Robotic Mapping into the Fourth Dimension - continued

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L-CAS

STRANDS

Spatio-Temporal Representations and Activities for Cognitive Control in Long-Term Scenarios

http://strands-project.eu

STRANDS will produce **intelligent mobile robots** that are able to run for **months** in **dynamic human environments**. We will provide robots with the **longevity** and **behavioural robustness** necessary to make them **truly useful assistants** in a **wide range of domains**. Such long-lived robots will be able to **learn from a wider range of experiences** than has previously been possible, creating a whole new generation of autonomous systems able to **extract and exploit the structure** in their worlds.

Our approach is based on **understanding 3D space and how it changes over time**, from milliseconds to months. We will develop novel approaches to extract spatio-temporal structure from sensor data gathered during months of autonomous operation. Extracted structure will include reoccurring 3D shapes, objects, people, and models of activity. We will also develop control mechanisms which exploit these structures to yield adaptive behaviour in highly demanding, **real-world security and care scenarios**.

WP8 has **created and deployed two long-running robot systems**, one at the *Haus der Barmherzigkeit* care home in Vienna, Austria, and the other at *G4S Technology* office building in Tewkesbury, UK. Their target is to run for 15 days without expert intervention.

Consortium

UNIVERSITY OF BIRMINGHAM

KTH

RWTH AACHEN UNIVERSITY

TU WIEN

UNIVERSITY OF LEEDS

UNIVERSITY OF LINCOLN

HAUS DER BARMHERZIGKEIT
AKADEMIE FÜR ALTERSFORSCHUNG

G4S

Coordinator

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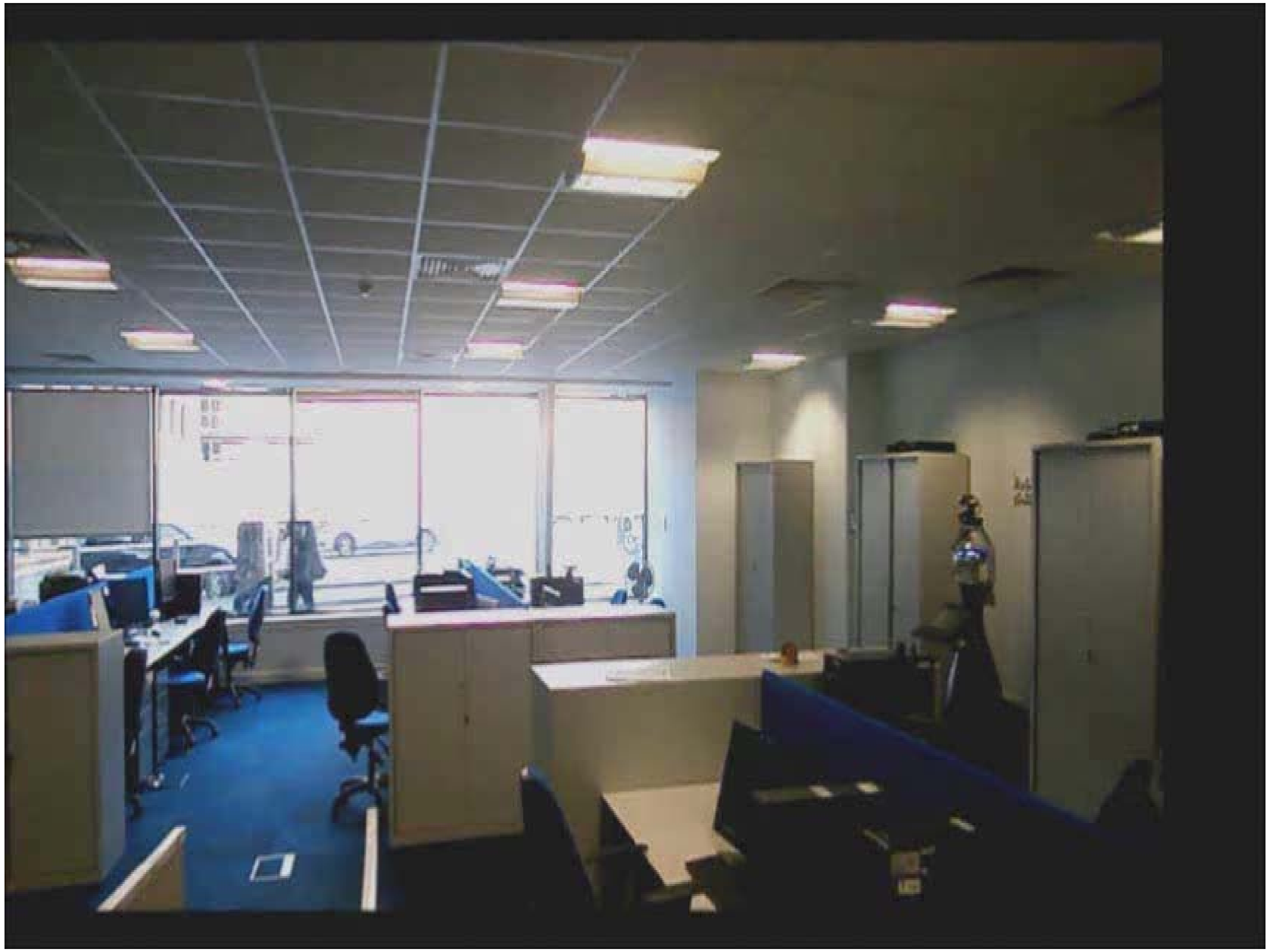
School of Computer Science
University of Birmingham
Edgbaston
Birmingham, B15 2TT
UK

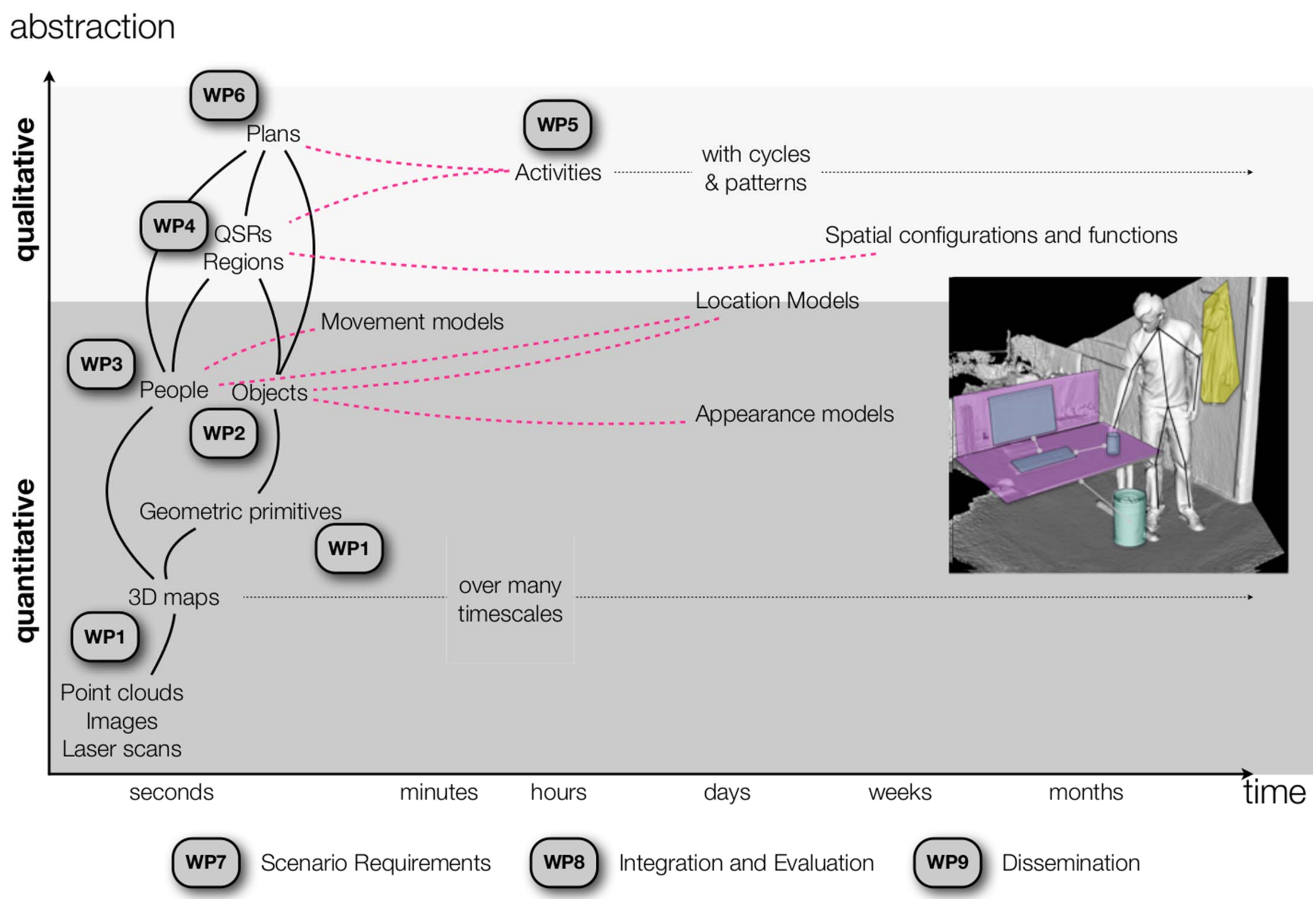
SEVENTH FRAMEWORK PROGRAMME

STRANDS

This project is funded by the European Community's

Robots on patrol

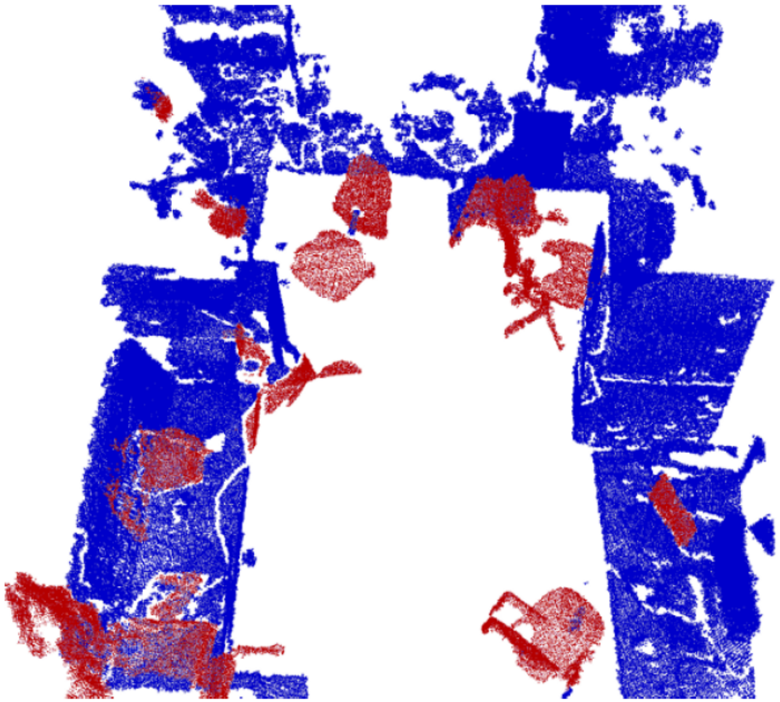



abstraction
qualitative
quantitative
WP6
Plans
WP5
Activities
with cycles
& patterns
WP4
QSRs
Regions
Spatial configurations and functions
Location Models
Movement models
WP3
People
Objects
WP2
Appearance models
Geometric primitives
WP1
3D maps
over many
timescales
WP1
Point clouds
Images
Laser scans
seconds
minutes
hours
days
weeks
months
time
WP7
Scenario Requirements
WP8
Integration and Evaluation
WP9
Dissemination

MAPPING & LOCALISATION IN CHANGING ENVIRONMENTS – APPROACH 2: META-ROOMS

Meta-Rooms

- A volumetric-based method for re-creating the static structure of cluttered environments ("meta-rooms").
- Iterative improvement over time from partial observations
- Segmenting clusters of dynamic objects



(a) Dynamic clusters (red) and the static room (blue)

R. Ambrus, N. Bore, J. Folkesson and P. Jensfelt. *Meta-rooms: Building and Maintaining Long Term Spatial Models in a Dynamic World*. ICRA 2014 Workshop on Visual Place Recognition in Changing Environments

Coloured 3D point cloud data

- Down-sampled and filtered to remove noise

Observations – input data

- Pan-tilt sweeps at predefined waypoints
- Red ellipses indicate missing sensory data
- Filtering, boundary detection
- Registration

Scans of the same room from 4 different days

Meta-Room

- Definition: the static structure of cluttered office environments
- Created through an iterative process where dynamic elements are eliminated from the scene and previously occluded elements are added.
- Once a meta-room has been created, dynamic elements can easily be extracted from new observations
- Based on point cloud differencing:

$$S = \{p \mid p \in P \ \wedge \ \forall q \in Q, \ ||p, q|| > d\}$$

- P,Q – input point clouds, S – resulting point cloud, d – distance threshold

Meta-Room Update

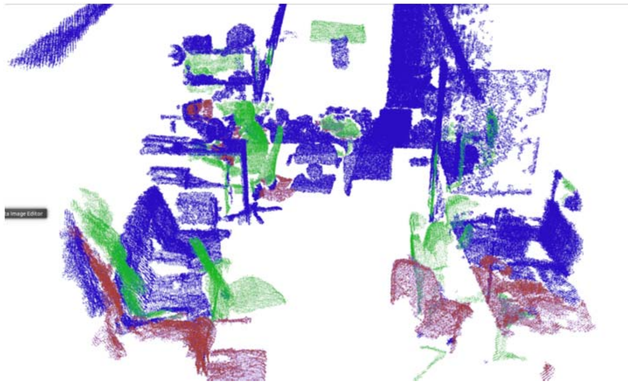
Current meta-room

New observation

Meta-Room Update

Current meta-room

New observation

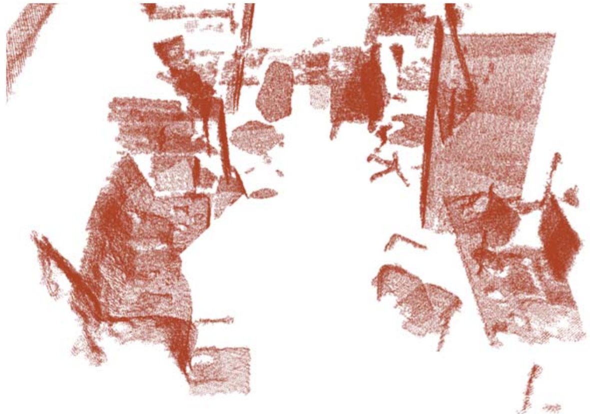


Occluded clusters

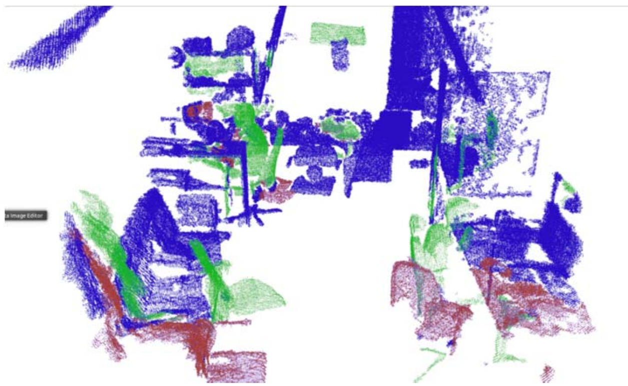
Green = deleted parts, Red = added parts

Meta-Room Update

Current meta-room



New observation



Occluded clusters

Updated meta-room

Green = deleted parts, Red = added parts

Dynamic clusters

Dynamic clusters


Office chair


Pillow


Lamp


Office chair


PhD student on chair

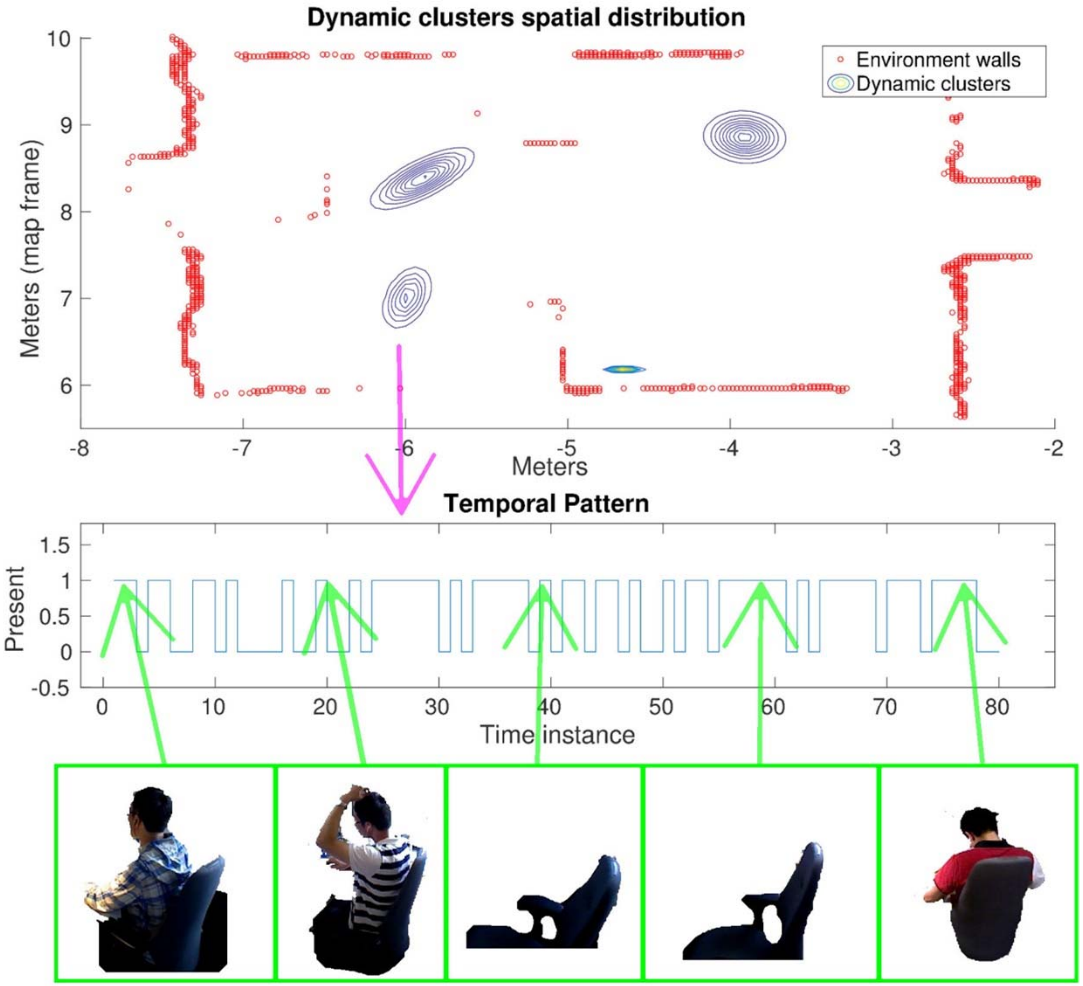

Bicycle


Kitchen chair


Fruit basket

Unsupervised learning of objects

- Segment the dynamic elements into distinct clusters and re-identify them across observations.
- Use appearance models, spatial distribution, and temporal behaviour
- Significant improvement of the object detection rate compared to the original MetaRoom method.



R. Ambrus, J. Ekekrantz, J. Folkesson and P. Jensfelt. *Unsupervised learning of spatial-temporal models of objects in a long-term autonomy scenario*. Proc. IROS 2015.

MAPPING & LOCALISATION IN CHANGING ENVIRONMENTS – APPROACH 3: FREQUENCY MAPPING

A Frequency-based Approach to Robotic Mapping (FreMEn)

- Explicitly models the environment's dynamics based on spectral analysis
- Enables prediction of environment state at a particular time of day, based on history of past observations

T. Krajnik, J. P. Fentanes, G. Cielniak, C. Dondrup, and T. Duckett. *Spectral Analysis for Long-Term Robotic Mapping.* In Proc. ICRA 2014.

Objectives

- "Total recall"
    - Security, assistive care, etc.
- Compactness
    - Online reasoning
- Prediction
    - What will happen at time *t*?
- Novelty detection

Temporal domain modelling

Classical world models neglect the temporal domain:

- uncertainty of any state $\mathbf{s_i}$ is modelled by its probability $\mathbf{p_i}$

Including temporal aspect means that:

- uncertainty of $\mathbf{s_i (t)}$ is modelled by probability $\mathbf{p_i (t)}$

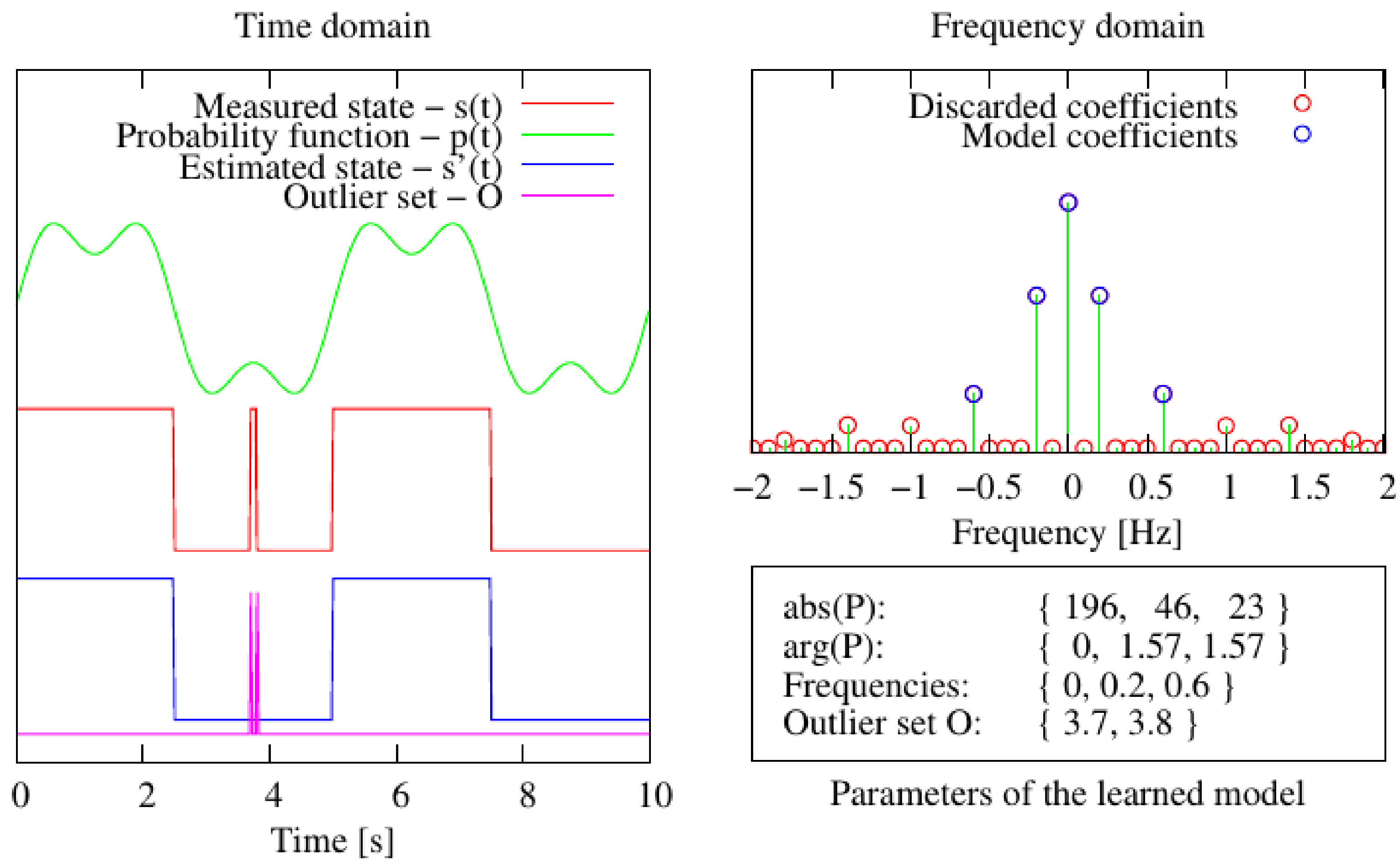
However:

- storing all observed $\mathbf{s_i (t)}$ and $\mathbf{p_i (t)}$ is not feasible

Basic idea:

- in days-to-months scales, $\mathbf{s_i (t), p_i (t)}$ are quasi-periodic
- represent $\mathbf{p_i (t)}$ as superposition of harmonic functions
- identify harmonic functions by Fourier transform

FREquency Map ENhancement



T. Krajnik, J. P. Fentanes, G. Cielniak, C. Dondrup, and T. Duckett. *Spectral Analysis for Long-Term Robotic Mapping.* In Proc. ICRA 2014.

Fourier Transform

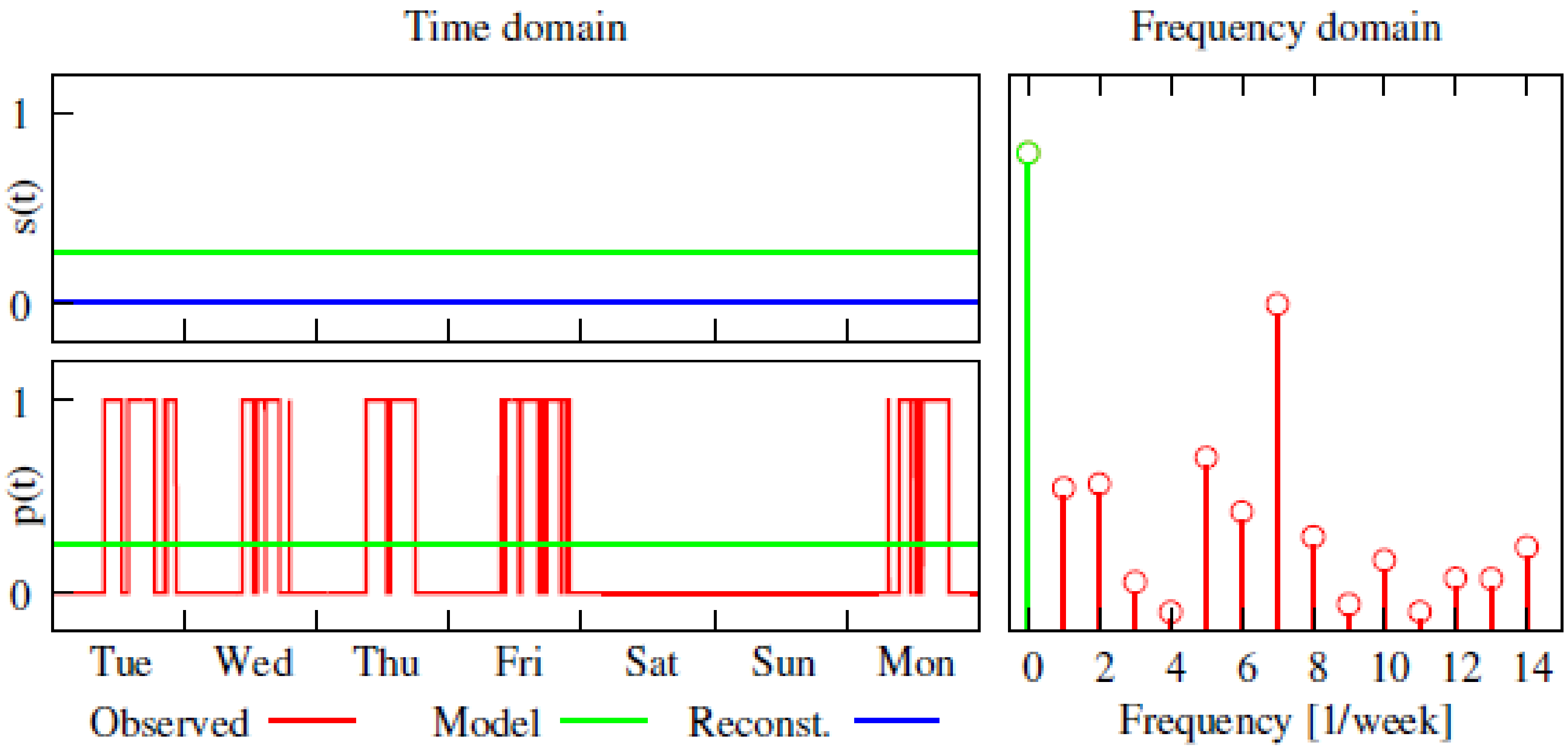
- See video

Temporal domain model: example

Continuous observation of an office door (open/closed)

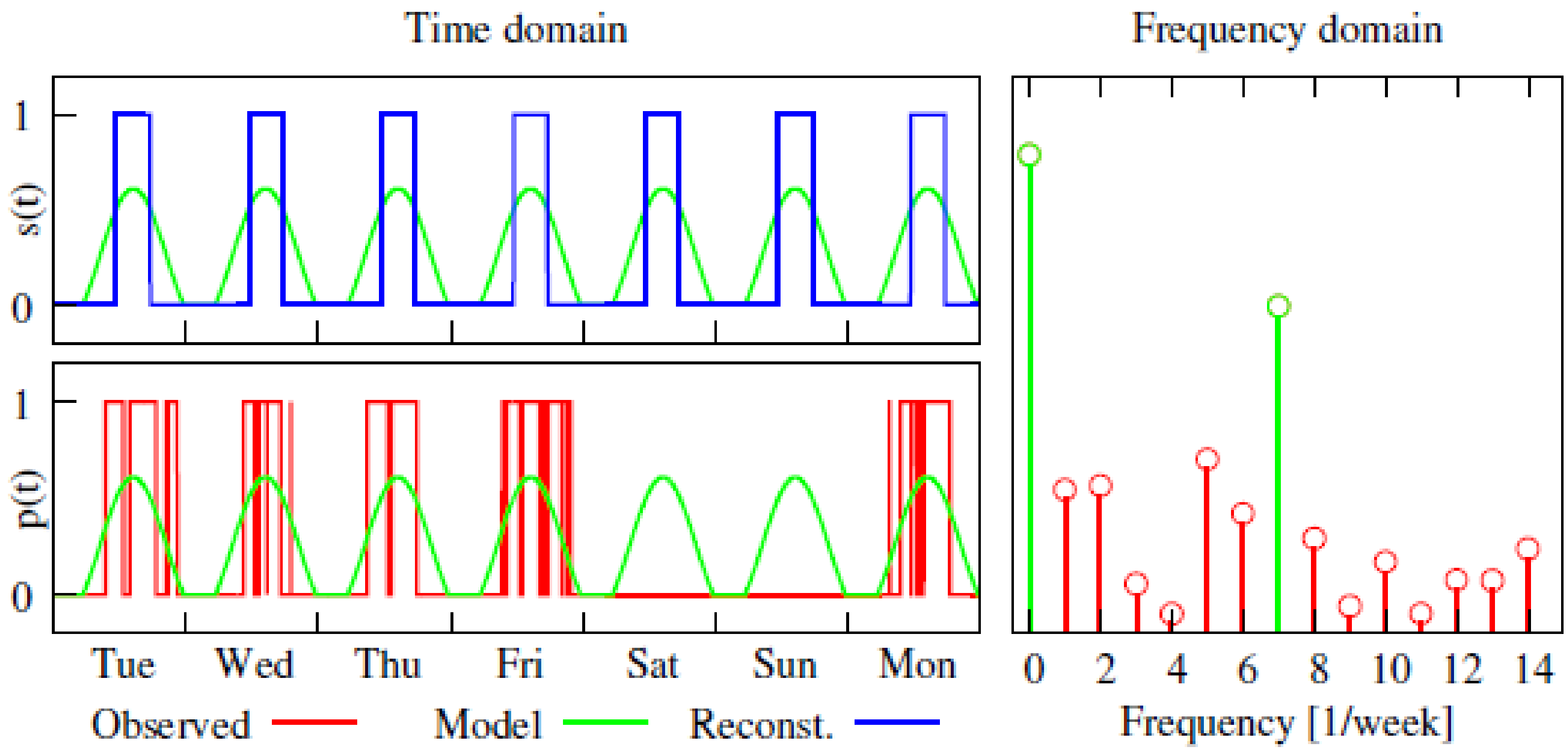
State **s(t)**:
•open/closed
Timescale:
•one week
Measurements:
•30Hz x 7 days
•≈ 18 000 000

Temporal domain model: example



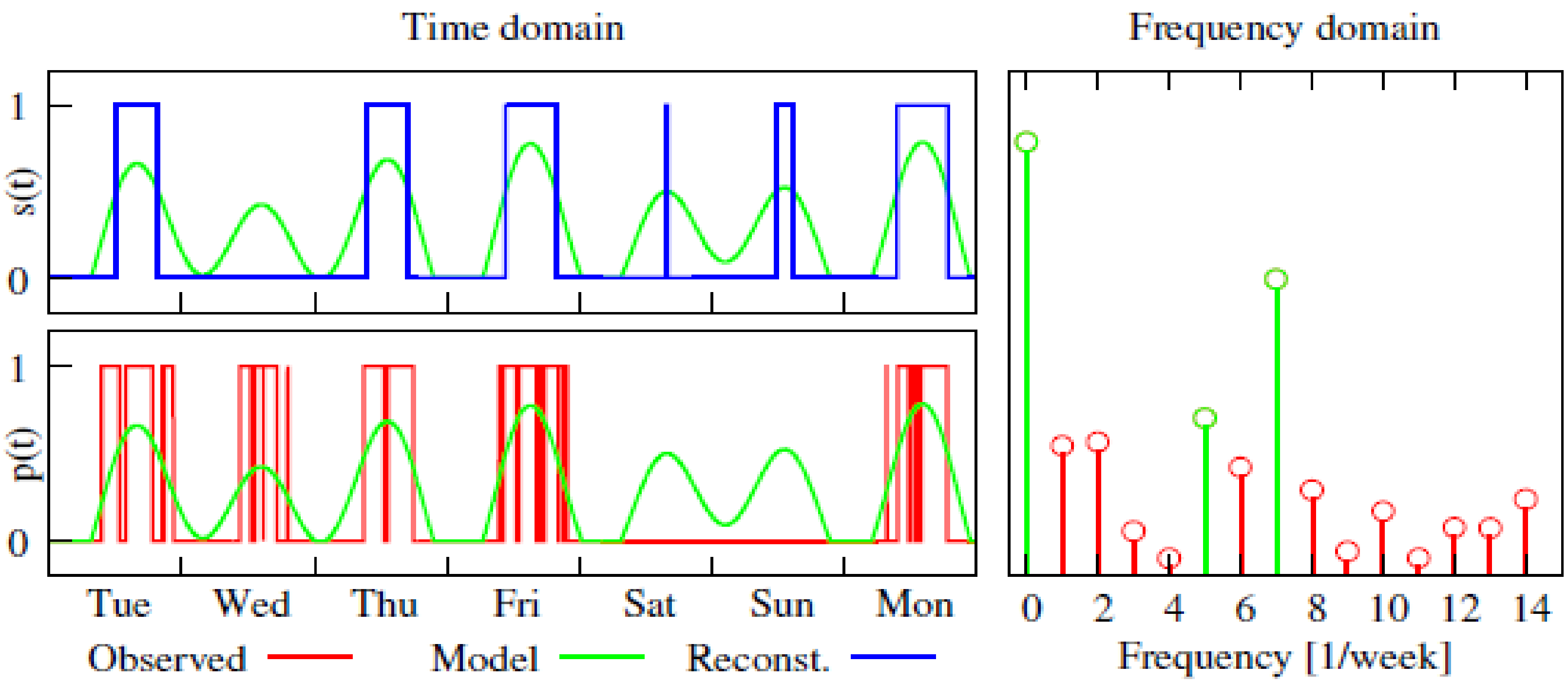
$$p(t) = p_0$$

Temporal domain model: example



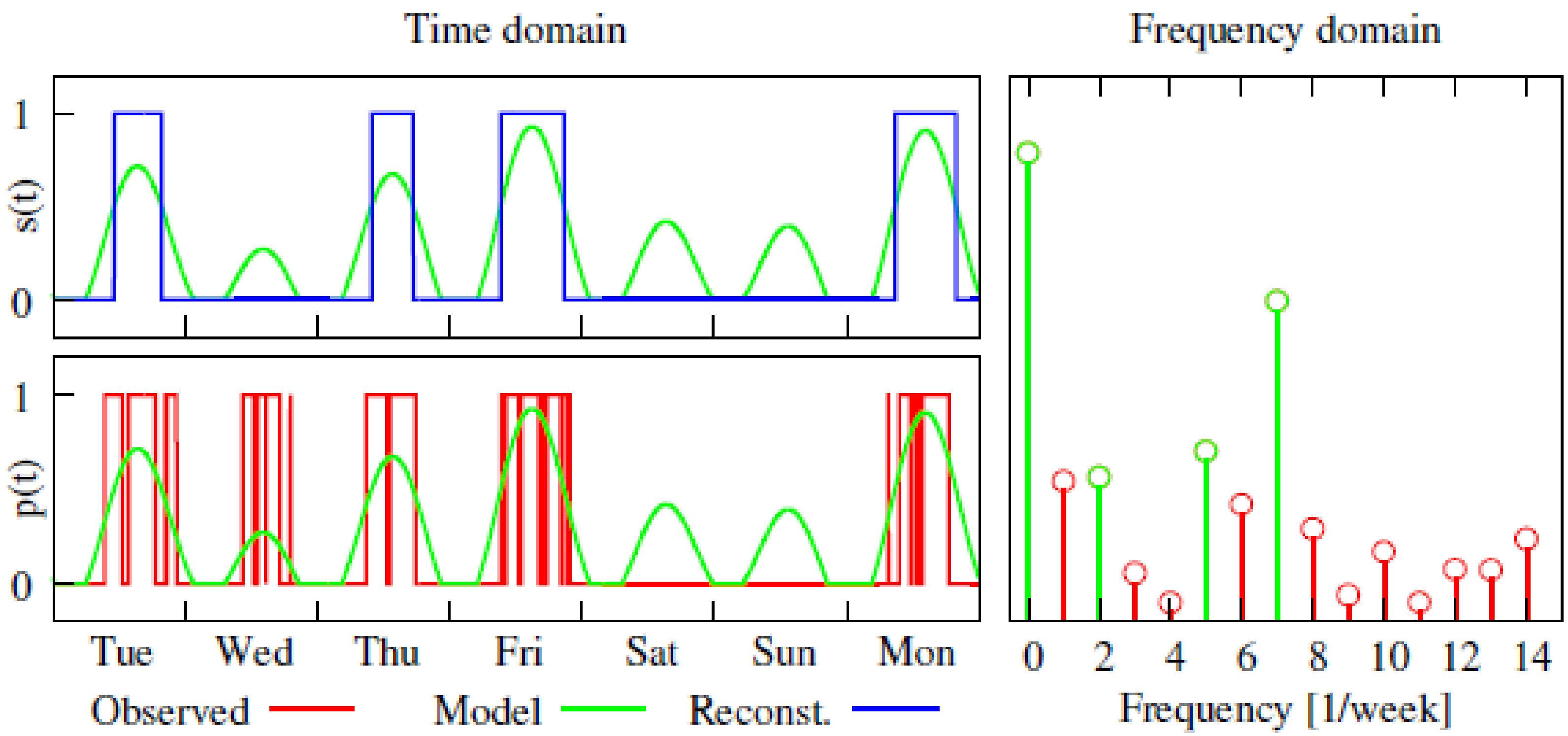
$$p(t) = p_0 + \quad p_1 cos(\omega_1 t + \varphi_1)$$

Temporal domain model: example



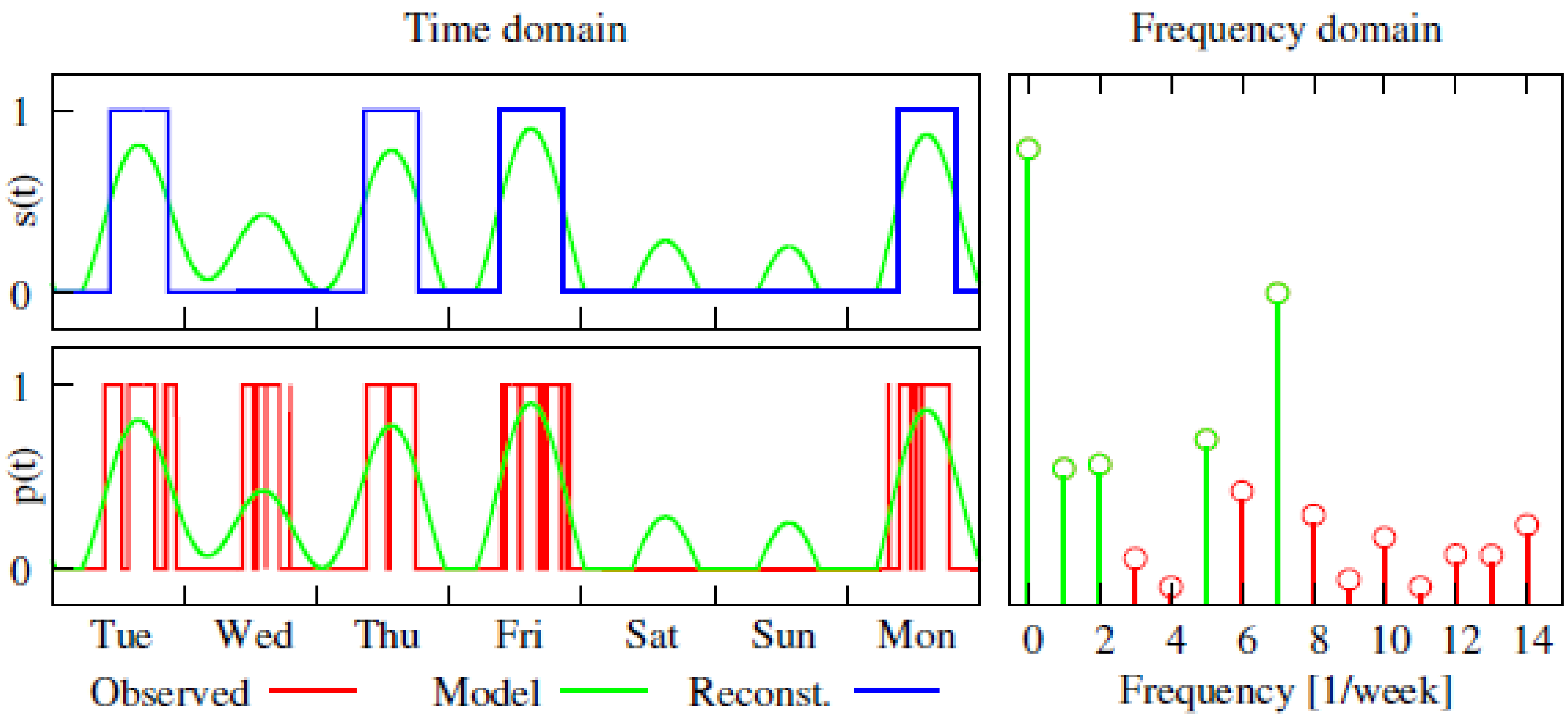
$$p(t) = p_0 + \sum_{j=1}^{2} p_j cos(\omega_j t + \varphi_j)$$

Temporal domain model: example



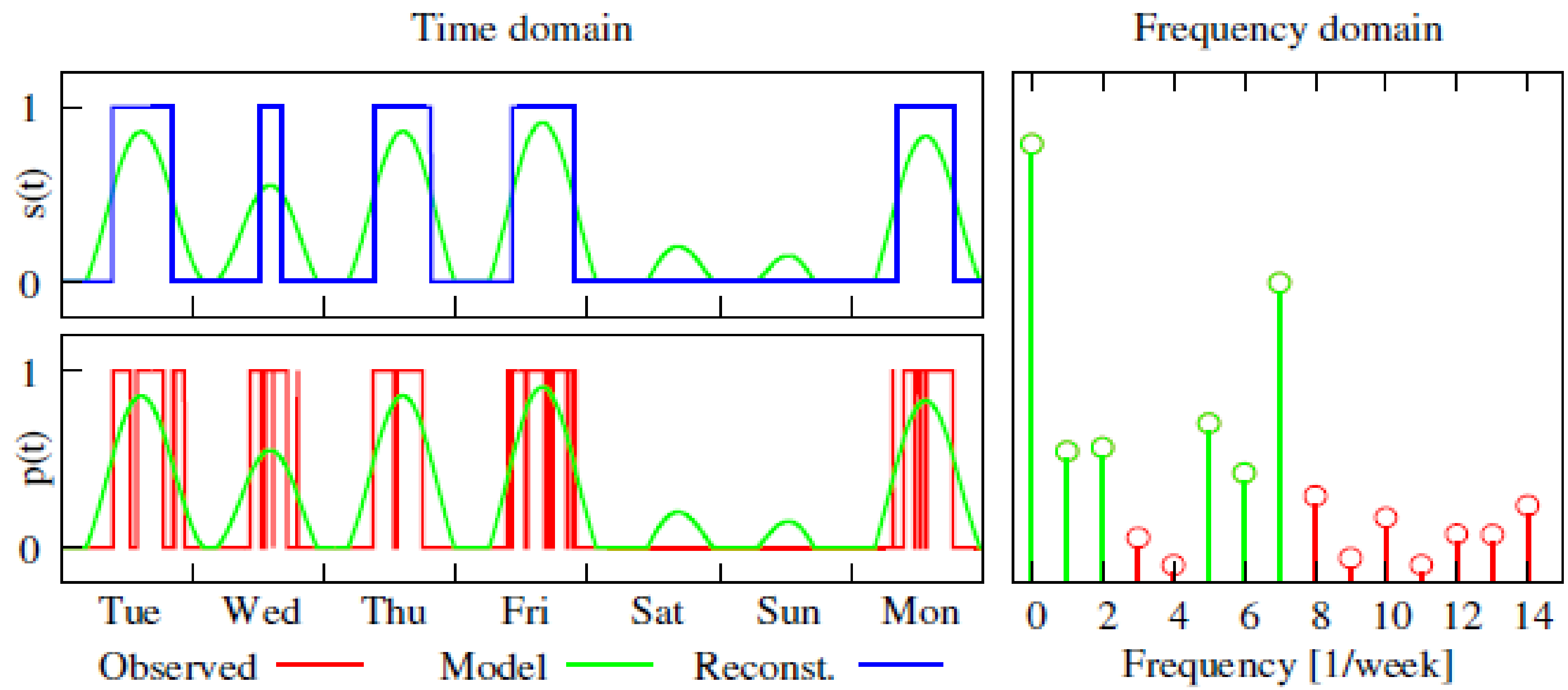
$$p(t) = p_0 + \sum_{j=1}^{3} p_j cos(\omega_j t + \varphi_j)$$

Temporal domain model: example



$$p(t) = p_0 + \sum_{j=1}^{4} p_j cos(\omega_j t + \varphi_j)$$

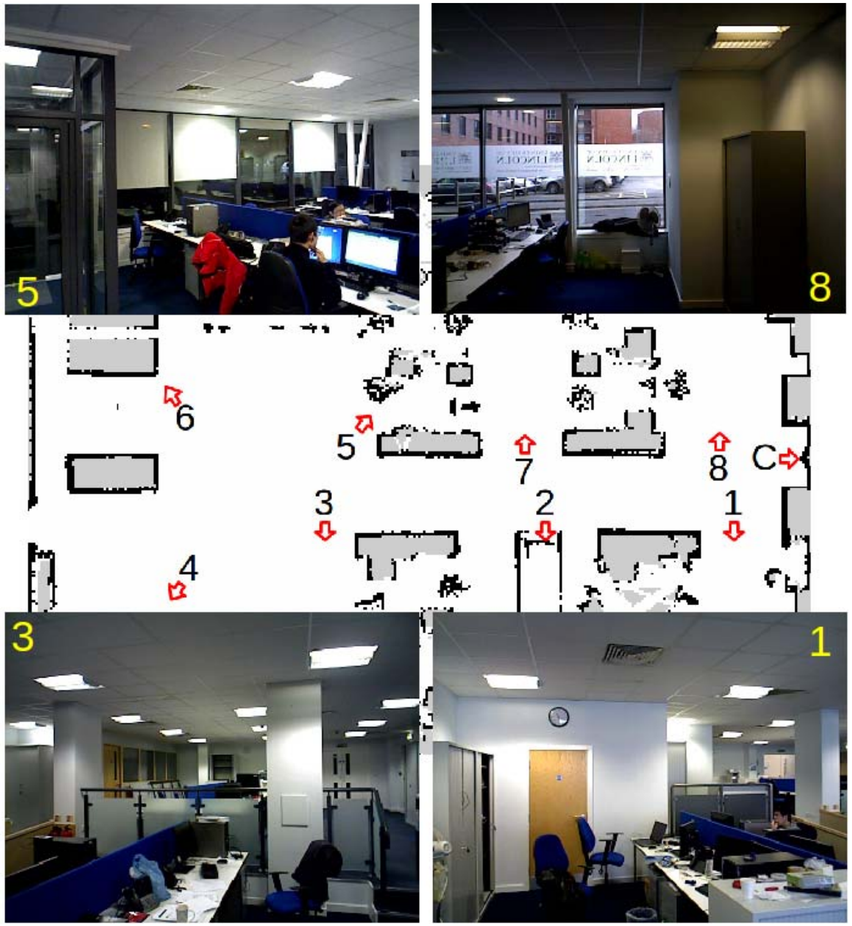
Temporal domain model: example



$$p(t) = p_0 + \sum_{j=1}^{5} p_j cos(\omega_j t + \varphi_j)$$

Example 2: Topological Localization

- Predict visual appearance of the environment and use the predicted model for topological localization



T. Krajnik, J. P. Fentanes, O. Mozos, T. Duckett, J. Ekekrantz and M. Hanheide. *Long–Term Topological Localisation for Service Robots in Dynamic Environments using Spectral Maps.* In Proc. IROS 2014.

Example 2: Topological Localization

- 3D point clouds and RGB images of eight locations recorded every 10 minutes
- Training:
  - Model constructed using one week of data in 2^{nd} week of Nov. 2013
  - approx. 8000 observations, 35 km travelled
- Testing
  - One day in the next week (Nov. 2013)
  - Another day in Feb. 2014

Example 2: Topological Localization

- Tested two types of place models:
  - 3D occupancy grids
    - Matched using Hamming distance
  - Visual descriptors
    - BRIEF algorithm

Example 2: Topological Localization

- See video

Example 2: Topological Localization

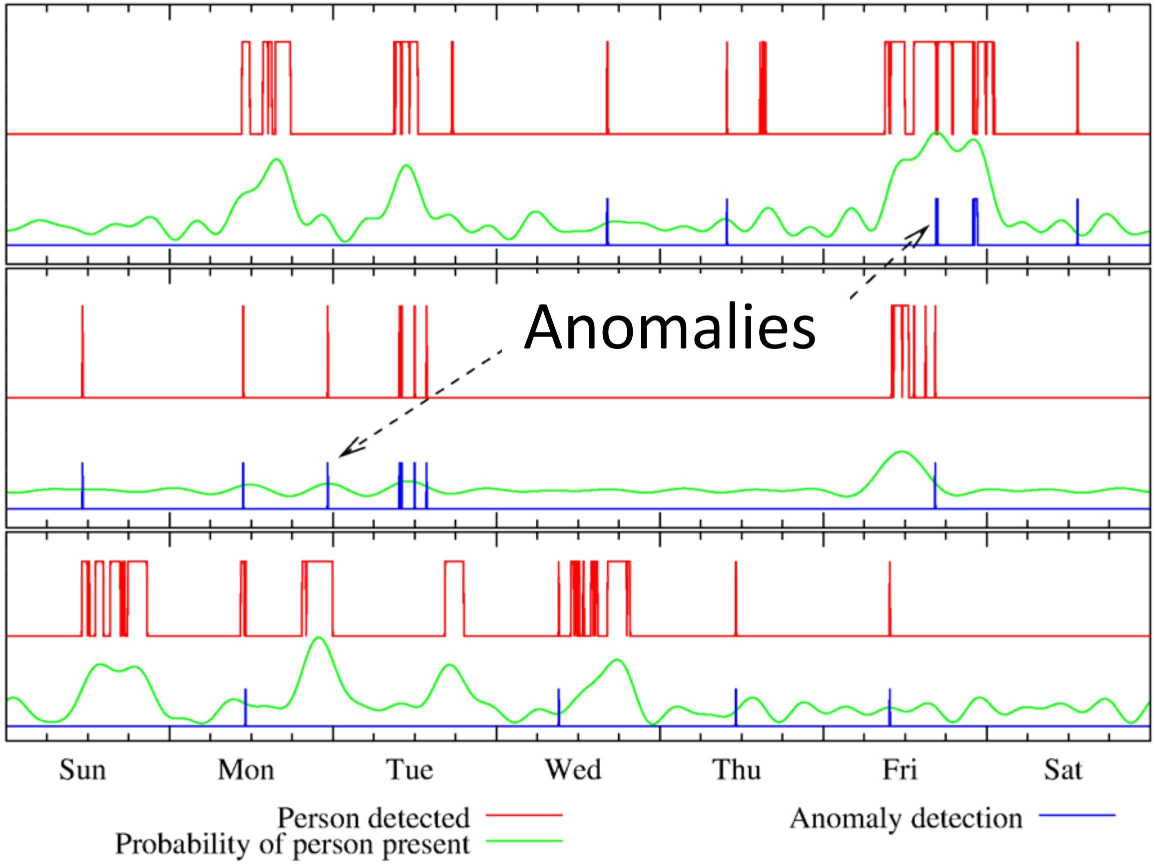
Spectral model learned during Nov 2013 was used
for localization on December 2013 and February 2014

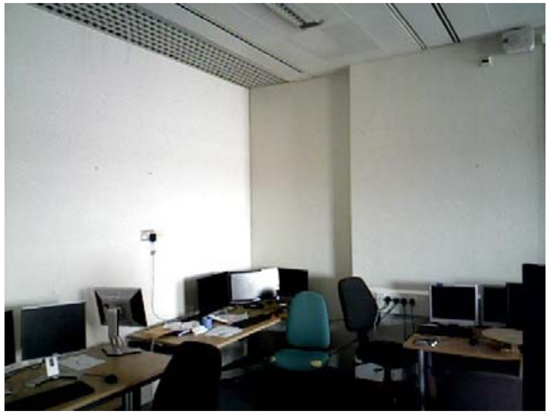
OVERALL LOCALIZATION ERROR (%)

Model type	Model order	Image features Nov	Image features Feb	Occupancy grids Nov	Occupancy grids Feb
static	-	35%	45%	21%	17%
spectral	1	25%	26%	14%	13%
spectral	2	22%	27%	14%	8%
spectral	3	18%	24%	14%	17%
spectral	4	17%	29%	7%	17%

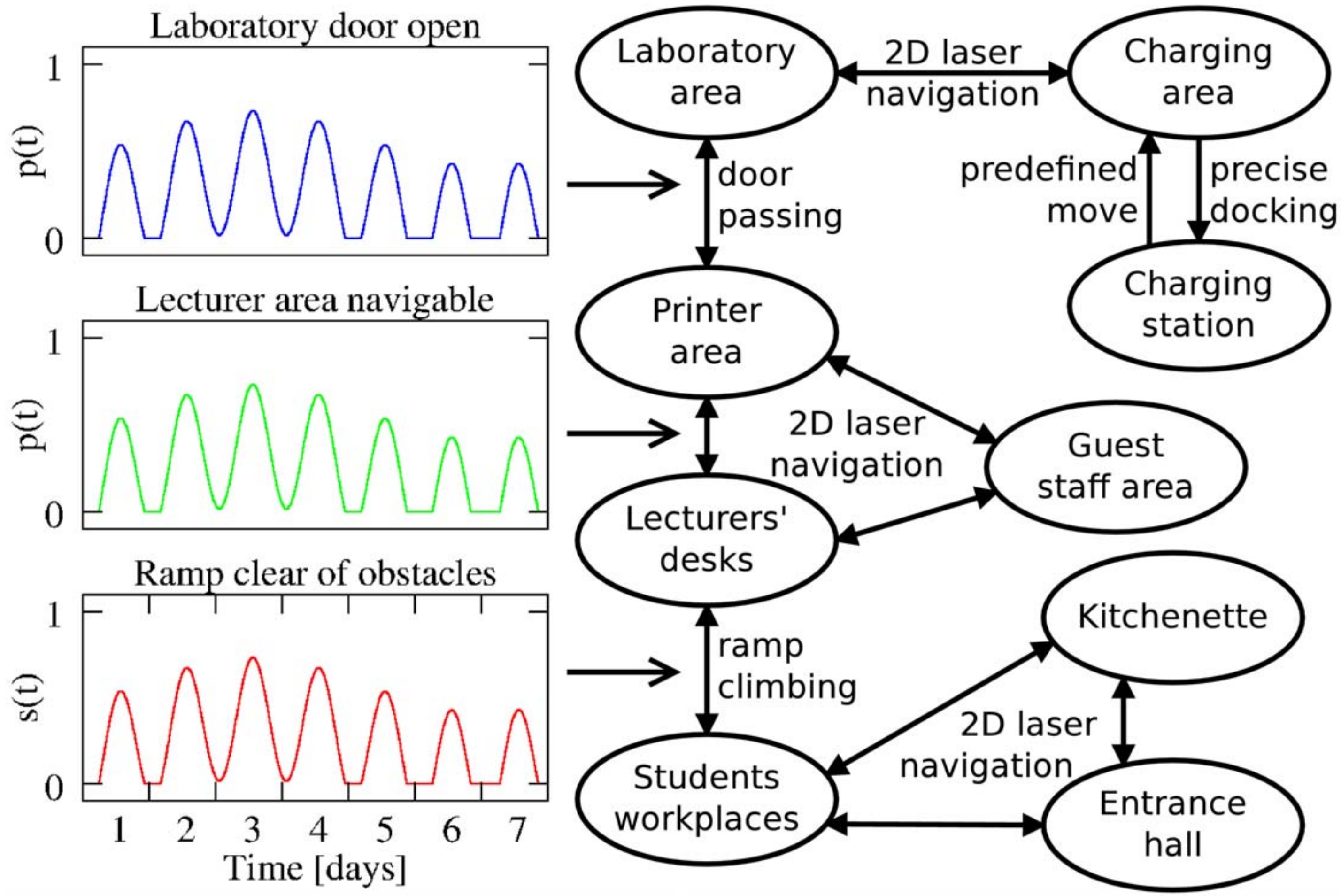
Example 3: Anomaly detection: Person presence

Location-specific model of person presence at three different locations





Example 4: Time-dependent topological maps for motion planning



J. P. Fentanes, B. Lacerda, T. Krajnik, N. Hawes and M. Hanheide. *Now or Later? Predicting and Maximising Success of Navigation Actions from Long-Term Experience.* In Proc. ICRA 2015.

Augmented Topological Map Representation

$$T=\langle \boxed{V}, \boxed{E}, \boxed{N}, \boxed{nav}, \boxed{P_E} \rangle$$

Set of Locations

Action Between Locations

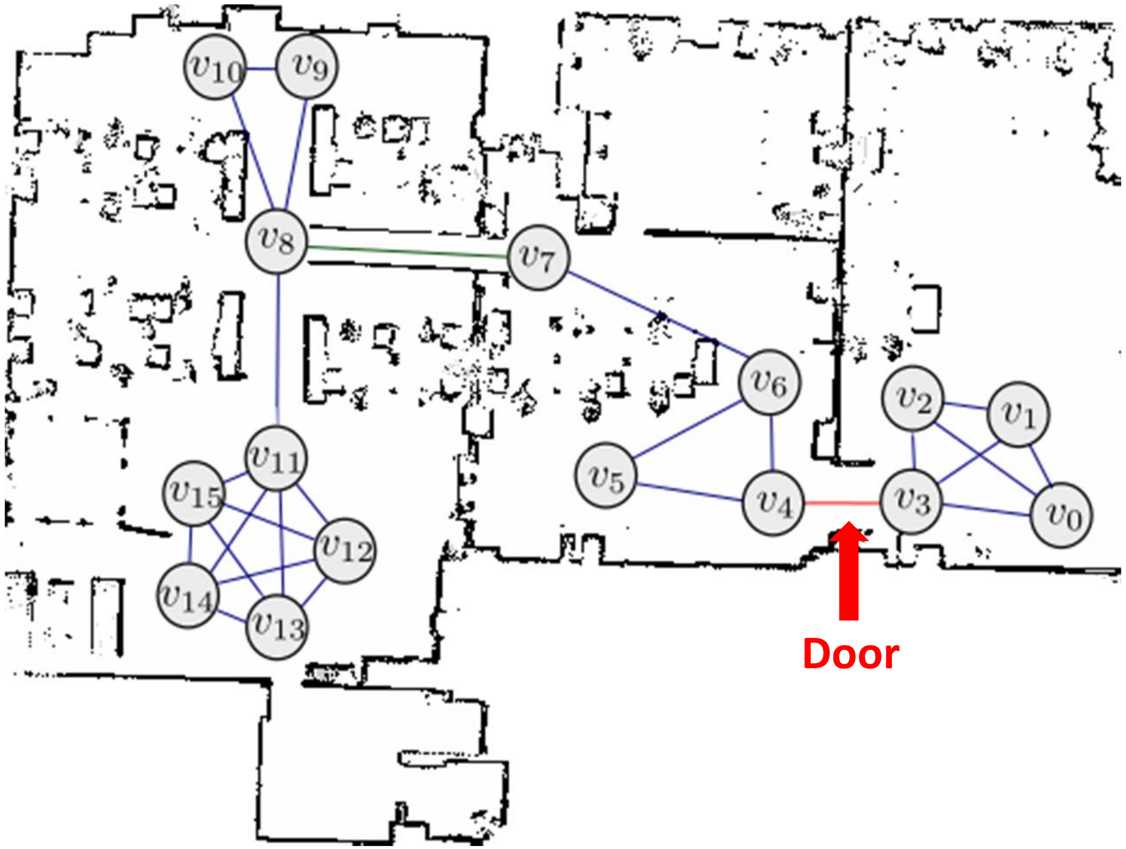
Set of Possible Actions

Function that maps an edge between two locations to an action

Is the set of probabilities of each edge being traversable at time *t*,

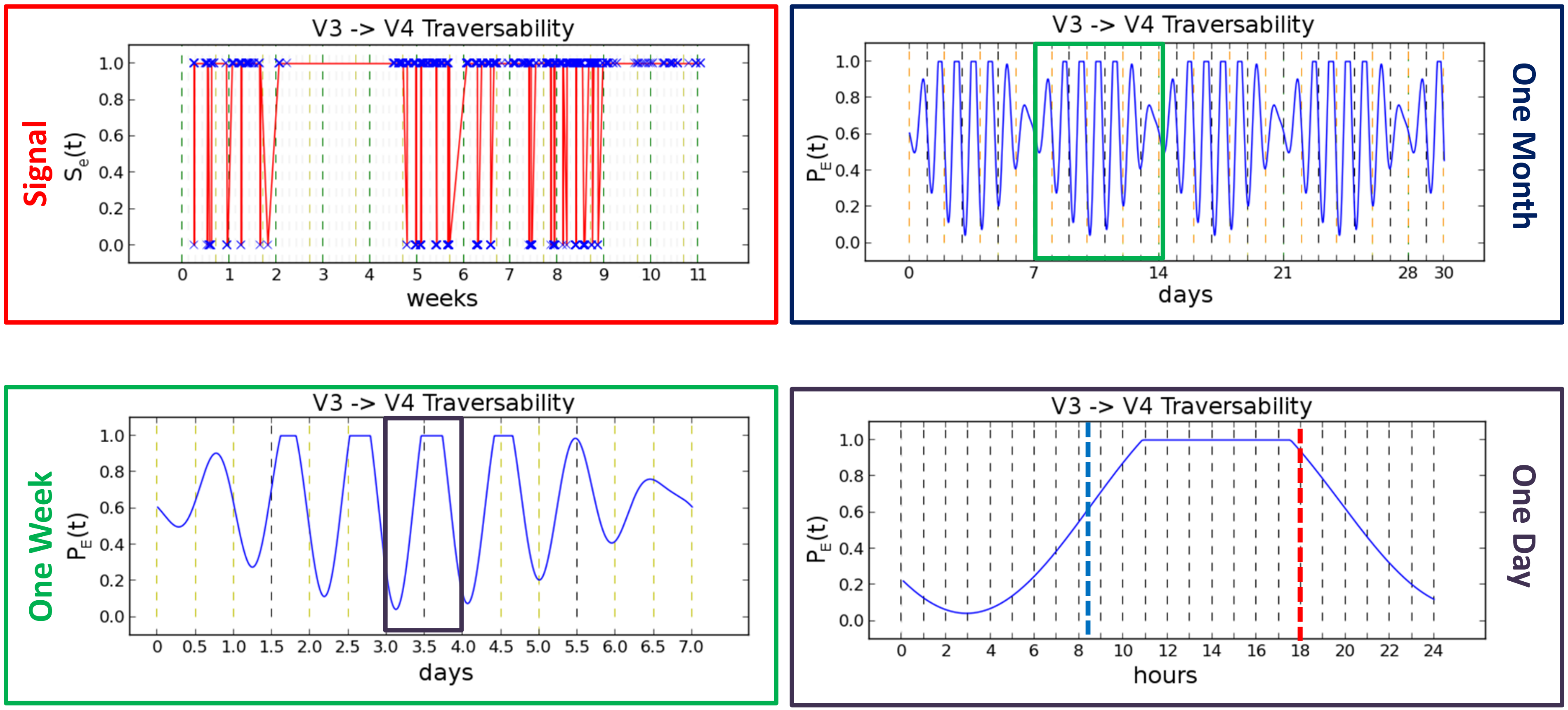
$$p_e(t) = \propto_0 + \sum_{j=1}^{m} \propto_j \cos(\omega_j t + \varphi_j)$$

Long-Term Deployment



Experimental Deployment	
Total Days	76
Days of Activity	35
Nodes In Topological Map	17
Edges In Topological Map	62

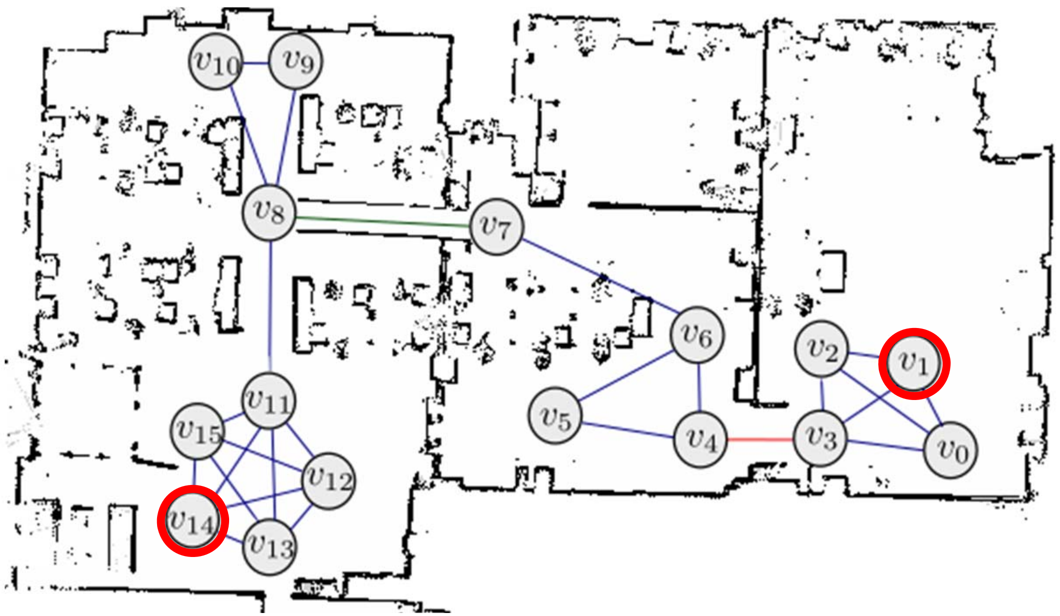
Periodicity and Prediction Analysis



High Level Motion Planning

Maximum Probabilities of fulfilling task (Fv1 V Fv14) at different dates and times of day

Date\Time	0h	2h	4h	6h	8h	10h	12h	14h	16h	18h	20h	22h
Tuesday, 07-10-2014	0.646	0.654	0.681	0.721	0.795	0.891	0.884	0.916	0.938	0.938	0.901	0.777
Thursday, 09-10-2014	0.717	0.693	0.704	0.746	0.803	0.857	0.946	0.971	0.938	0.877	0.751	0.687
Sunday, 12-10-2014	0.736	0.716	0.750	0.798	0.840	0.898	0.914	0.889	0.871	0.849	0.793	0.703



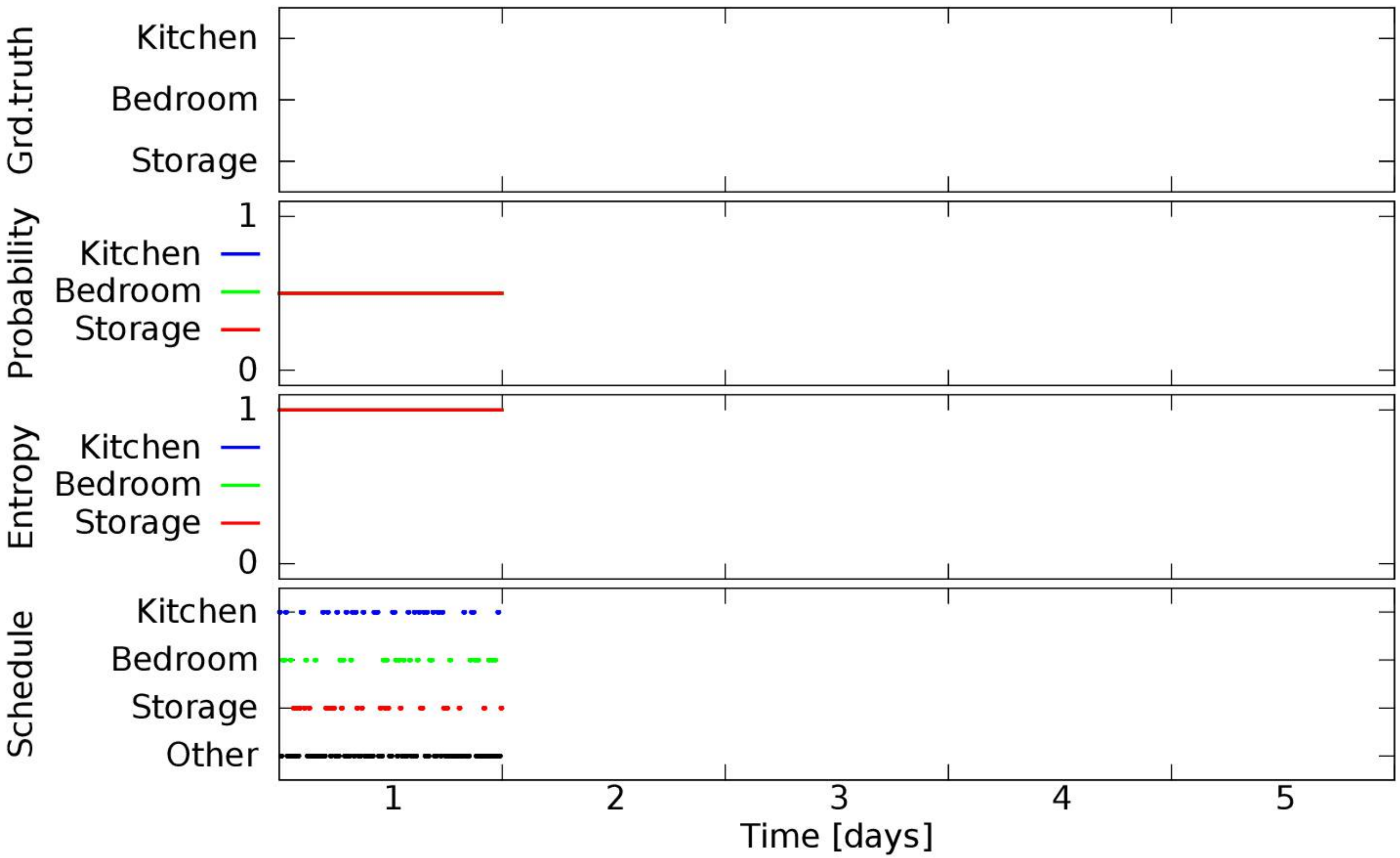
Example 5: Spatio-temporal exploration of dynamic environments

- Spatio-temporal exploration is a never-ending (life-long) process
- The robot has to determine both <u>where</u> to go and <u>when</u> to go there
- Our approach combines
  - Spatio-temporal entropy
  - Information-gain-based exploration

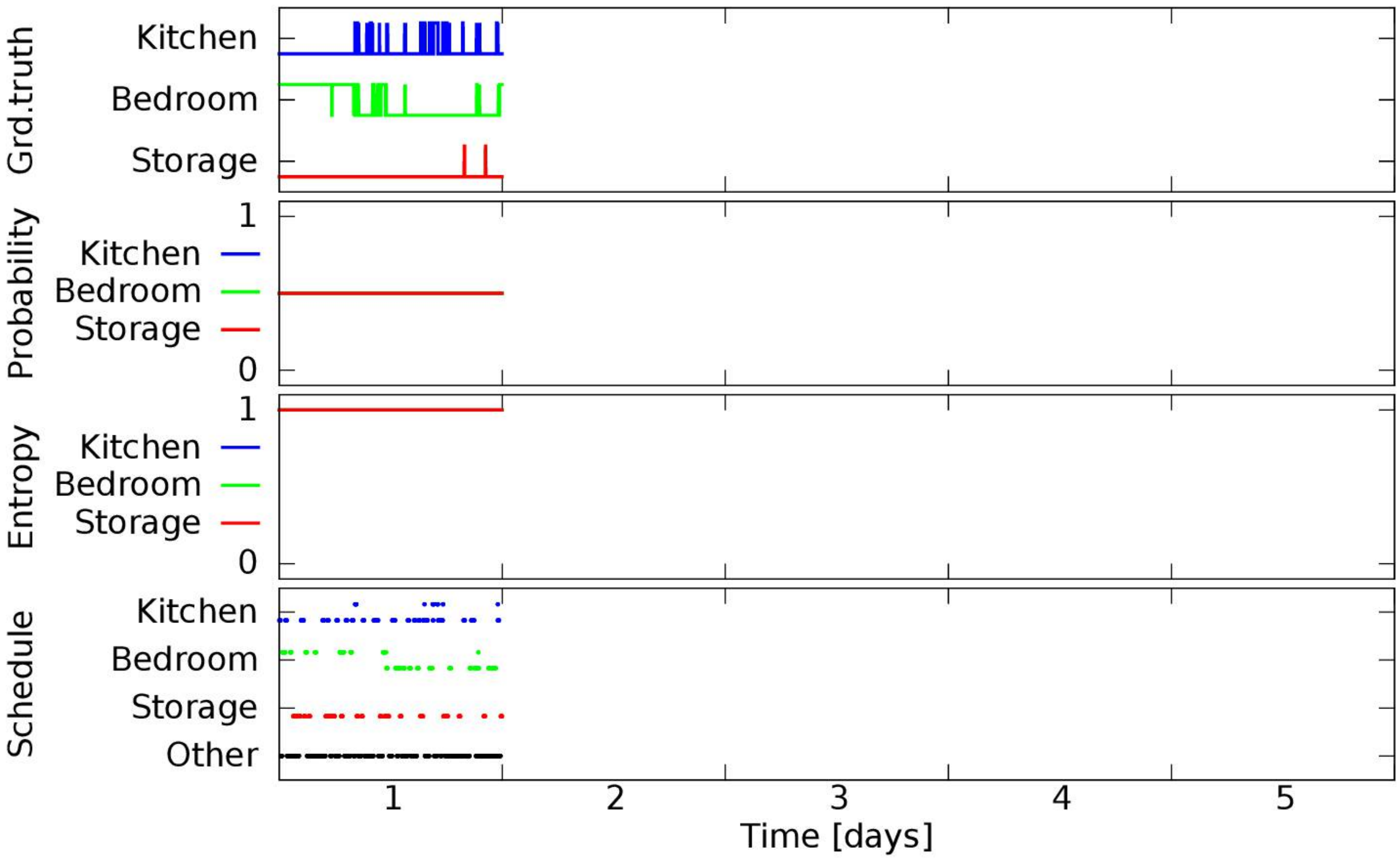
The CASAS-Aruba environment

T. Krajnik, J. Santos and T. Duckett. *Life-Long Spatio-Temporal Exploration of Dynamic Environments*. In Proc. ECMR 2015., Lincoln, UK.

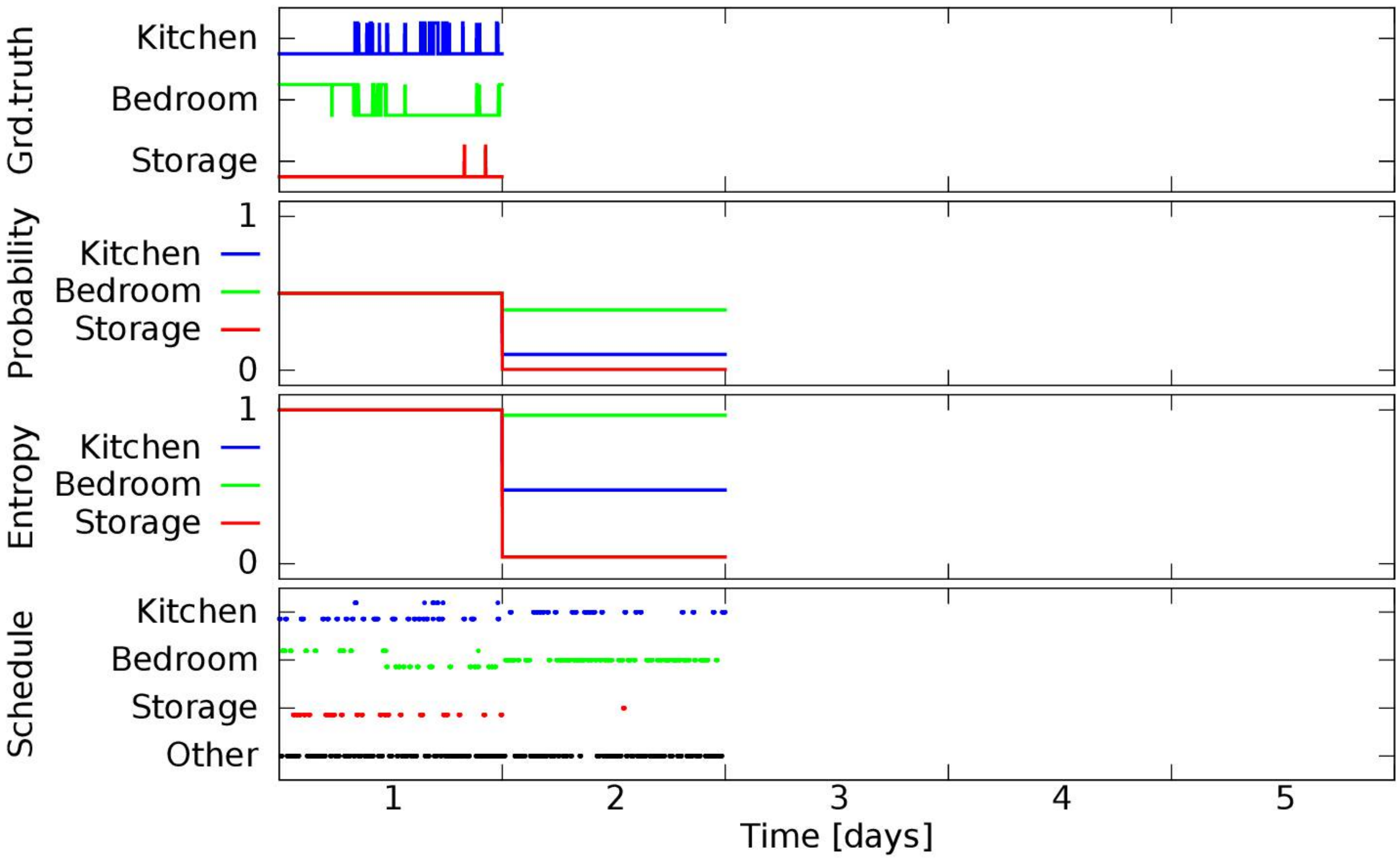
Spatio-temporal exploration



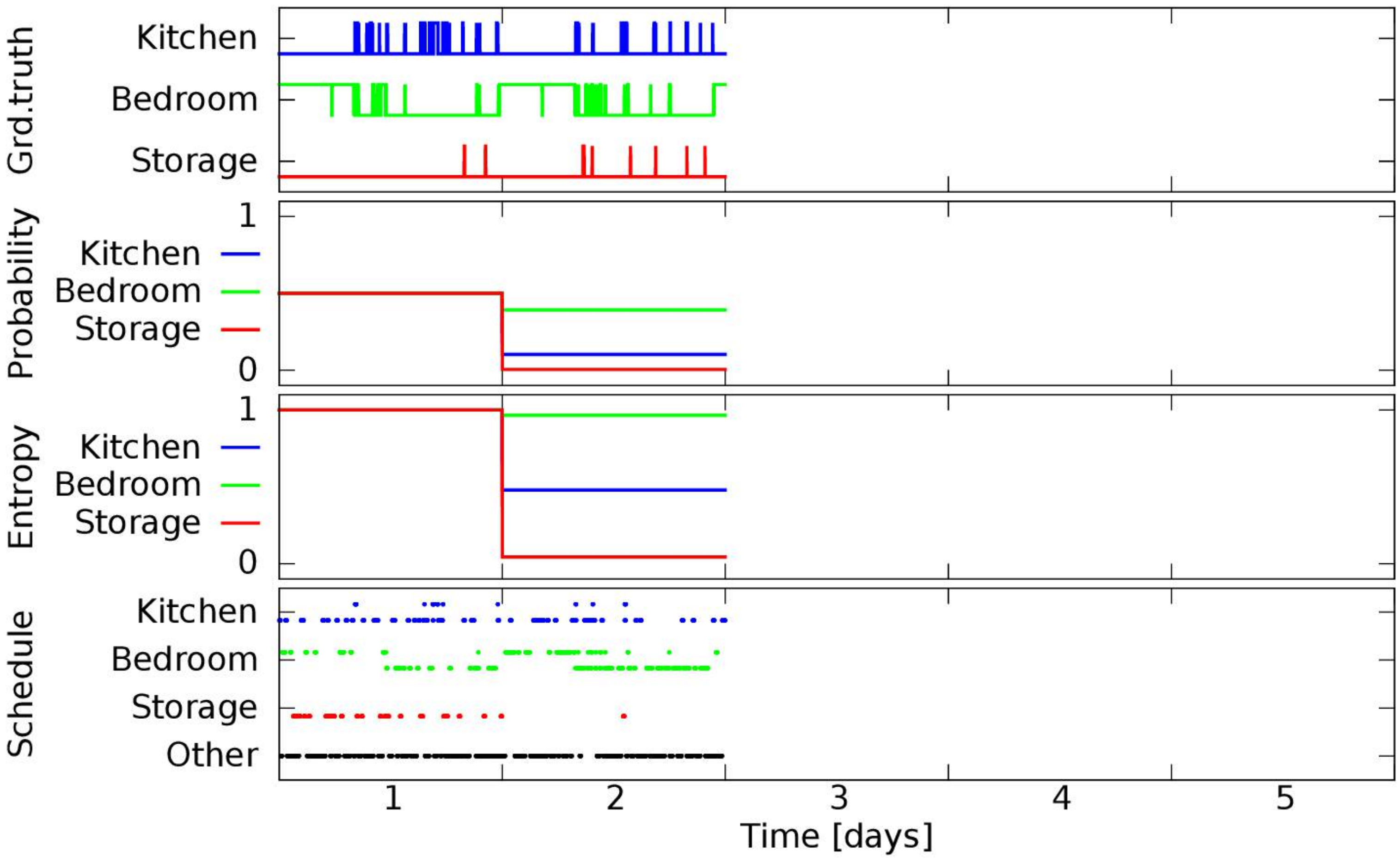
Spatio-temporal exploration



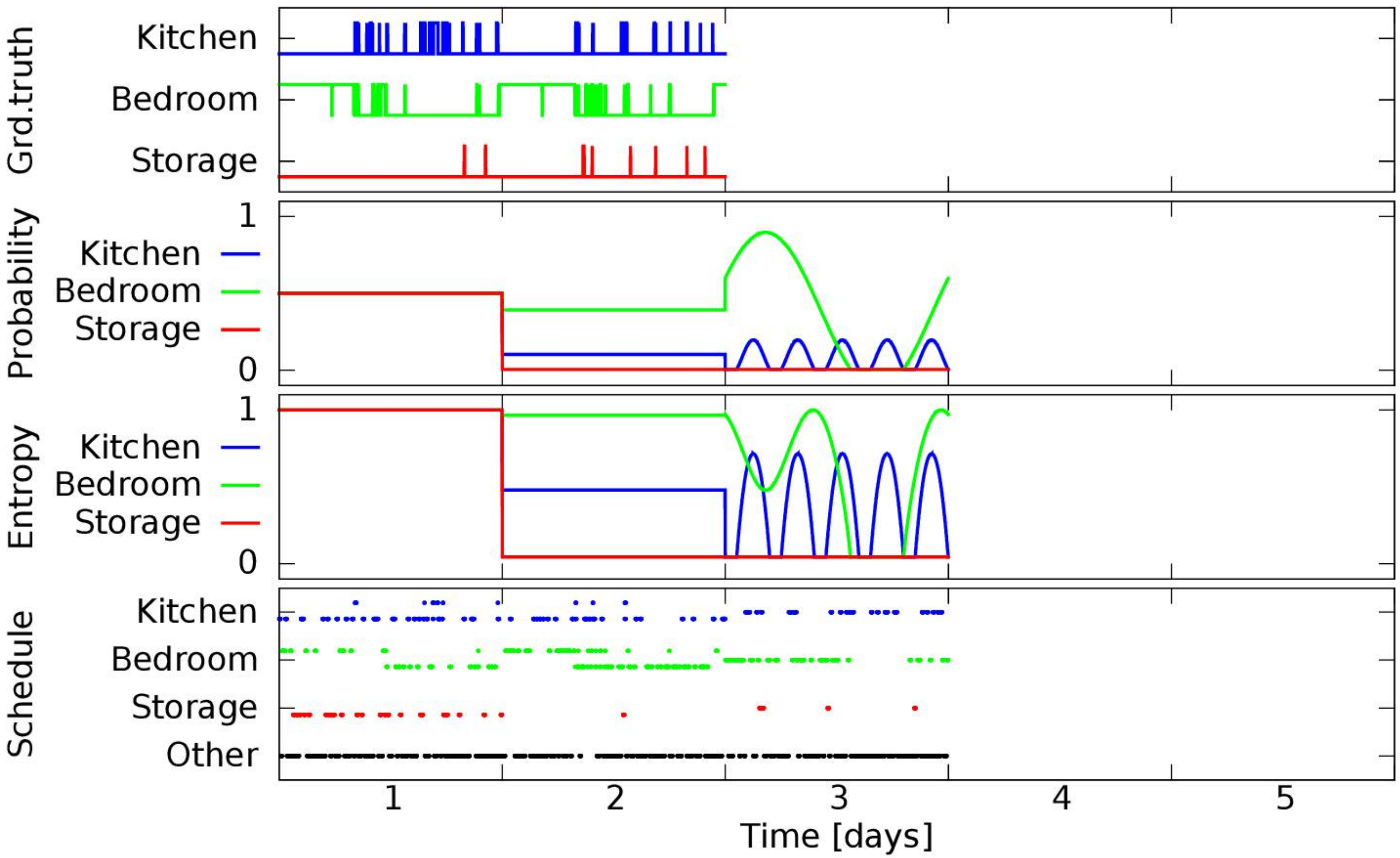
Spatio-temporal exploration



Spatio-temporal exploration



Spatio-temporal exploration



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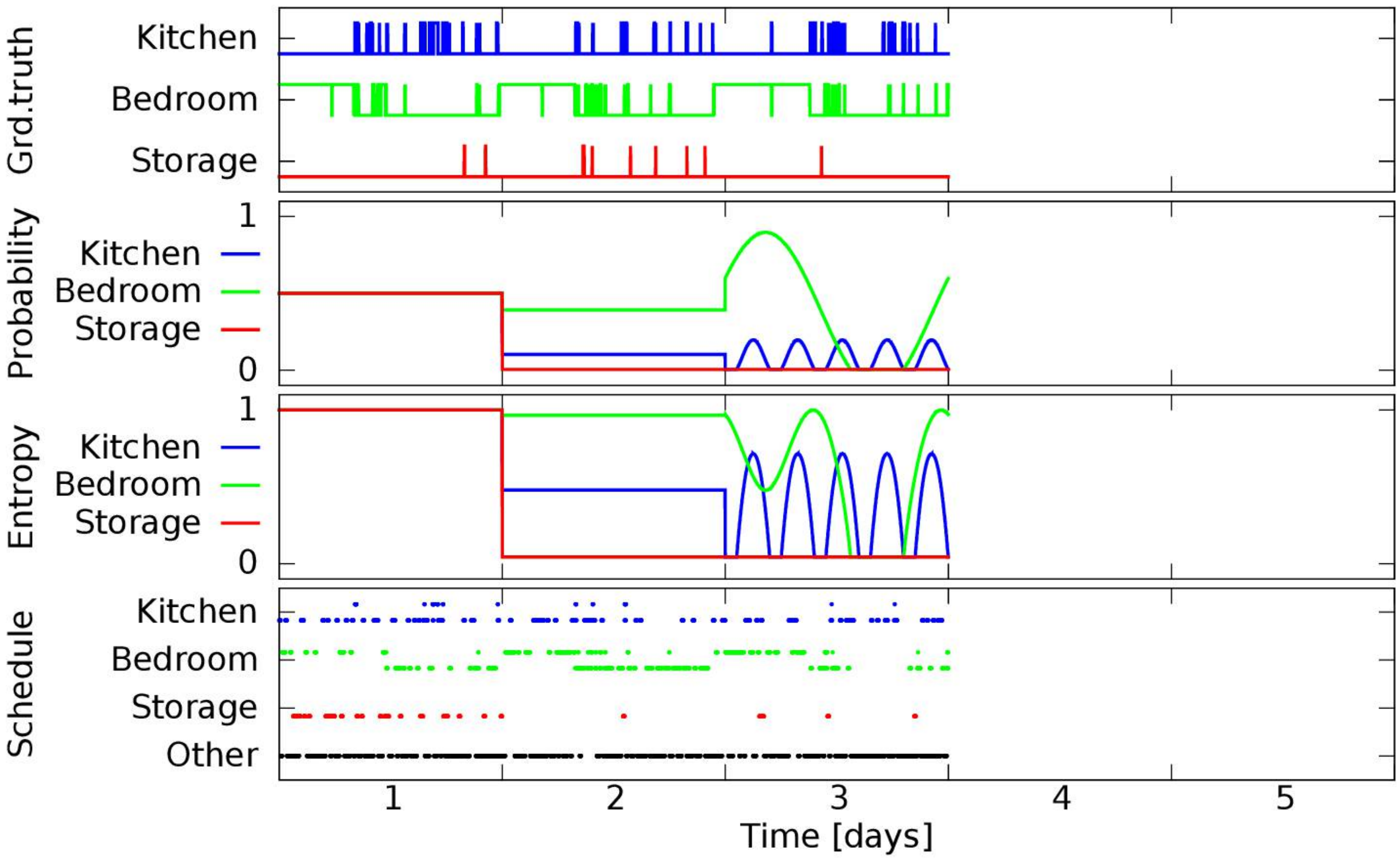
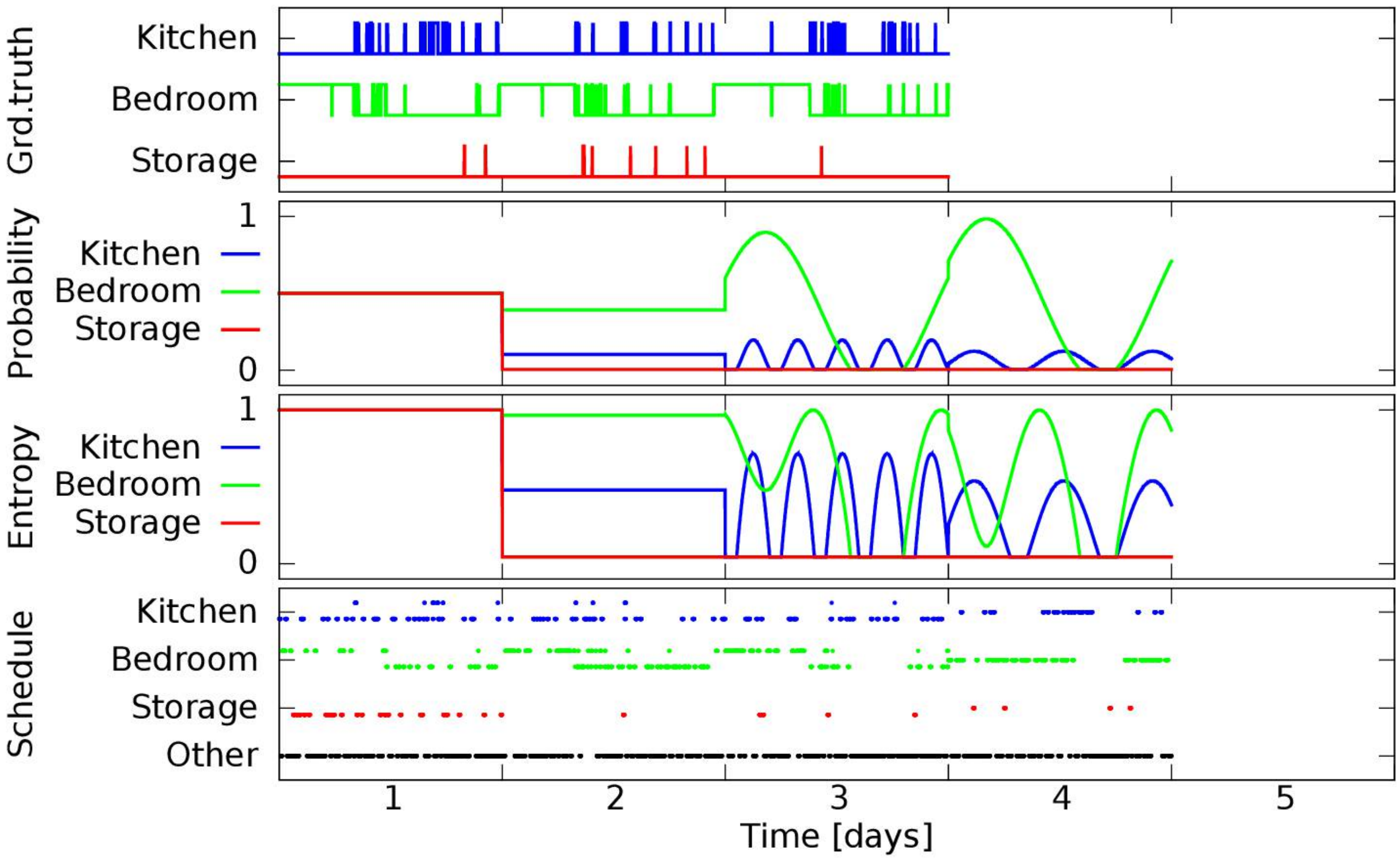
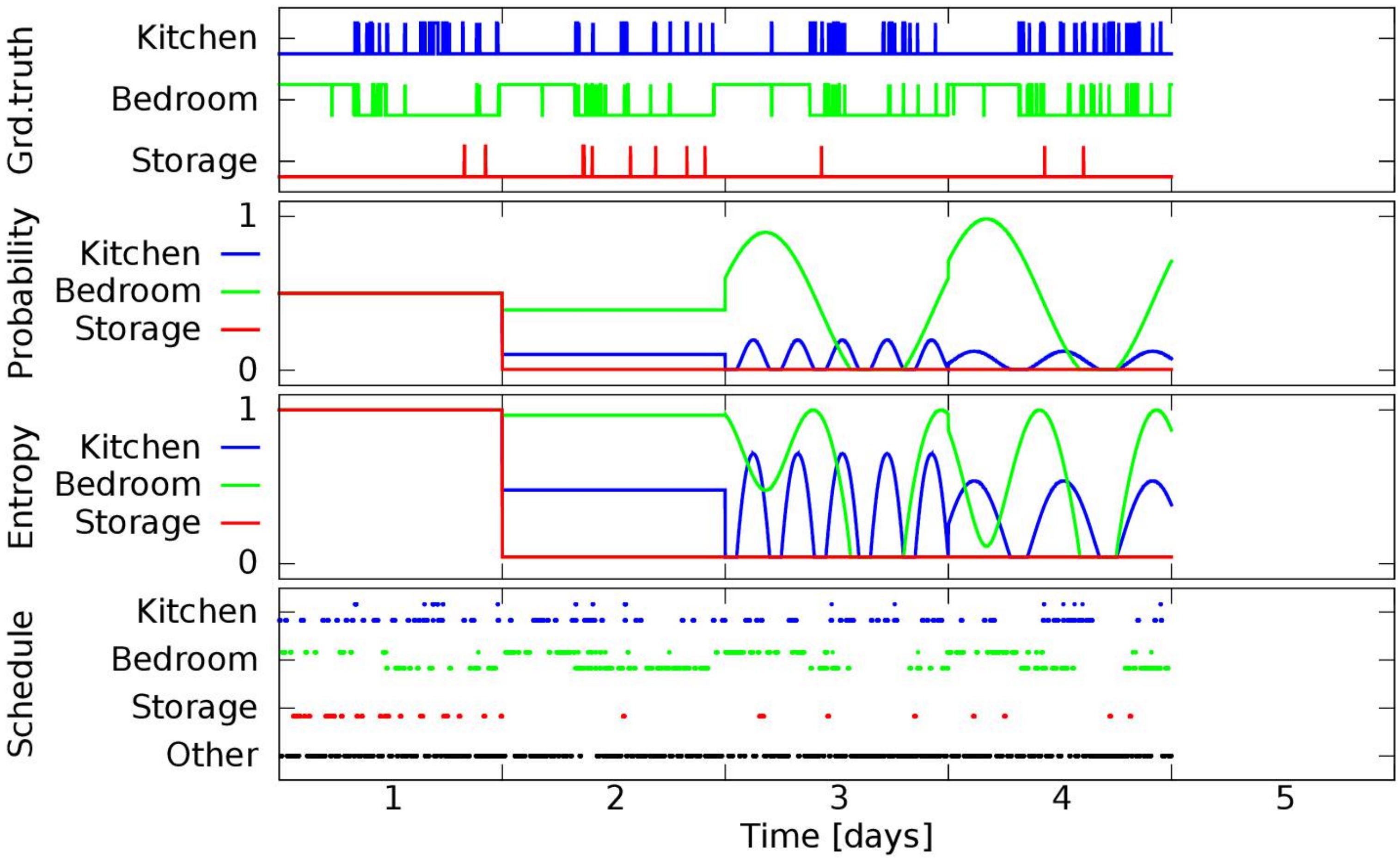


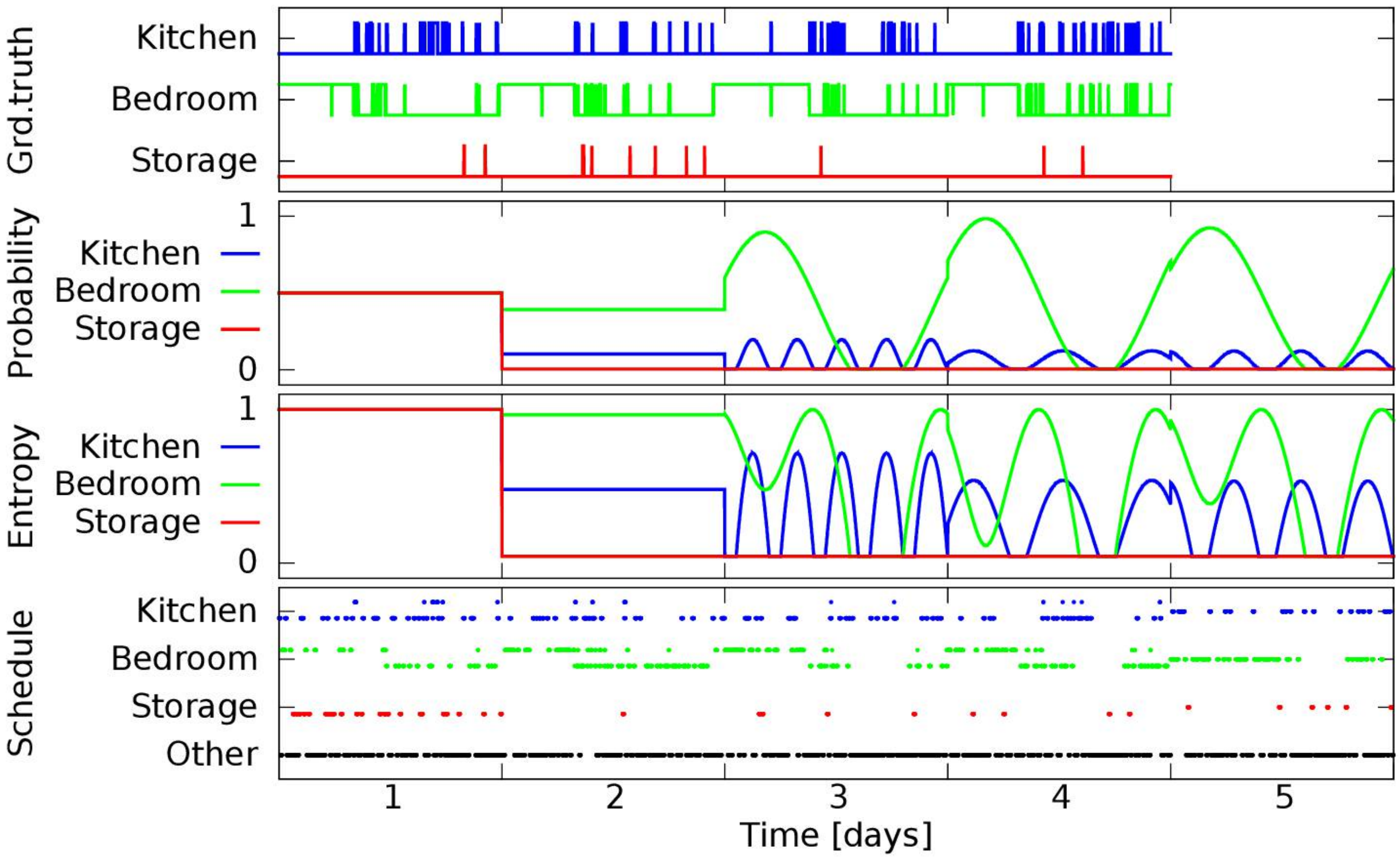
Spatio-temporal exploration



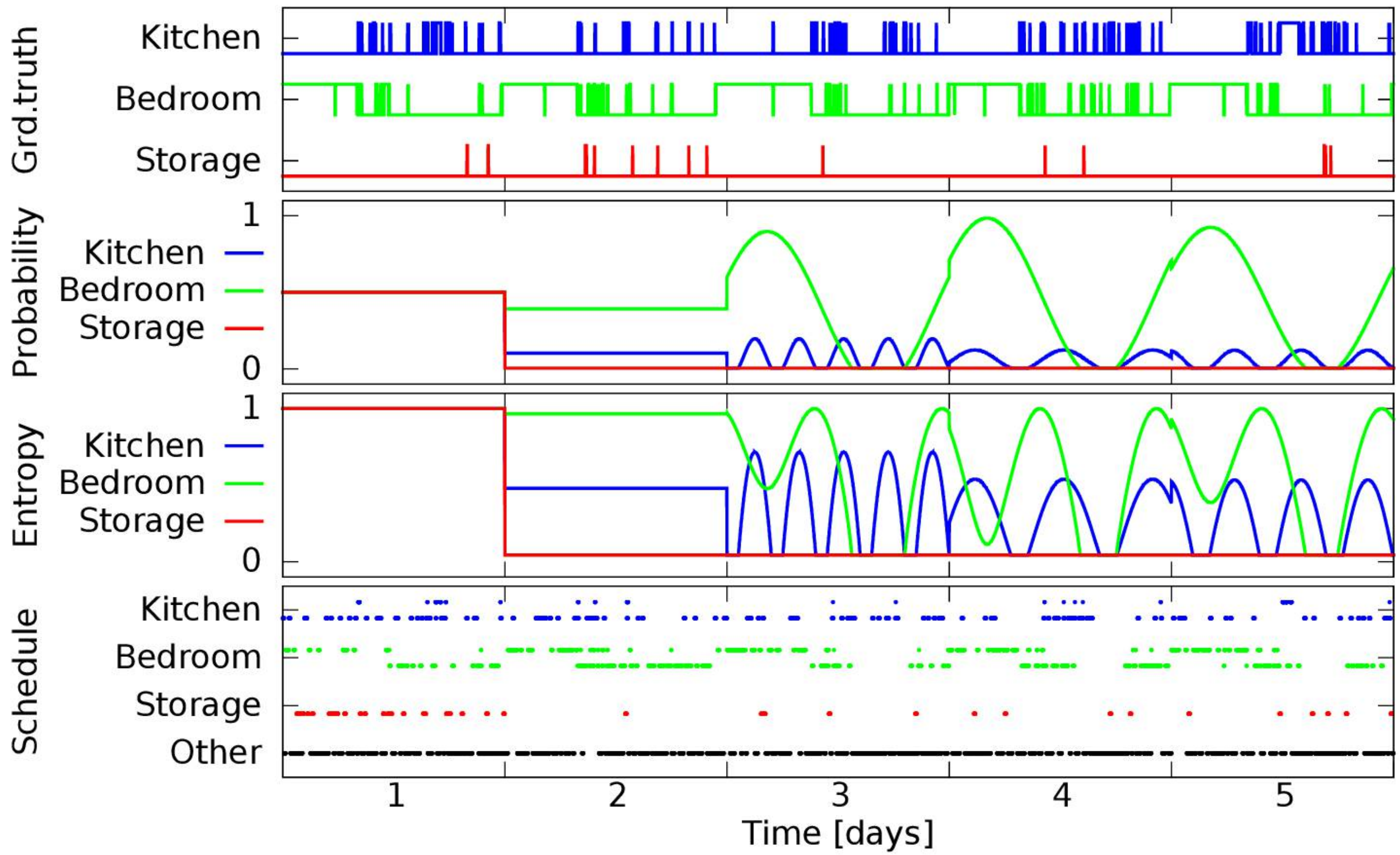
Spatio-temporal exploration



Spatio-temporal exploration

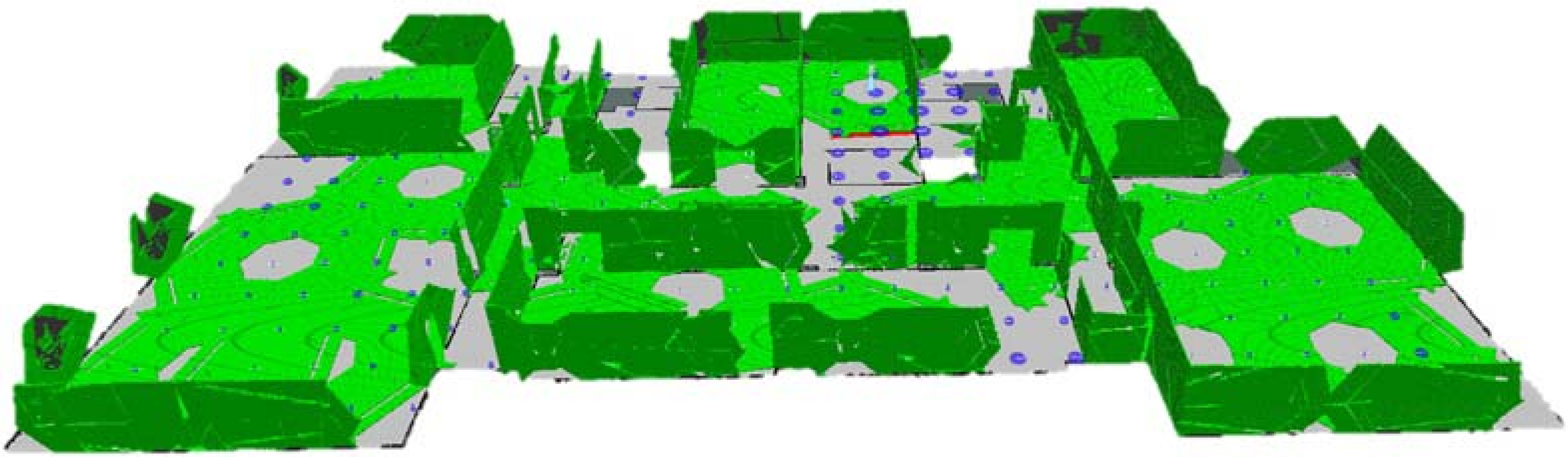


Spatio-temporal exploration

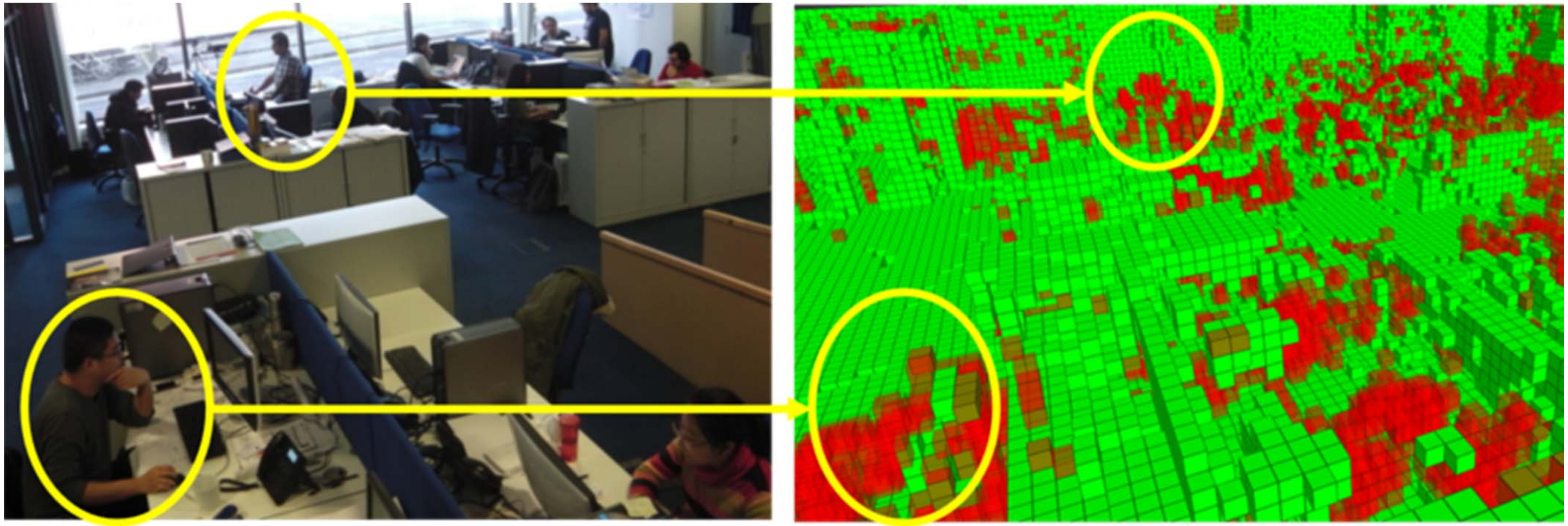


“4D” Spatio-temporal exploration

- Information-driven map updates
  - Spatio-temporal information-driven Next Best View.
  - FreMEn occupancy grids + spatio-temporal entropy estimates + temporal path planning
  - (Joao Santos’ PhD topic)



“4D” Spatio-temporal exploration



FreMEn-based occupancy grid of the Lincoln Centre for Autonomous Systems (L-CAS) office. The static cells are in green and cells that exhibit daily periodicity are in red.

T. Krajnik, J. Santos and T. Duckett. *Life-Long Spatio-Temporal Exploration of Dynamic Environments*. In Proc. ECMR 2015., Lincoln, UK.

Conclusions

- World model that takes into account the dynamics of the environment from a long-term perspective.
- We represent state changes using periodic functions, identified by means of the Fourier transform.
- FREMEN is suitable for different timescales with constant memory requirements.
- Can extend any world model with binary states, e.g. gridmaps (Octomap), landmarks and semantic maps
- Compression ratios 1:10^6, prediction accuracy 95%.
- Localization failure rate halved even after three months.


Thank you for your attention.
Questions ?

RELATED WORK

Related Work

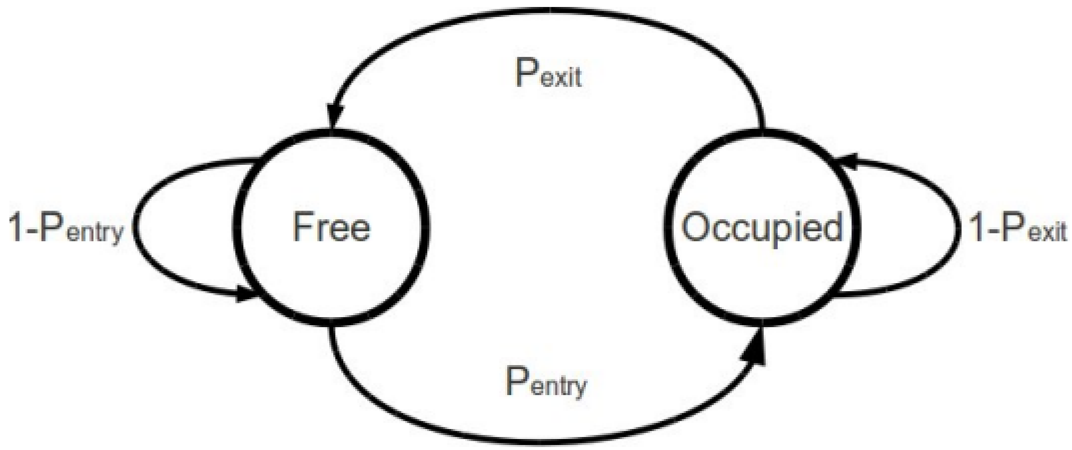
- Hierarchical Object Maps (Anguelov et al. 2002)
- SLAM with Detection And Tracking of Moving Objects (Wang and Thorpe, 2002)
  - partition the static elements from the non-static elements, and consider each set separately.
  - cannot handle long-term changes

Related Work

- Temporary Maps (Meyer-Delius et al., IROS 2010)
  - model the effect of temporary objects by performing local SLAM
  - localization with particle filter using these locally static maps

Related Work

- Independent Markov Chain Occupancy Grid Maps (Saarinen at al., IROS 2012)
  - independent Markov chains (iMac) stored with every cell on the grid



Related Work

- Rao-Blackwellized Particle Filter with Hidden Markov Model (Tipaldi et al., 2013)
- Dual –timescale NDT-MCL (Valencia et al., 2014)
  - Short-term map
  - Static map
- Episodic Non-Markov Localization (Biswas & Veloso, 2014)
  - Reasoning About Short-Term and Long-Term Features