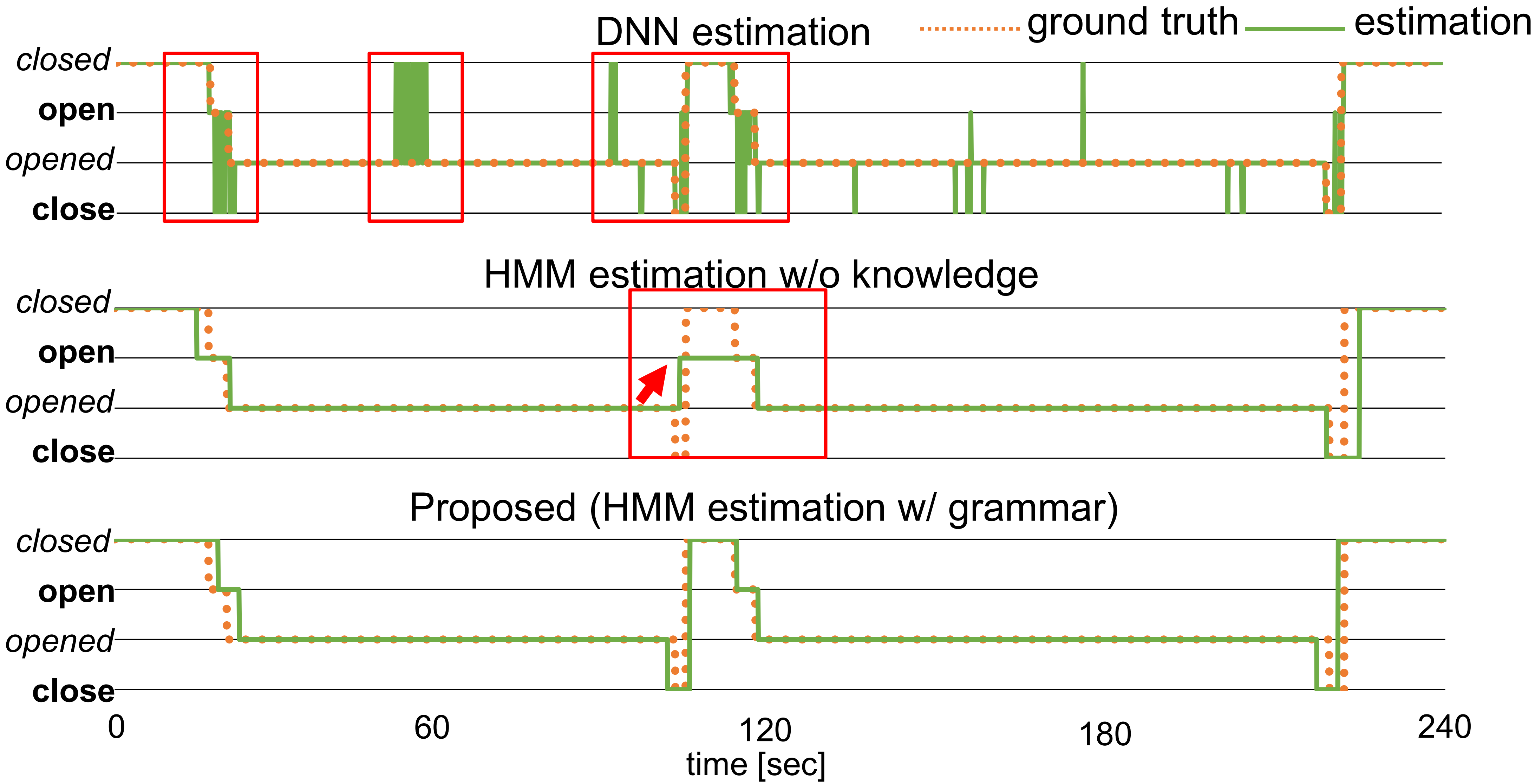
Overview of Proposed Method



HMM

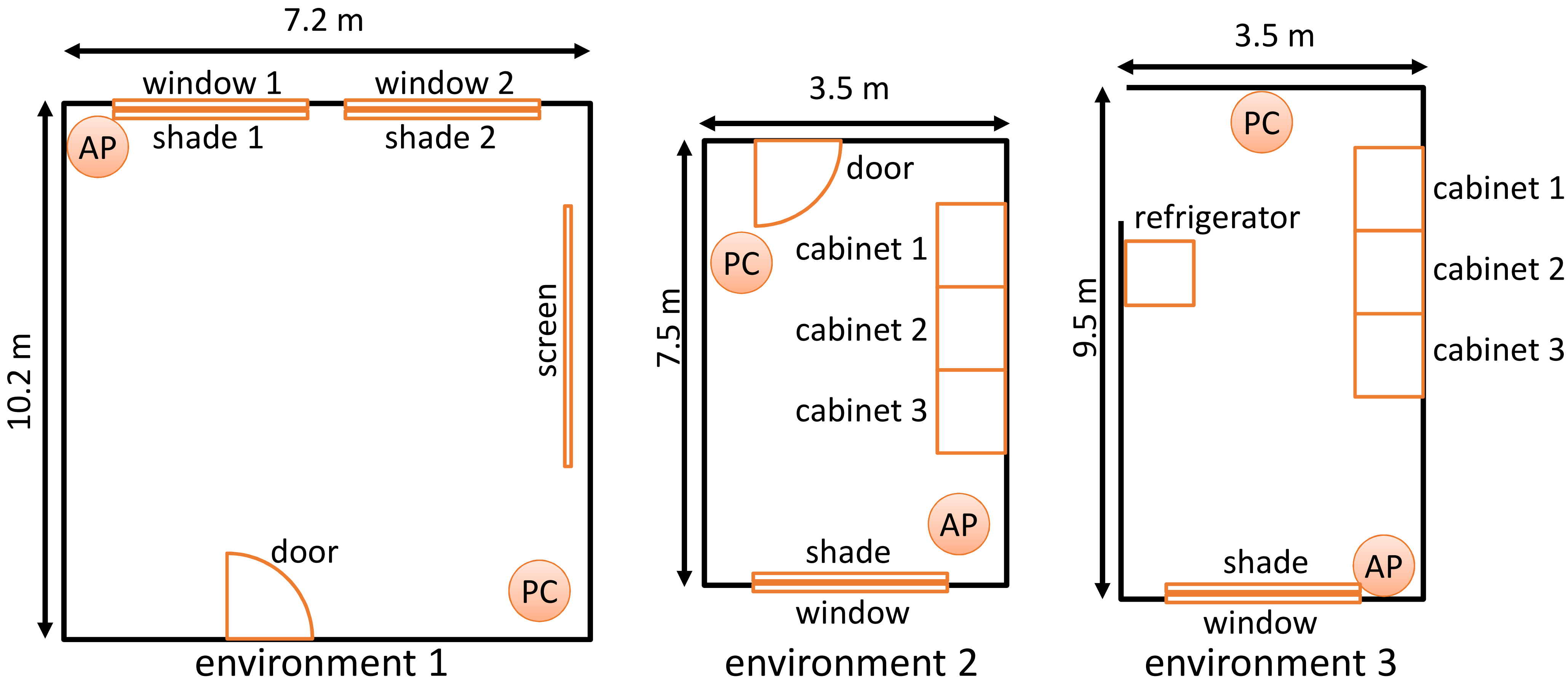

Output of DNN for each time window
Knowledge of objects
closed→open→opened→···
Left-to-Right HMM
t
t + 1
t + 2
t + 3
DNN (door)
open
close
opened
closed
closed
open
open
opened

HMM


DNN estimation
ground truth
estimation
closed
open
opened
close
HMM estimation w/o knowledge
closed
open
opened
close
Proposed (HMM estimation w/ grammar)
closed
open
opened
close
0
60
120
180
240
time [sec]

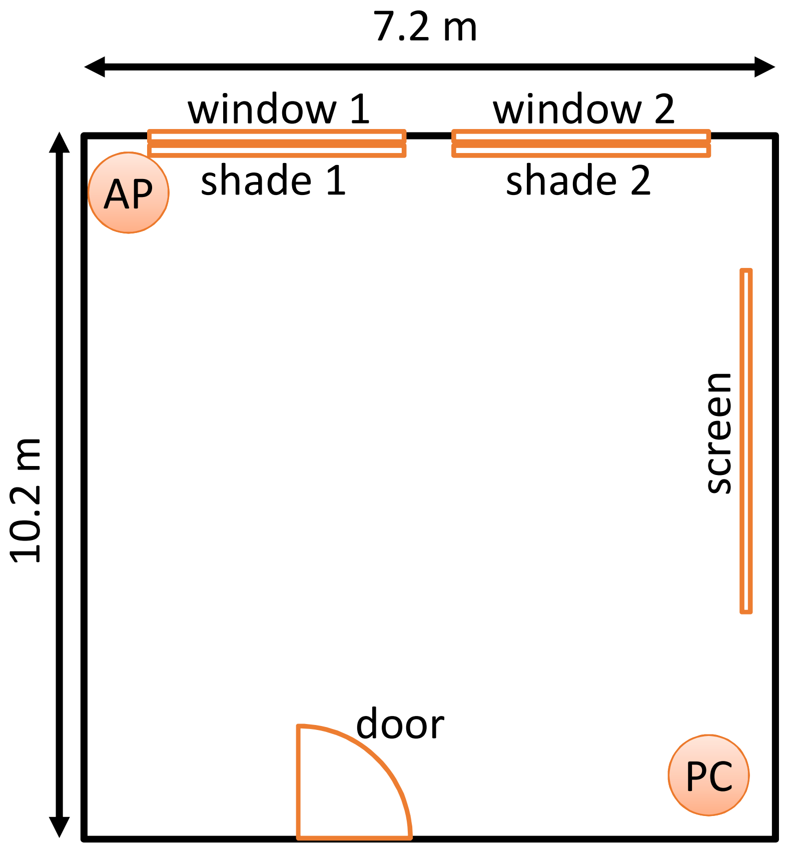
Evaluation dataset

- Each event of object occurred in an arbitrary order × 150 sessions (train: 90%, test: 10%)
- Dimension of CSI: $N_\mathrm{T} \times N_\mathrm{R} \times N_\mathrm{S} = 2 \times 3 \times 30$, CSI was obtained at the rate of 1000Hz.
- We estimate states of objects every 0.1 sec.



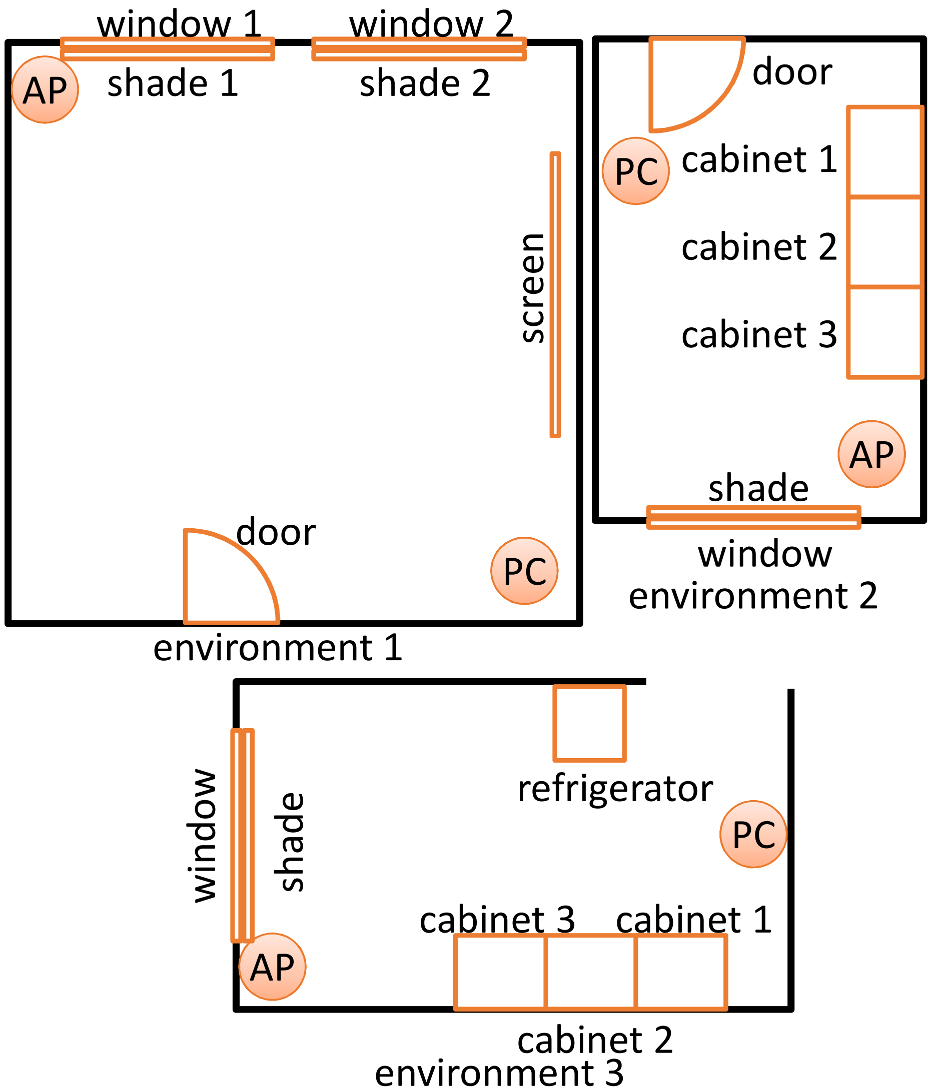
Evaluation dataset

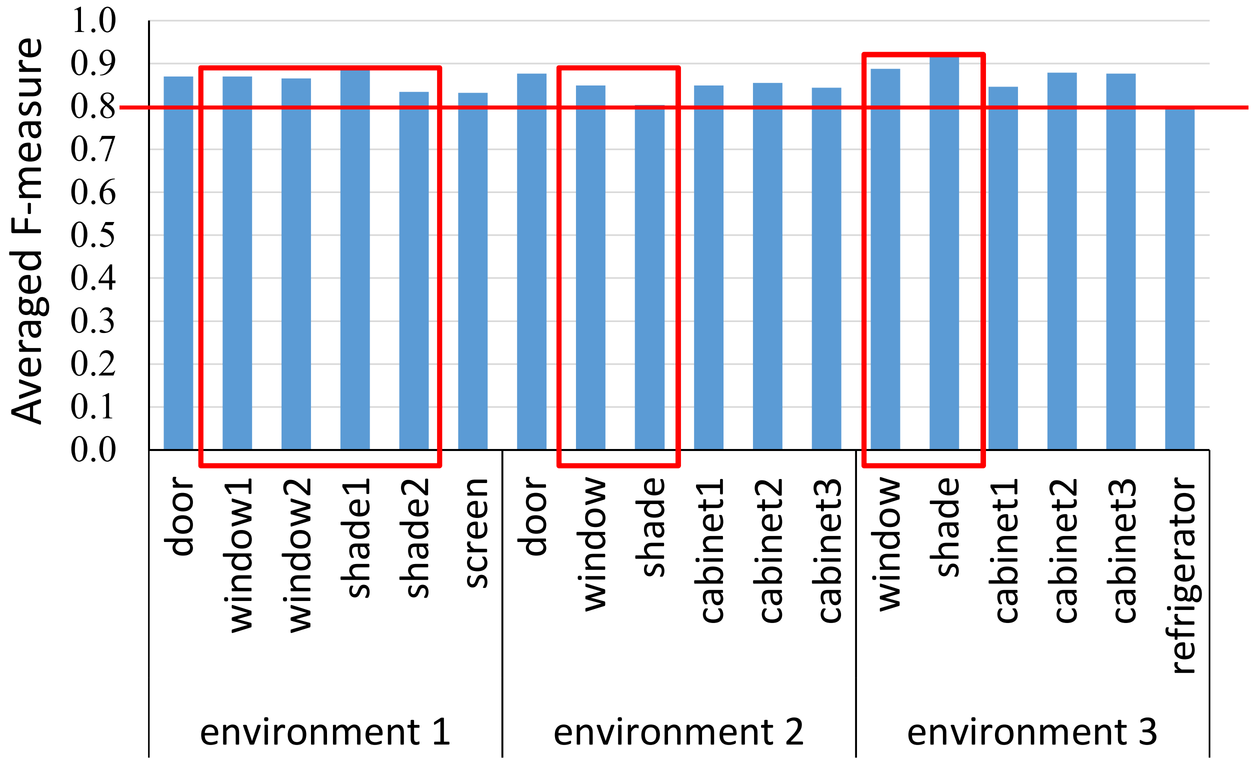
- Each event of object occurred in an
- Dimension of CSI: $N_{\mathrm{T}} \times N_{\mathrm{R}} \times N_{\mathrm{S}} =$
- We estimate states of objects every



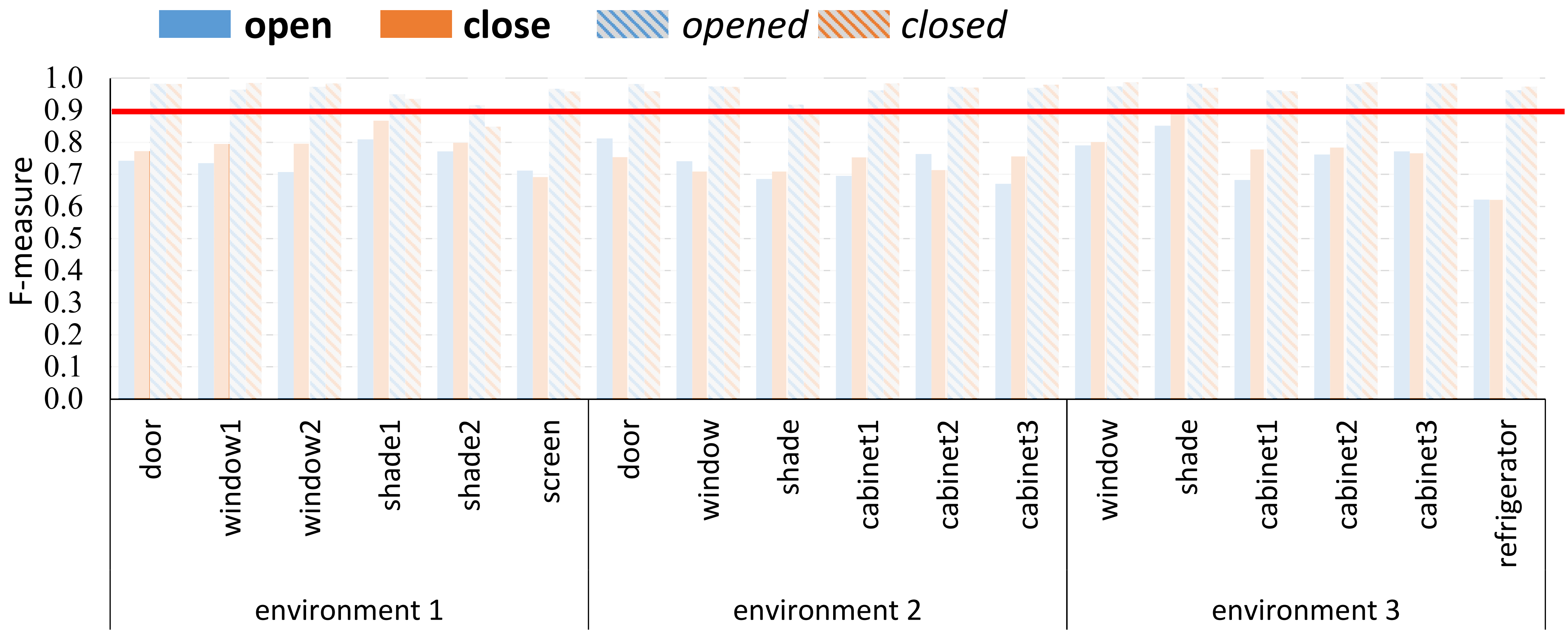
environment 1

Result for each objects





Result for each event/ *state*



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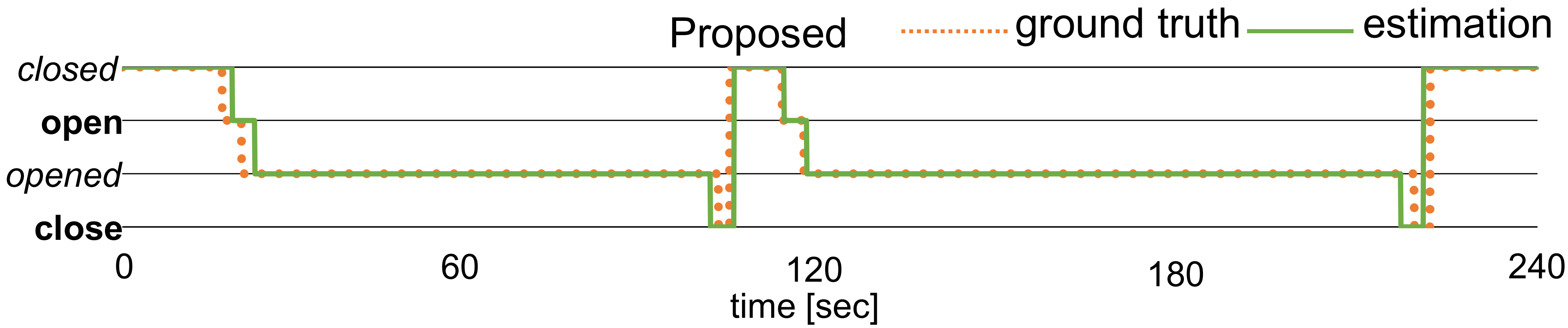
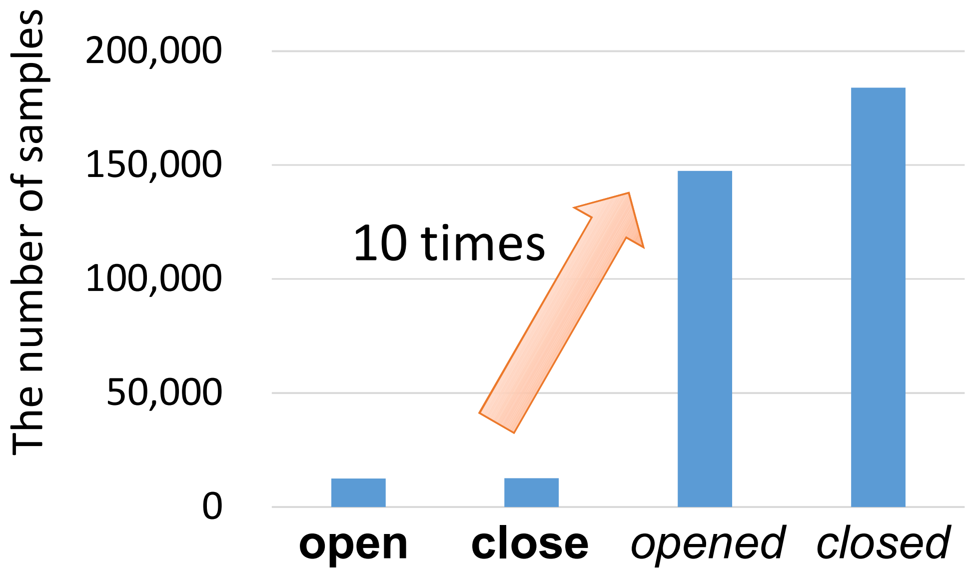
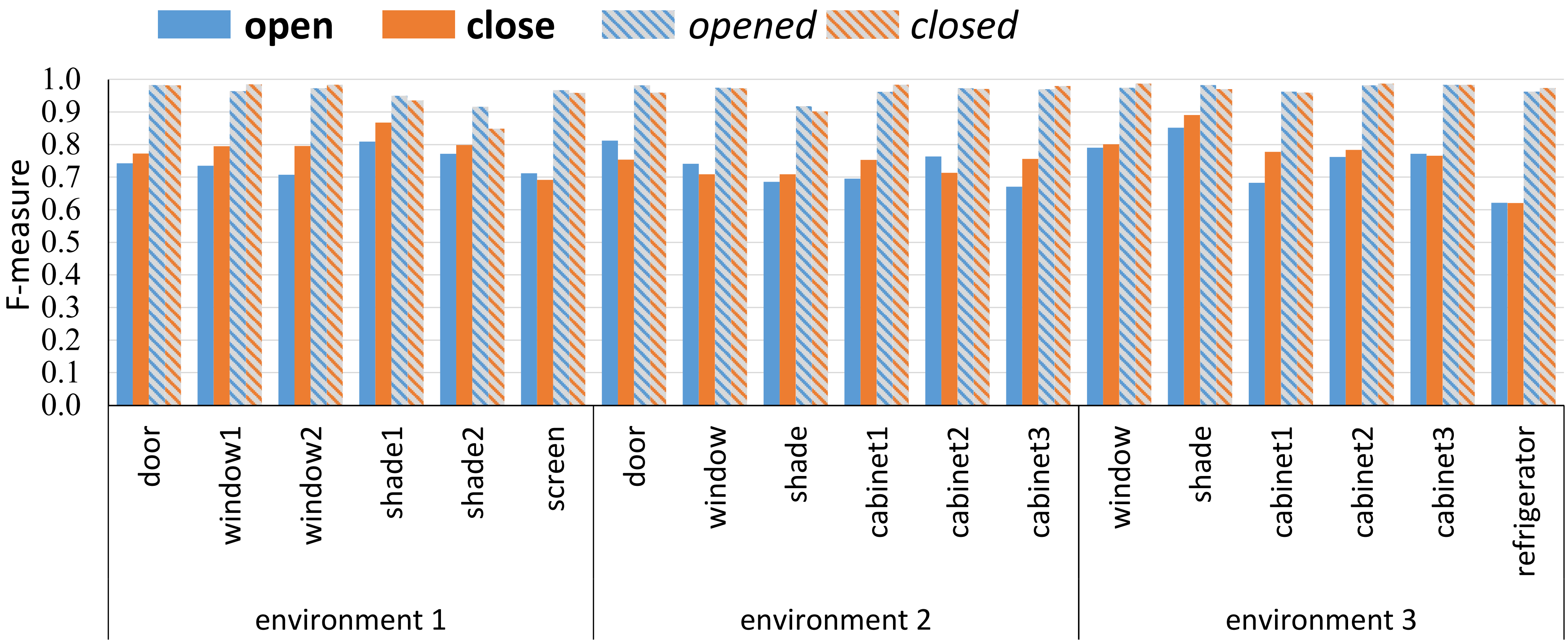


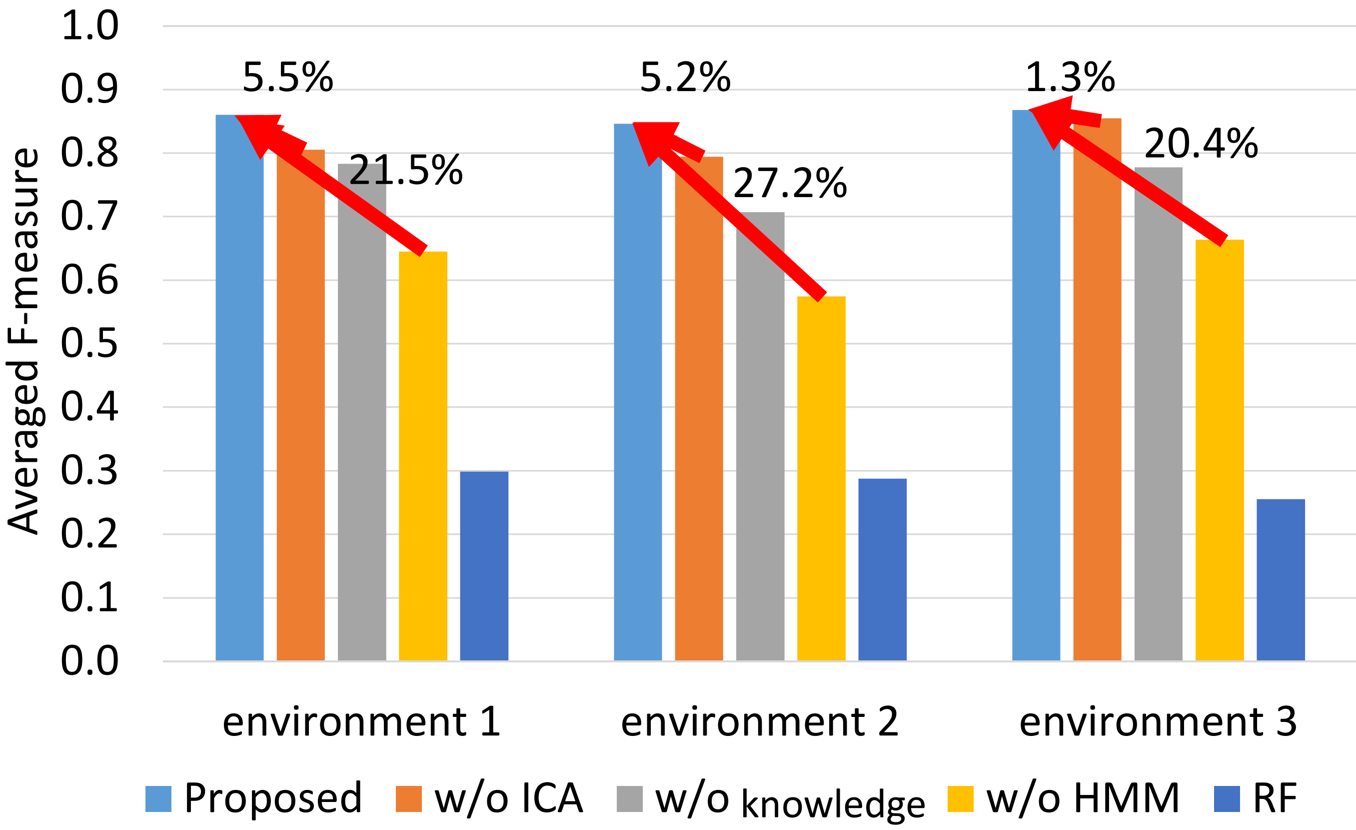


Result for each event/*state*



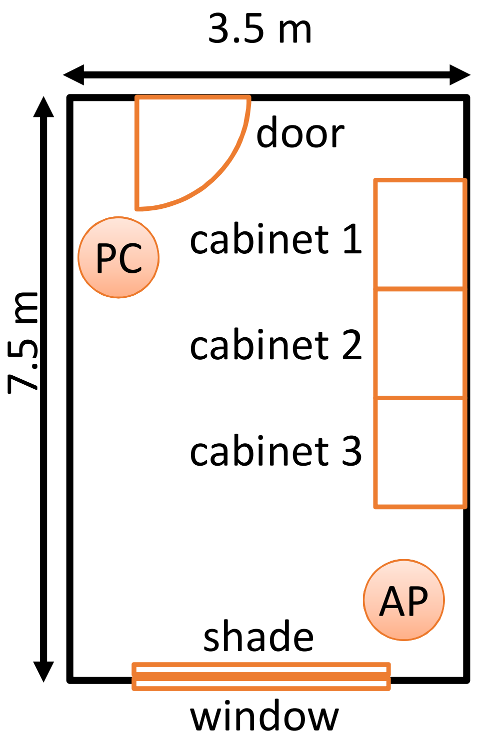
Comparison with Baselines

- Proposed: our proposed method
- w/o ICA: don't use decomposed amplitude and decomposed phase
- w/o knowledge: don't use knowledge of objects
- w/o HMM: estimate states of objects by DNN
- RF: estimate states by Random Forests using CSI denoised by PCA

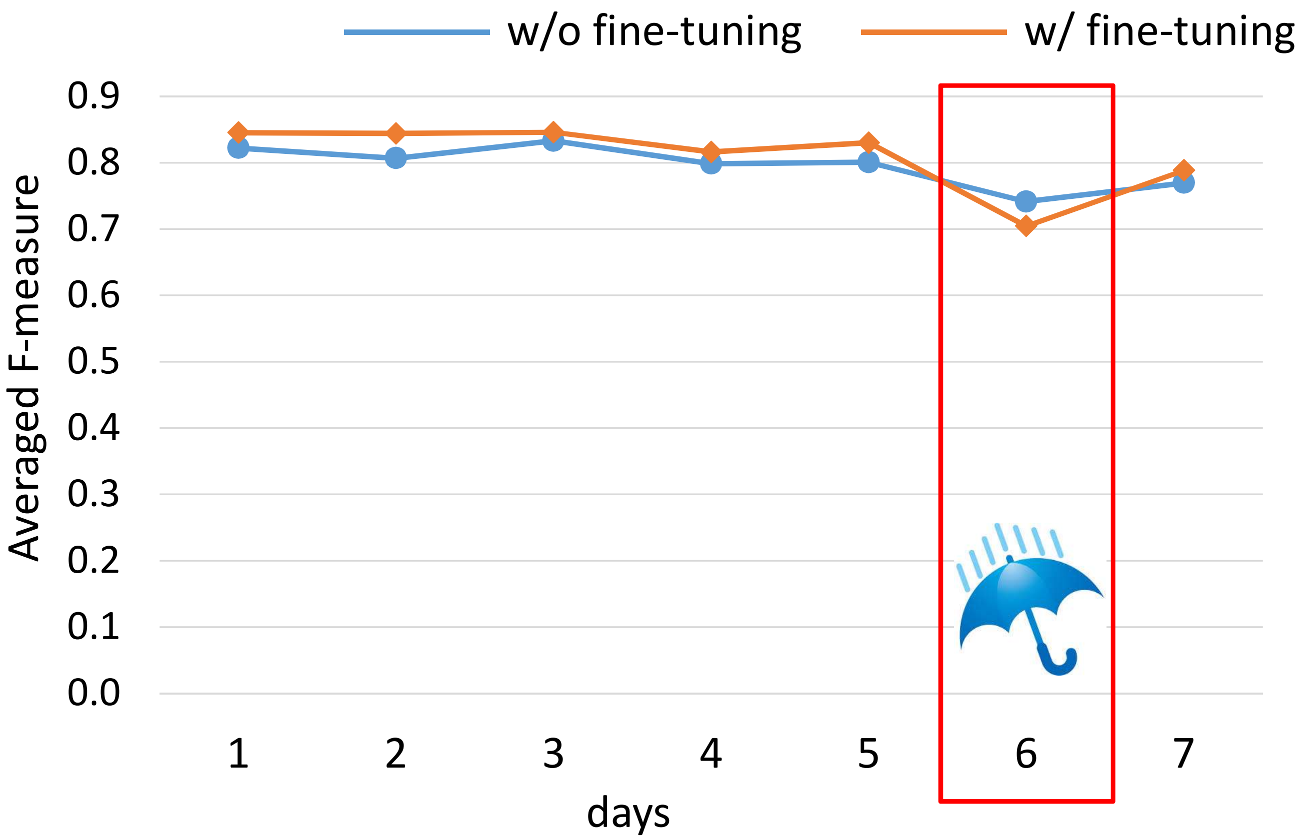


Result of Long-term experiment

- Collect data for 10 days in environment 2 (20 sessions/day)
- train: first 3 days (60 sessions), test: last 7 days (140 sessions)
- Fine-tuning DNN by recognized result as pseudo ground truth for each day

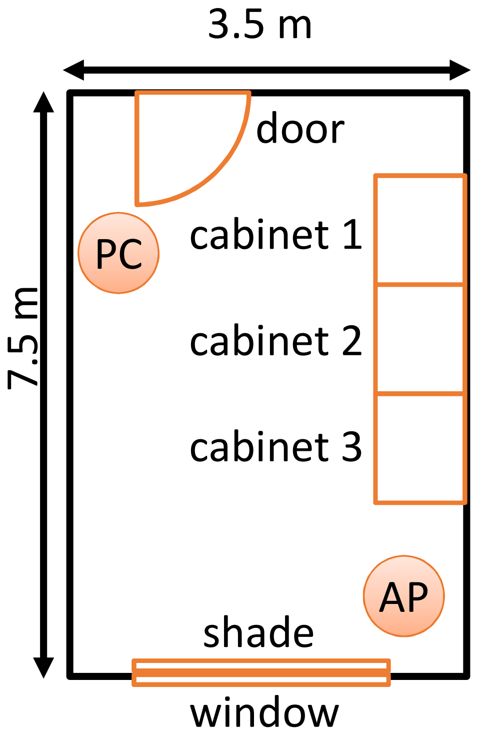


environment 2



Amount of training data

- Change amount of training data from 1 day to 3 days
  i.e. train: 20 sessions, 40 sessions, 60 sessions



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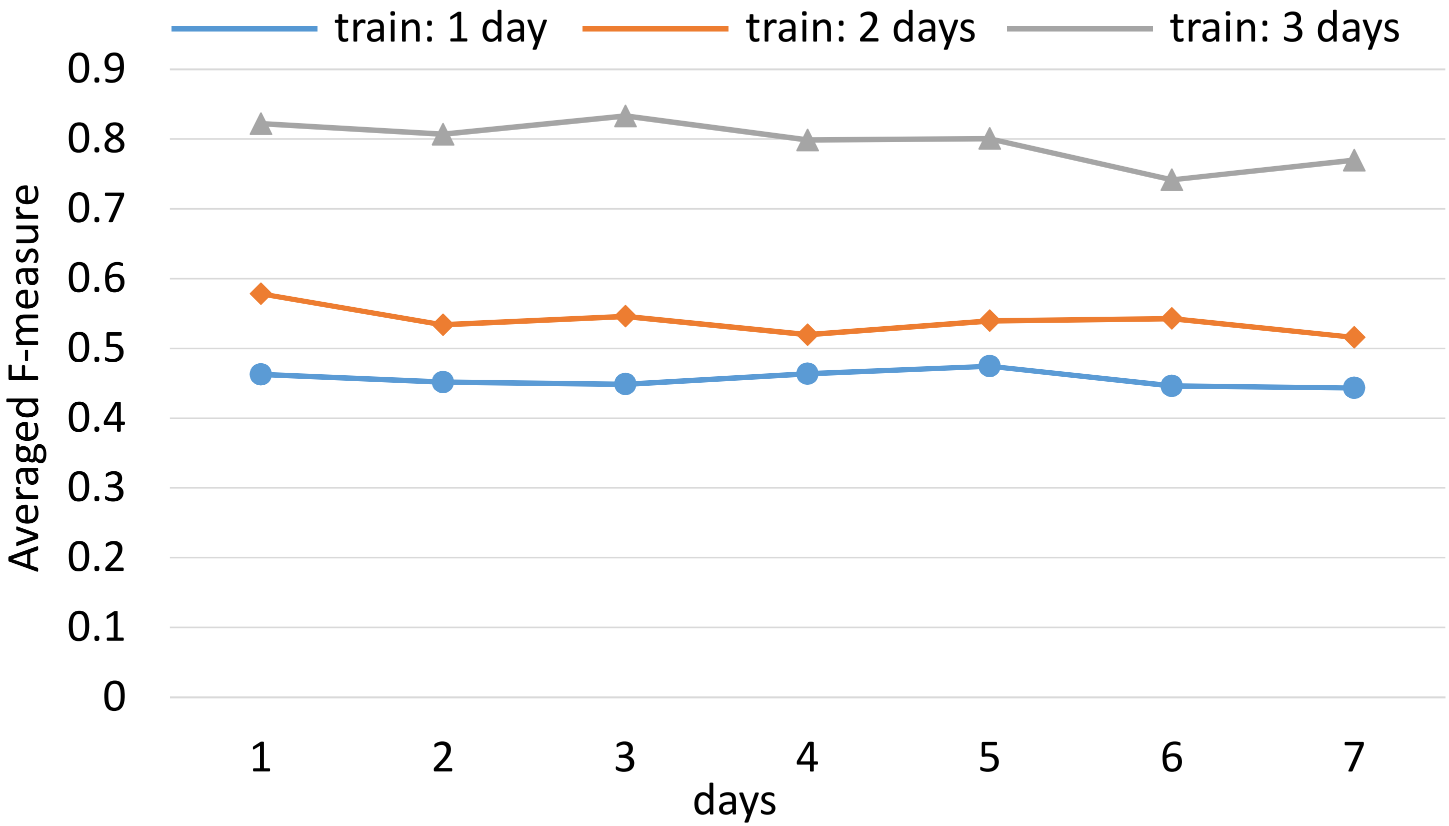

future task: method that does not require vast training data

Conclusion

- We proposed a method for detecting events and states of indoor everyday objects such as doors and windows using Wi-Fi CSI
- We designed a novel processing pipeline based on ICA, DNN, and HMM with a grammar based on knowledge of an object.

- We investigated the effectiveness of our method using real data. And we confirmed that our approach significantly outperformed a classic machine learning-based approach.

- However, because our method relies on deep learning, much training data results in poor recognition accuracy.
- Cope with this problem is one of our important future tasks.