Bayesian-based channel quality estimation method for LoRaWAN with unpredictable interference

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Background

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Low Power Wide Area Network (LPWAN)

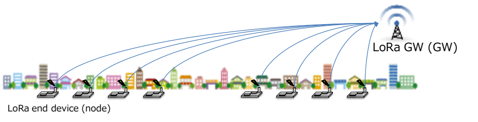
- Capable of long distance communication (1km~100km)
- Low power consumption (≈10 mW)

→ Longer system lifetime and coverage design can be easily achieved

Long Range Wide Area Network (LoRaWAN)

- One of LPWAN that uses LoRa modulation in the PHY layer
- User can construct self-managed private networks

→ Important communication technology for the spread of IoT services



Problem in Media Access Protocol of LoRaWAN

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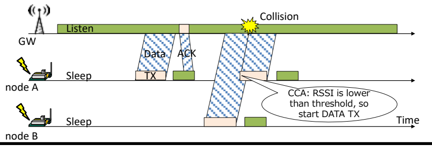
Problem: data collisions

- LoRaWAN uses ALOHA protocol with sleeping NIC during idle times
- Since users can build a self-managed network, many LoRaWANs using the same radio channel are expected to coexist in geographically close areas
- Most communication modules have a carrier-sense function, but the antenna reception sensitivity of devices is so high that collisions may occur at the GW even if each node judges the channel is idle after a CCA (clear channel assessment)

Solution: assign an appropriate radio channel to each node



Challenges and Approach

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Challenges in Channel Assignment

- How to know the **congestion degree** for each of the available radio channels?
  - Limited spatio-temporal information can be used because LoRaWAN assumes that the amount of node communications are low
  - Observed values may contain noise

Approach: Human brain-like estimation

- Estimate the congestion degree for each channel in a sequential Bayesian manner
  - Define the confidence level of the estimated results based on the estimated probability distribution
  - Perform radio channel assignment based on the estimation results when the confidence level is high enough
- The Bayesian attractor model, which models the human brain's information cognition, is used as a state estimation method[1]

[1] S. Bitzer, J. Bruineberg, and S. J. Kiebel, "A bayesian attractor model for perceptual decision making," PLoS Computational Biology, 2015.

Bayesian attractor model (BAM)

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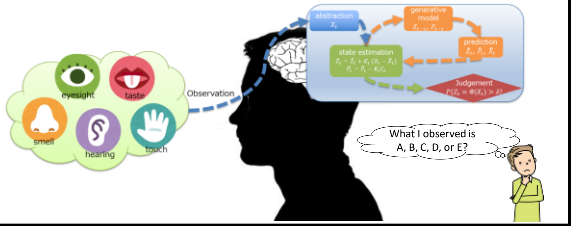
BAM models neural information processing

- Comparing the observed information with own memories
- Judging what they observed even if the information is noisy and incomplete



Description of the BAM

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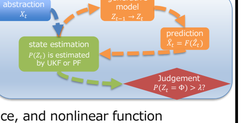
Abstraction

- Feature variables are extracted from observation

Generative model

- Hidden variable (Z_t) representing the decision state of the brain is defined on the state space, and this variable follows the dynamics with multiple attractors (Φ_i , $i = 1 \dots K$)
- Feature variables (X_t) are defined in the feature space, and nonlinear function converting the state space into the feature space is also defined
- Each feature corresponding to each attractor corresponds to a memory in the brain



Description of the BAM

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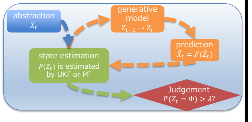

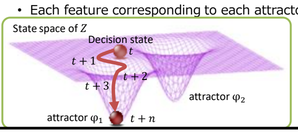

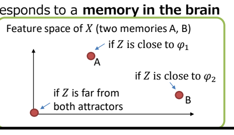

Description of the BAM

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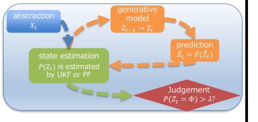
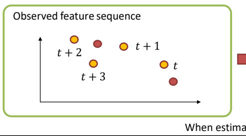
State estimation

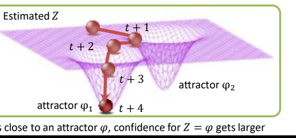
- Bayesian filter (i.e., Kalman filter, particle filter) is used for estimating the probability distribution of Z_t

Judgement

- Decision making is based on the probability density of $Z_t = \Phi_i$ (confidence)

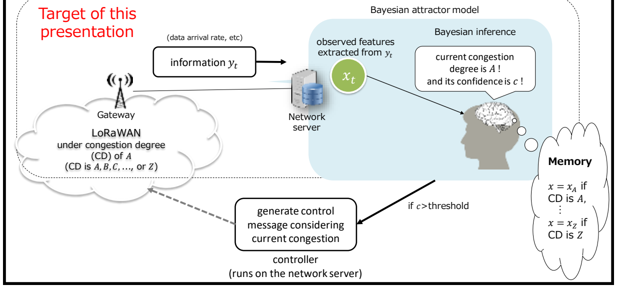






When estimated Z is close to an attractor φ, confidence for $Z = \varphi$ gets larger

Illustration of our proposal



Congestion estimation using the BAM

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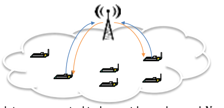
Definition of congestion degree and features

- Vector of three features in a radio channel with N **LoRa nodes**
  - Congestion degree is represented by the number of nodes
  - Features: Data reception rate (DRR), data decode success rate (DDR), and ACK reception rate (ARR)
- In the following evaluation, features at N=50, 100, and 150 are obtained from simulations in advance, and stored in the Bayesian attractor model



N_{sent} data are expected to be sent by nodes, and N_{recv} data are actually received and N_{decd} data are successfully decoded by the GW, and N_{ack} ACKs are successfully received by nodes.
DRR = N_{recv}/N_{sent}, DDR = N_{decd}/N_{recv}, ARR = N_{ack}/N_{decd}

	N=50	N=100	N=150
DRR	0.98	0.97	0.91
DDR	0.95	0.94	0.83
ARR	0.91	0.90	0.76

(Details of the simulation are shonw in the next slide)

Simulation settings

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Network model

- **200 nodes and 1 GW** are deployed in a 5 x 5 km² area
- Nodes location follows uniform distribution and GW location is (0, 0)

Radio model

- A node chooses one of **4 radio channels** (in the beginning, each channel has 50 nodes) and GW uses all channels
- Received signal strength is determined by a free space propagation model (920MHz, attenuation factor of 2.5)
- TX power 13 dB and antenna gain is 5 dB
- Antenna reception sensitivity is -131 dB

MAC layer model

- Data and ACK frame size are 50 byte and 10 byte, and communication speed is 1.5 kbps
- Frame error occurs stochastically based on SNR
  - SNR is less than 0 dB: 100%, 0~5 dB: 50%, 5~10 dB: 10%, 10~20 dB: 1%, and larger than 20 dB: 0%
- 5-ms carrier sense is performed before DATA/ACK TX with a threshold of -83 dB
  - When a node detects a signal, the transmission is aborted, and tries retransmission only once
  - When a node does not receive ACK, it tries retransmission once

Data generation model

- **Each node generates a data every 5 minutes with random seconds $\sim U(-2.5, 2.5)$**

Network change model

- **50 nodes are added in one channel after 200 minutes from the beginning of the simulation**

BAM interval

- **Network server calculates three features every 1 minute and inputs them to the BAM**

Simulation results

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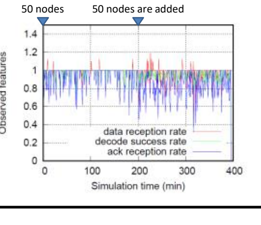
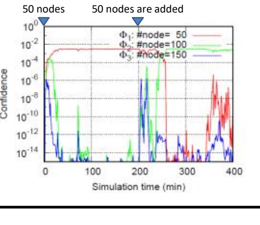
Observed features and Confidence levels

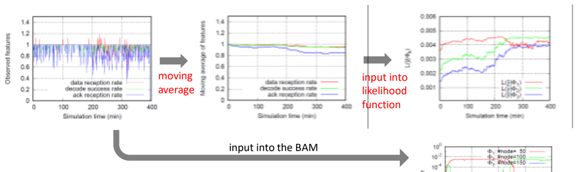
- Congestion degree is estimated correctly with little noise effect
- Since the confidence is defined for attractors, it is stable at a constant value

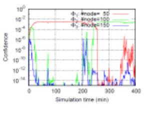




Simulation results

Comparison with moving average based estimator





- Multivariate normal distribution is used for likelihood function (average and var-cov-matrix are obtained from preliminary simulation)
- Setting an appropriate threshold in advance for the moving average based estimator is difficult

Conclusion and future works

Conclusion

- We proposed a method for estimating radio channel congestion in LoRaWAN using Bayesian attractor model, a cognitive mechanism model of the human brain
- We showed that the proposed method of confidence-based control is expected to realize channel assignment without significant fluctuations in temporal observations

Future work

- Proposal and evaluation of a channel assignment method based on the Bayesian attractor model
- Further investigation for dynamically updating the number of attractors and the stored feature vectors