Long-Term Perception for Service Robots

Tomas Krajnik, Jaime P. Fentanes
Oscar M. Mozos, Tom Duckett,
Johan Ekekrantz, Marc Hanheide

LCAS, University of Lincoln, UK
CAS, KTH, Sweden

Lincoln Centre for Autonomous Systems Research (L-CAS)

- Prof Tom Duckett
- Prof Shigang Yue
- Dr Grzegorz Cielniak
- Dr Nicola Bellotto
- Dr Marc Hanheide
- Dr Oscar Martinez Mozos
- Currently 4 postdocs, 12 research students and 5 visiting academics
- (research centre in the School of Computer Science, now based at Witham Wharf next to Lincolnshire Echo)

Lincoln Centre for Autonomous Systems Research (L-CAS)

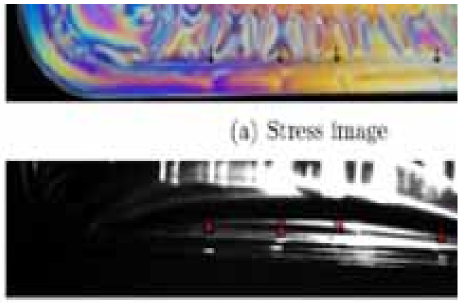
- Human-Centred Robotics
  - Long-term Adaptation & Learning
  - Human-Robot Interaction & Collaboration
  - Mapping & Navigation

FP7 IP project STRANDS develops intelligent mobile robots that are able to run for months in dynamic human environments, learning from their long-term experience

Lincoln Centre for Autonomous Systems Research (L-CAS)

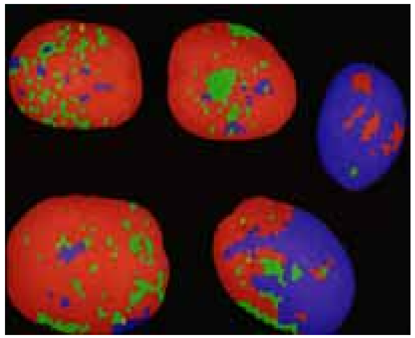
- Agri-Food Technology
  - Agricultural Robotics
    - Sensing and
    - control

  - Food Quality Inspection
    - Raw,
    - processed, and
    - packaged products



(a) Stress image

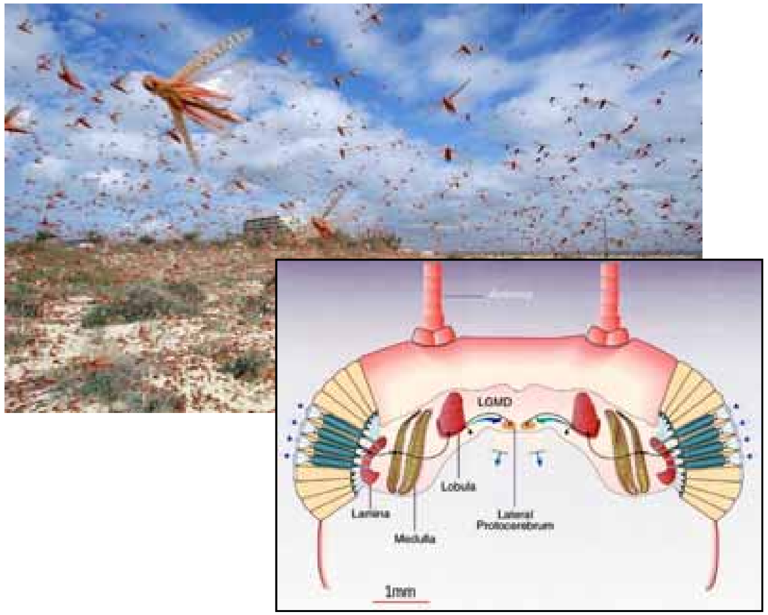
(b) Laser scatter



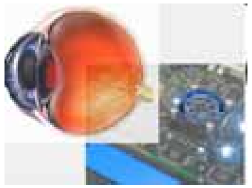
3 current TSB-funded projects

Lincoln Centre for Autonomous Systems Research (L-CAS)

- Bio-inspired Embedded Systems
  - Bio-inspired Vision Systems
  - Image Processing
  - VLSI Realisation



HAZCEPT, toward zero road accident – bio-inspired hazed perception (FP7)



EYE2E, building visual brain for human machine interaction (FP7)

LIVCODE, life-like vision system for collision detection (FP7)

Log-Term Perception for Service Robots

Tomas Krajnik, Jaime P. Fentanes
Oscar M. Mozos, Tom Duckett,
Johan Ekekrantz, Marc Hanheide

LCAS, University of Lincoln, UK
CAS, KTH, Sweden

[Krajnik et al: Spectral Analysis for Long-Term Robotic Mapping, ICRA 2014]

Temporal domain model: example

Continuous observation of an office door (open/closed)

0 spatial and 1 temporal dimension (0+1D)

State **s(t)**:

•open/closed

Timescale:

•one week

Measurements:

•30Hz x 7 days

•≈ 18 000 000

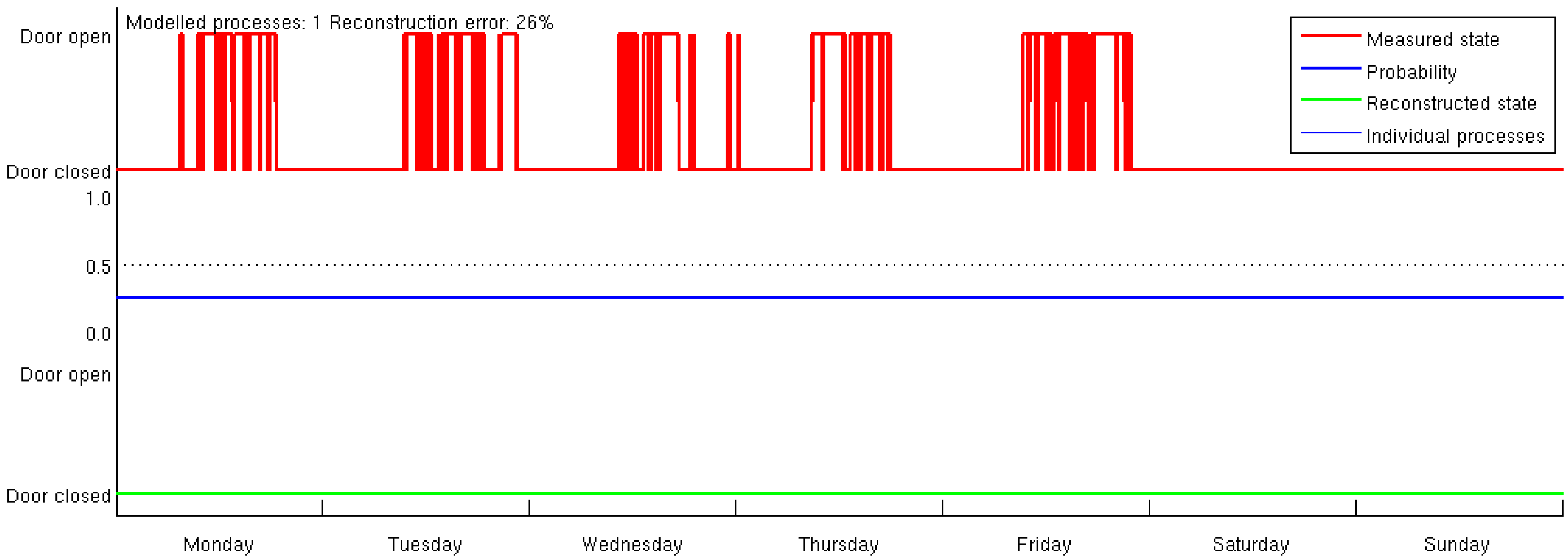
Temporal domain model: example

Continuous observation of an office door (open/closed)

Static model: **p(t)** = P(s(t)=`open') = 0.26 for all t

s(t)=`open' iff **p(t) >** 0.5 → **s(t)** = "closed" for all t

s(t) does not match the observations in 26% cases



Temporal domain modelling

- Classical models neglect the temporal domain: uncertainty of state **s** is modelled by its probability **p**
- Including temporal aspect means that uncertainty of **s(t)** is modelled by probability **p(t)**
- However, storing all observed **s(t), p(t)** is unfeasible
- Main idea: in days-to-months scales, **s(t), p(t)** are quasi-periodic represent **p(t)** as superposition of harmonic functions

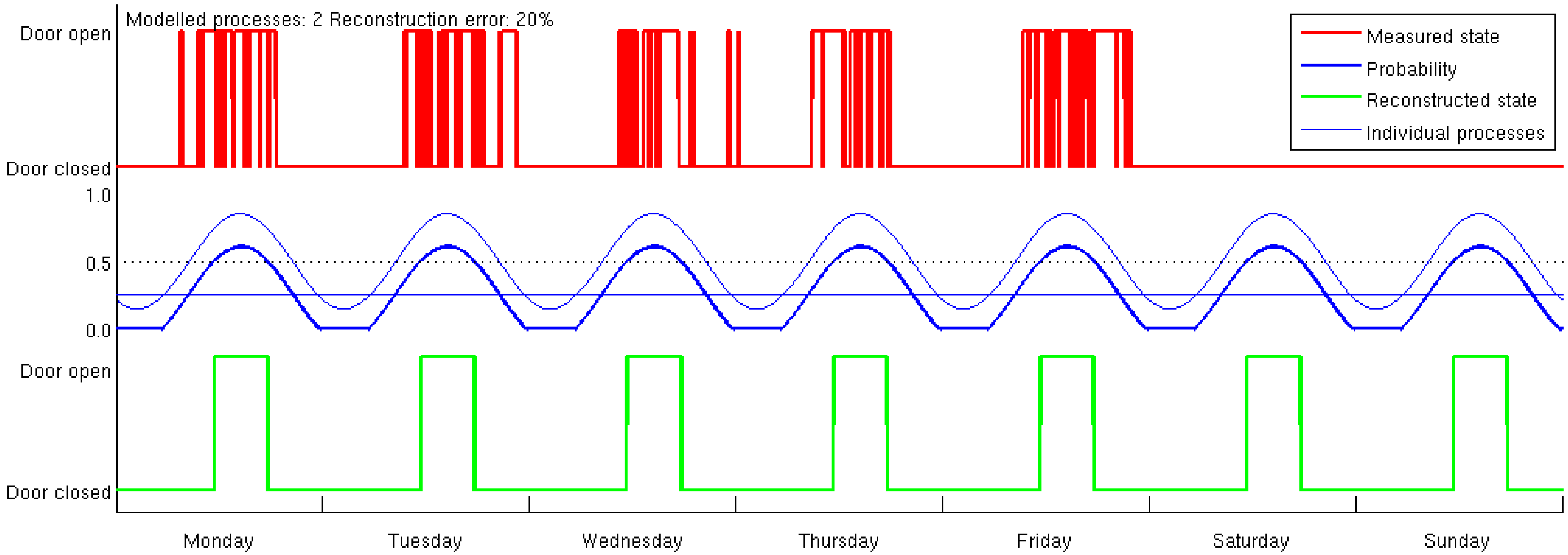
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with one periodic process:

p(t) = P(s(t)=`open') is a harmonic function

s(t) does not match the observations in 20% cases



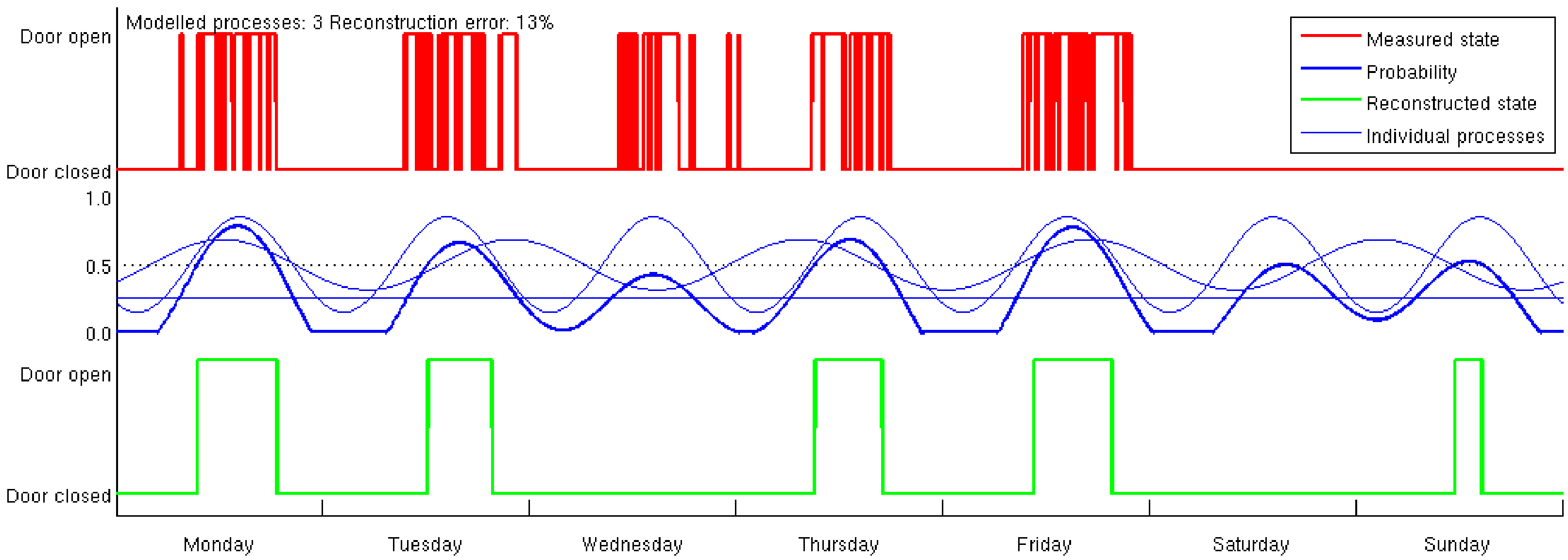
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with two periodic processes:

p(t) is a superposition of harmonic functions

s(t) does not match the observations in 13% cases



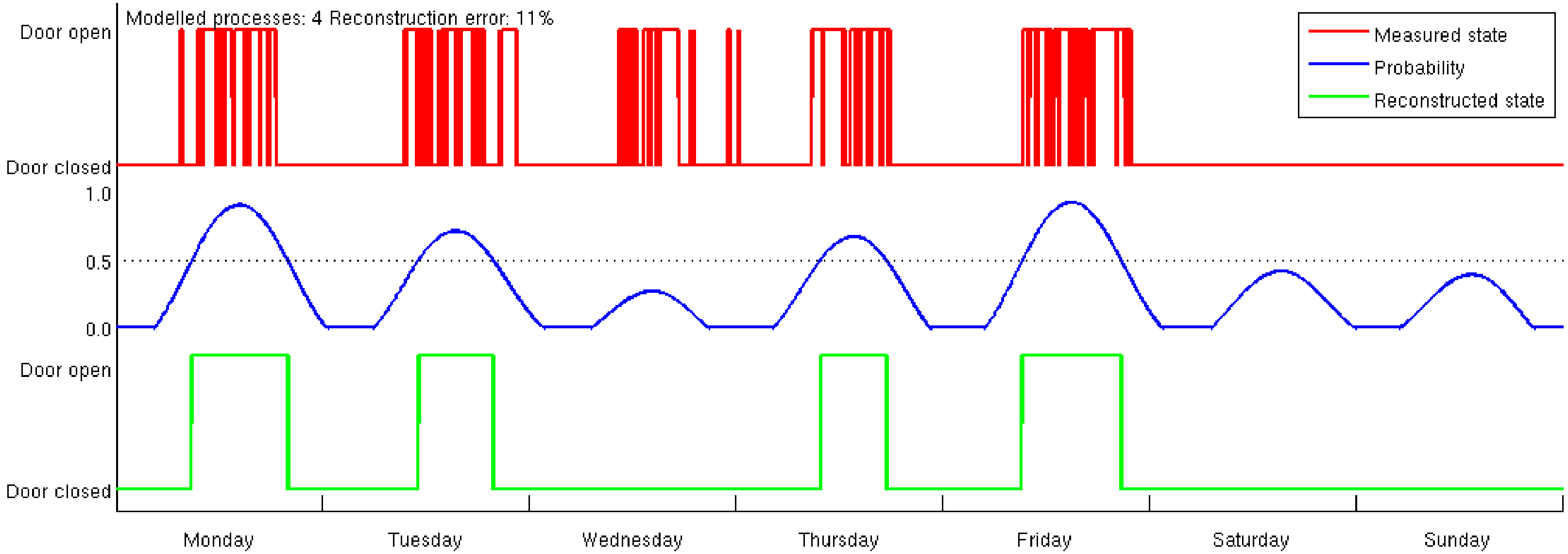
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



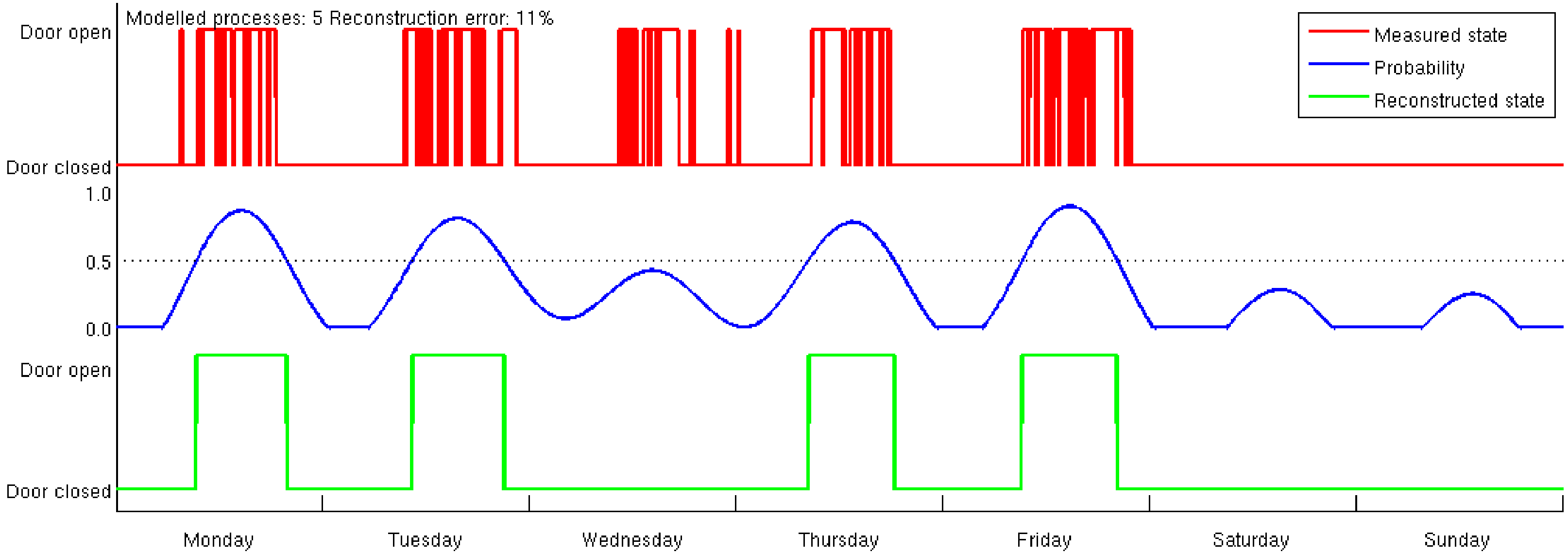
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



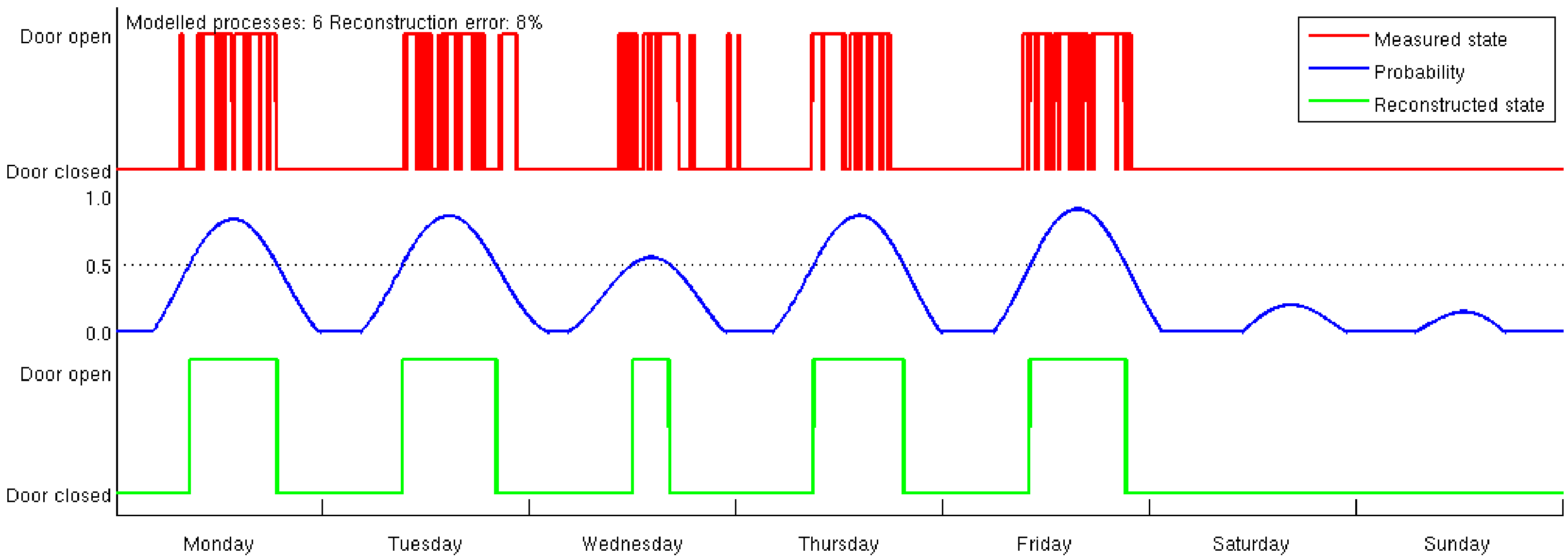
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



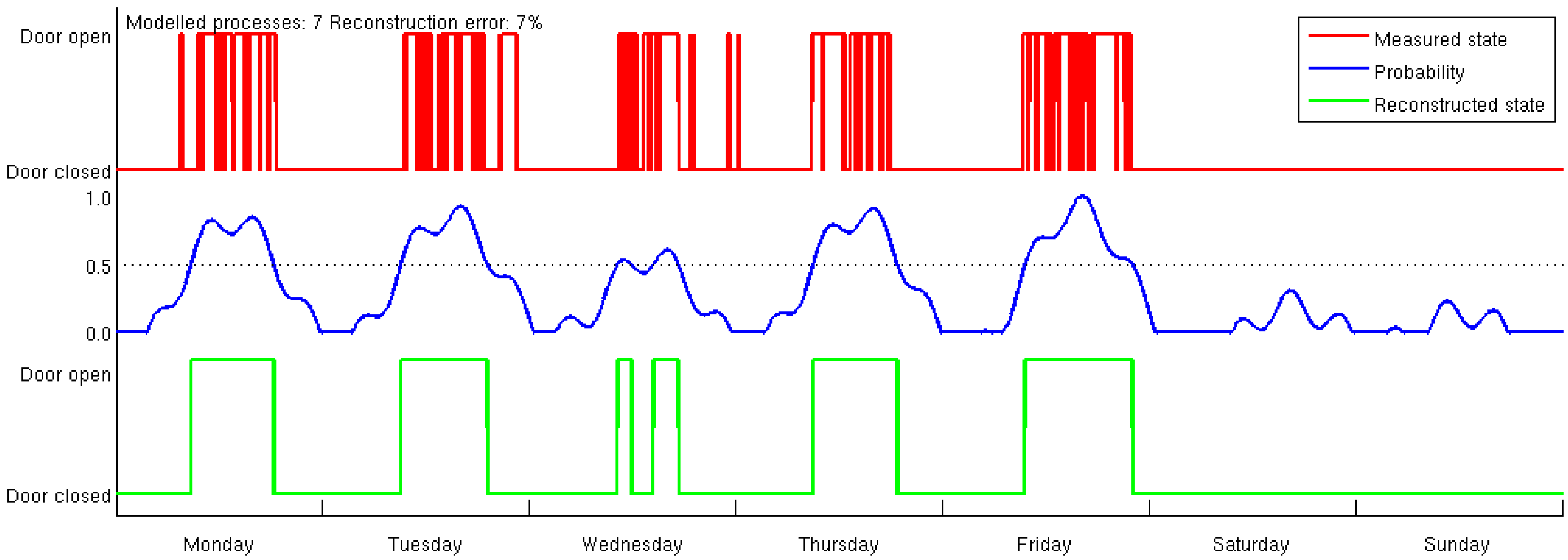
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



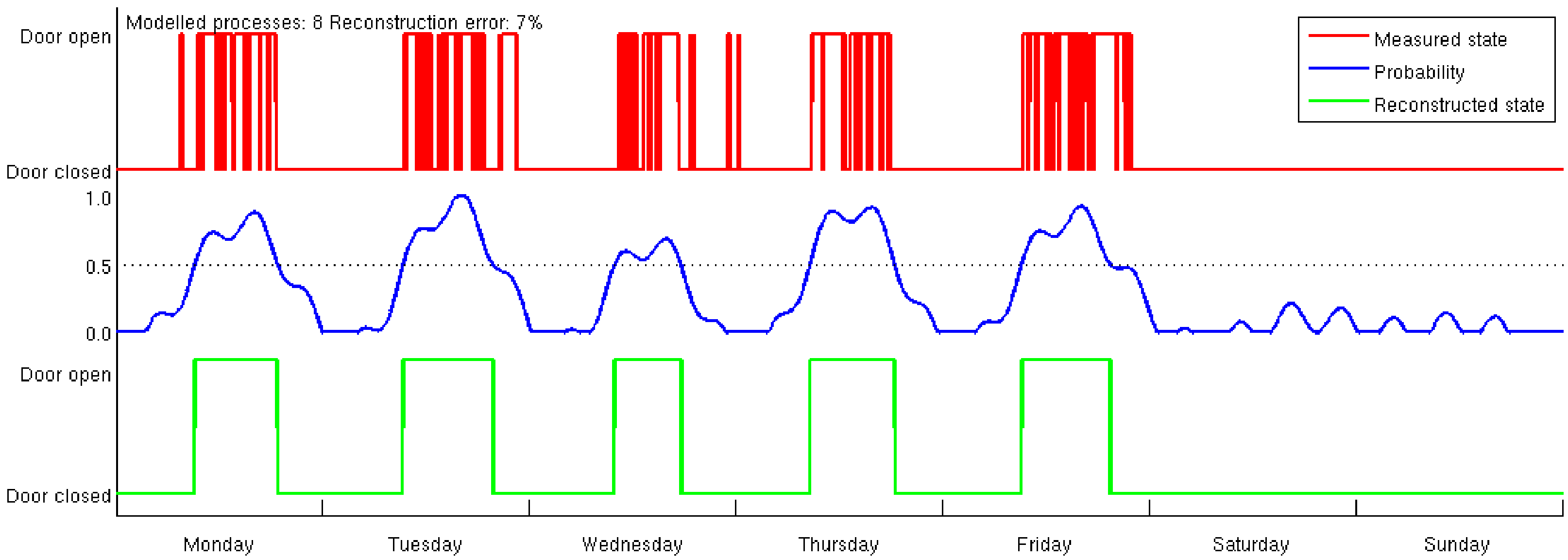
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



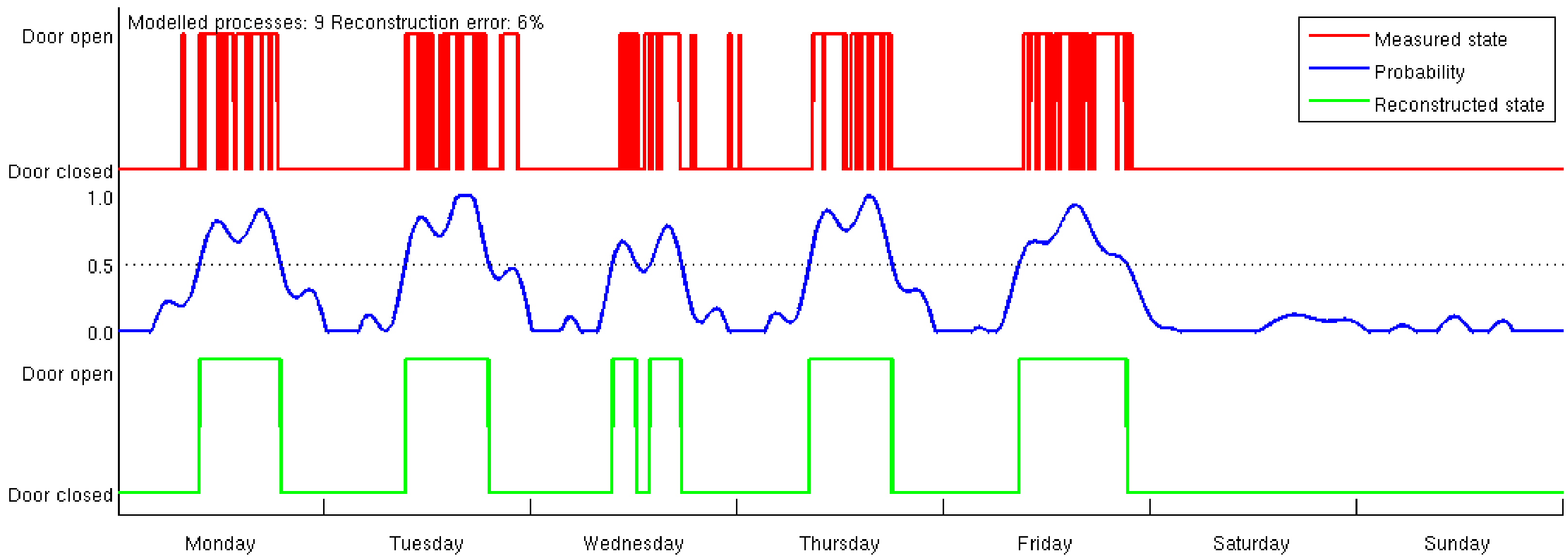
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



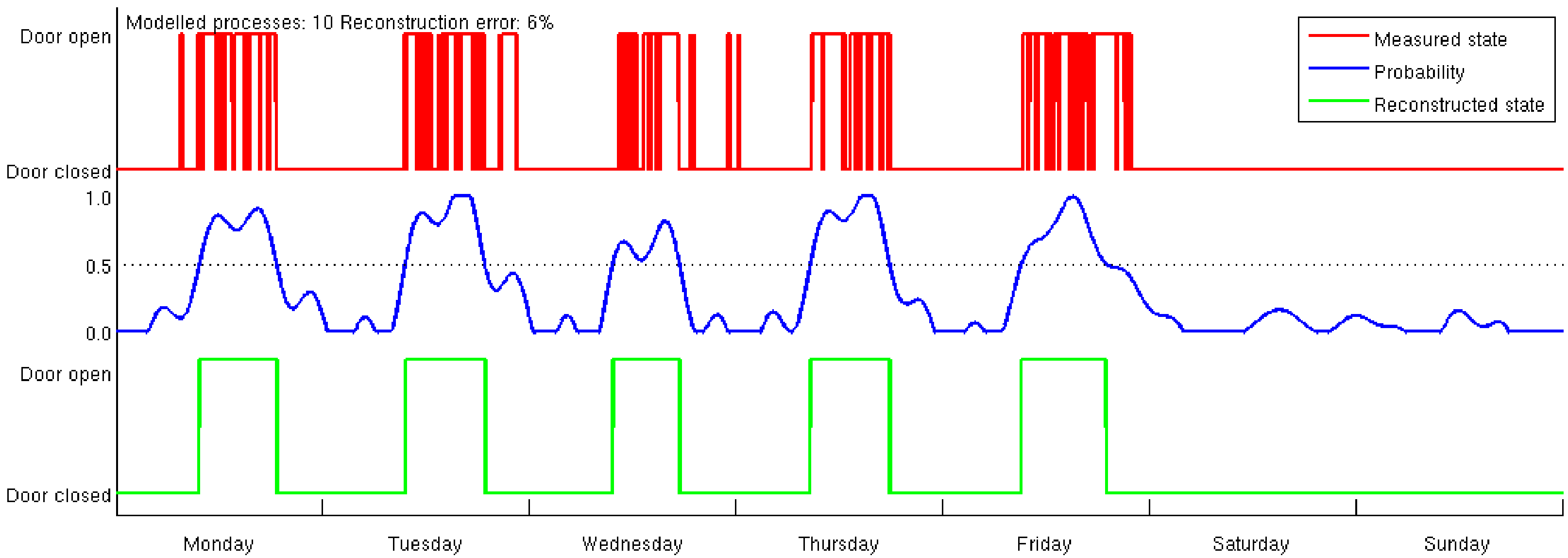
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



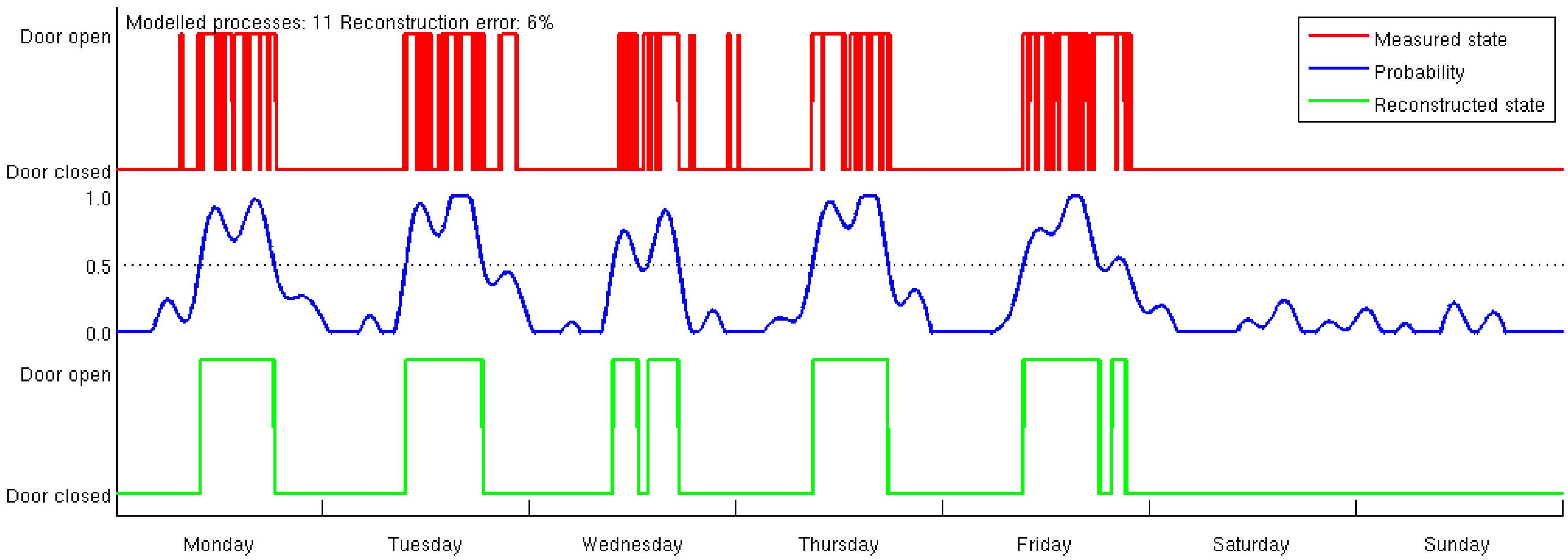
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



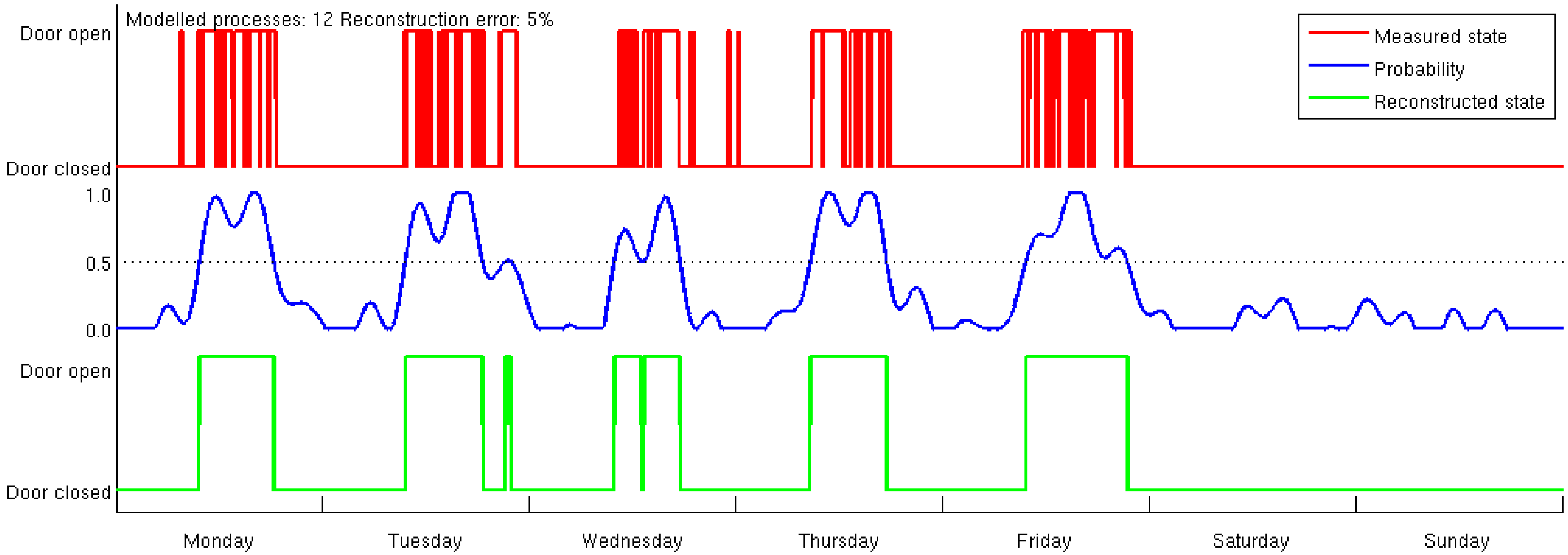
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



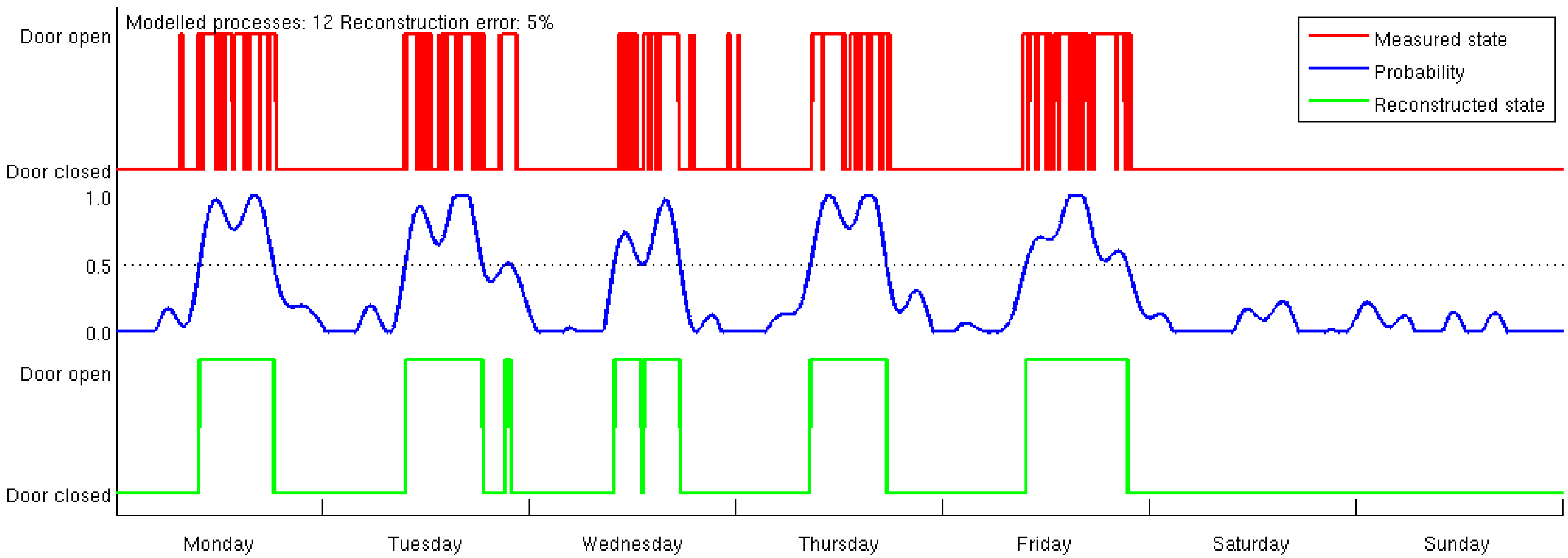
Temporal domain model: example

Continuous observation of an office door (open/closed)

Dynamic model with **n** periodic processes:

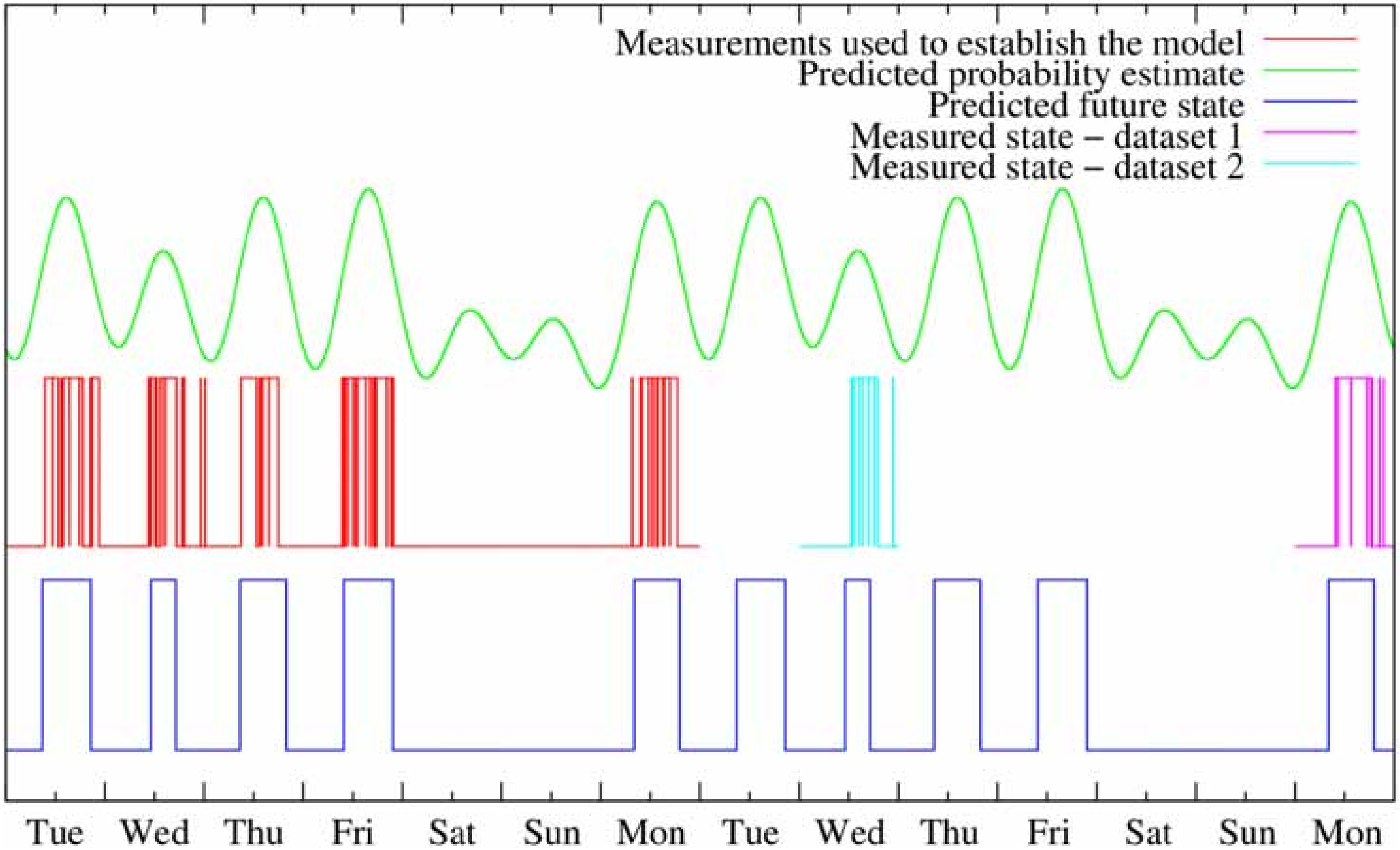
p(t) is a superposition of **n** harmonic functions

s(t) does not match the observations in 5-13% cases



Temporal domain model: example

Predict two days of the following week and compare with the reality (12% and 6% error)



FREquency **M**ap **EN**hancement

- Let the world model be a set of (binary) states, e.g. occupancy grid
- Assume, that the states are influenced by a set of periodic (yet unknown) processes
- Use frequency transforms such as FFT to identify these processes

FREquency **M**ap **EN**hancement

Example of open door detection:

- One week continous measurement -> 18 million values
- The spectral model with 12 processes achieves 5% error
- 18 million values represented by 36 real numbers -> compression rate aprox. 1:500 000
- Error of prediction 12% and 5%

3D occupancy grids

Occupancy grid dynamics at the lab entrance

States **s(t)**:

•3D occ. grid

$\approx 25^3$ cells

Timescale:

•one week

Measurements:

•7 days × 5 min

$\approx 2000 \times 25^3$

3D occupancy grids

Occupancy grid dynamics at the lab entrance

Red:

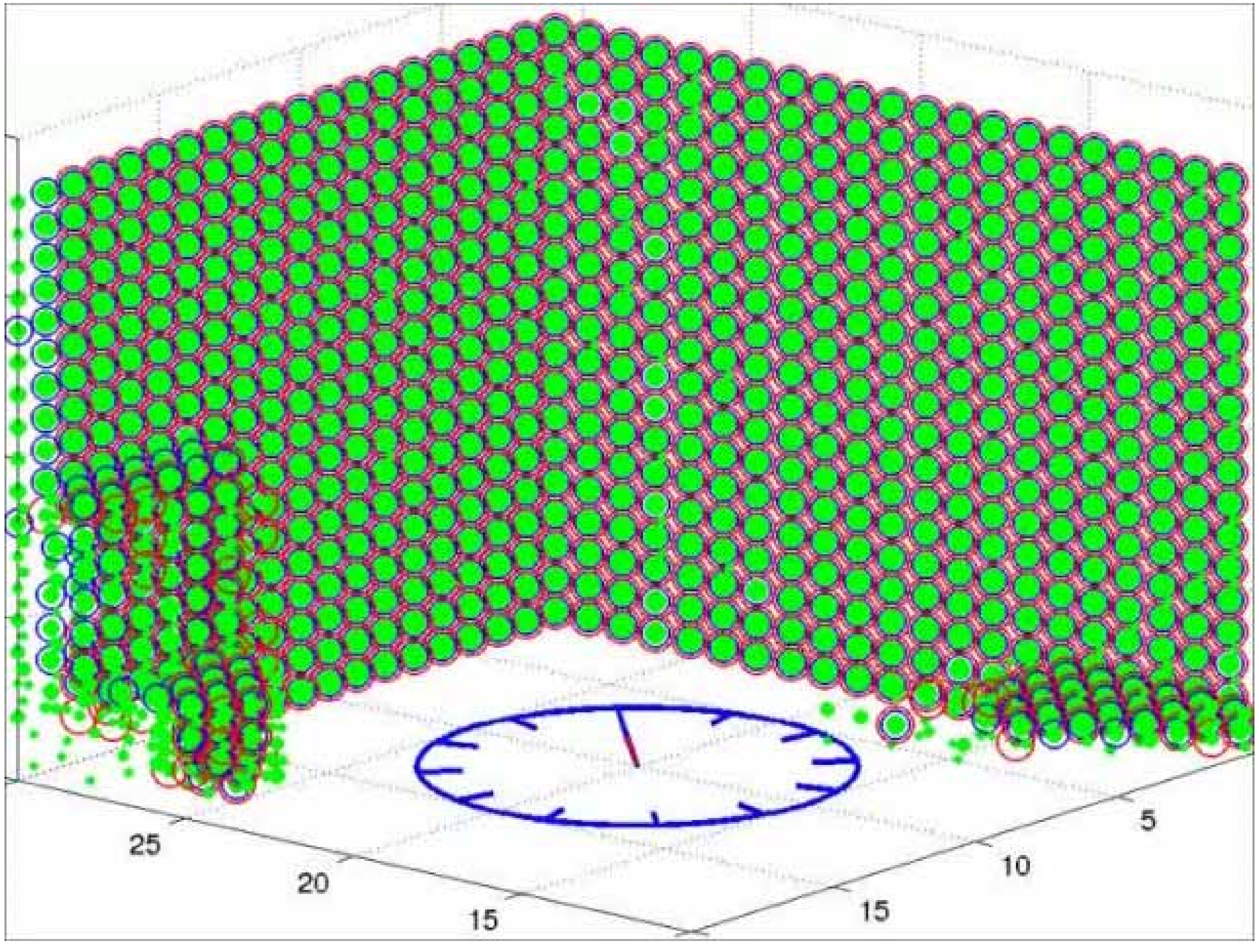
cell occupied (real)

Green:

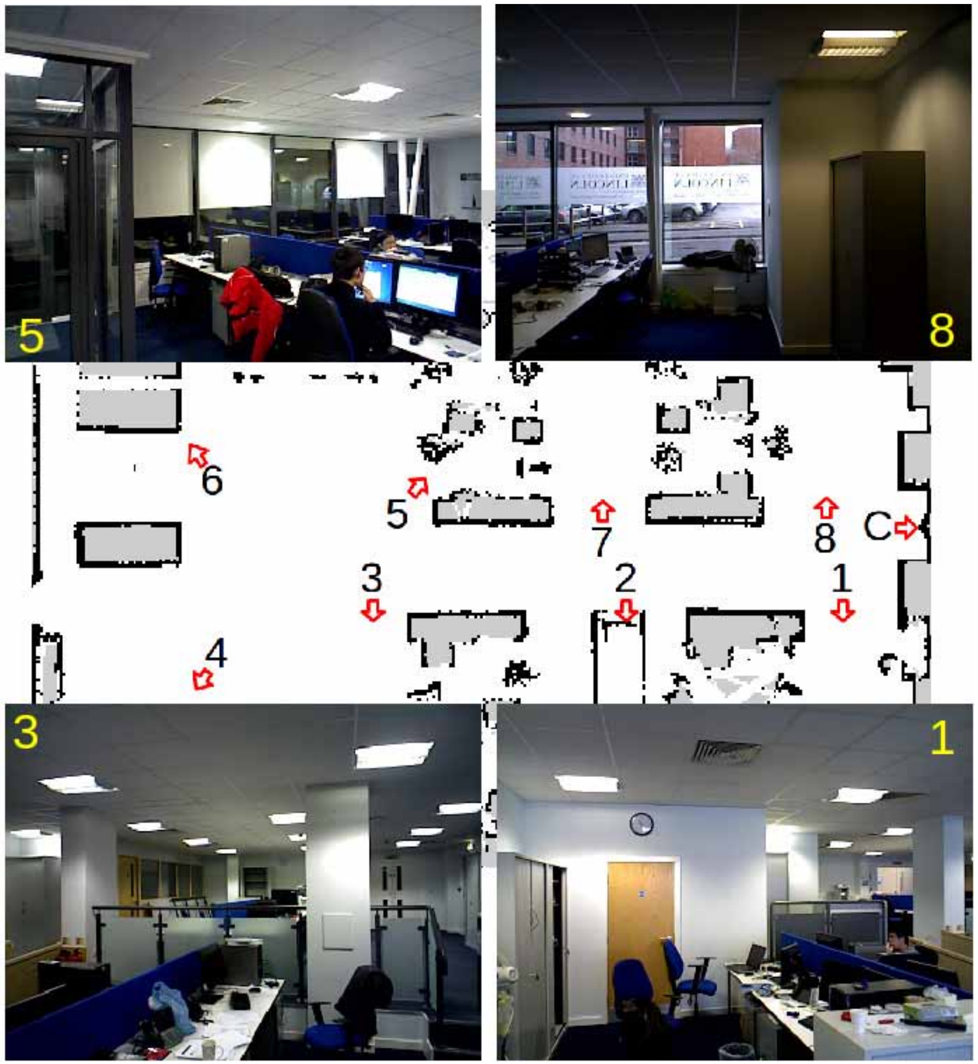
probability **p(t)**

Blue:

cell occupied (estimate)



Visual Topological localization

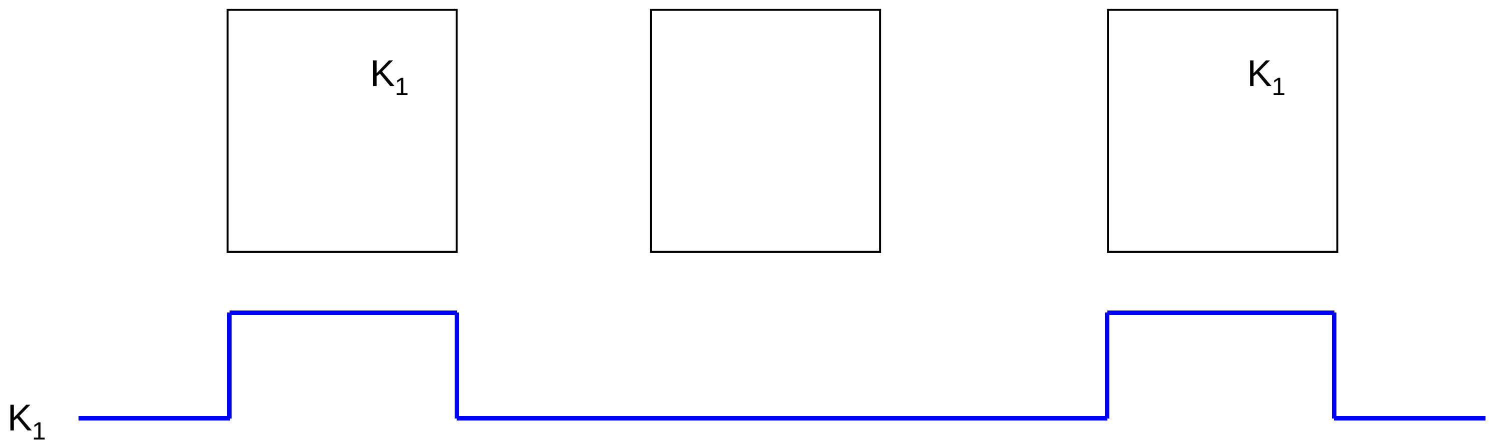


Visual Topological localization

Visual Topological localization

How to binarize visual observations:

- Images represented by key points + key descriptors
- Presence and absence of the same key descriptor in the (approx.) same positions is treated as a binary process.



Visual Topological localization

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

- A robot scans eight locations every ten minutes for one week, extract visual features
- Visibility of each feature modelled by FREMEN
- Then, a robot has to identify a location it is placed in
- Training set gathered on November 2013
- Testing sets December 2013 and February 2014
- Localization error halved compared to static models

Localization Results

Localization error for 8 different locations:

Model type	Model order	Image features Dec	Image features Feb
statical	-	35%	45%
spectral	1	25%	26%
spectral	2	22%	27%
spectral	3	18%	24%
spectral	4	17%	29%

Krajnik et al: Topological localization in Dyn. Env. using Spectral Maps, IROS 2014 (in review)

Conclusion

- Long-term perception takes into account the dynamics of the environment.
- We represent state changes using periodic functions, i.e. Fourier transform.
- Our FREMEN representation keeps dynamics while achieving high compression rates.
- FREMEN is suitable for different mobile robotic tasks, e.g. topological localization.

Thank you very much for your attention.

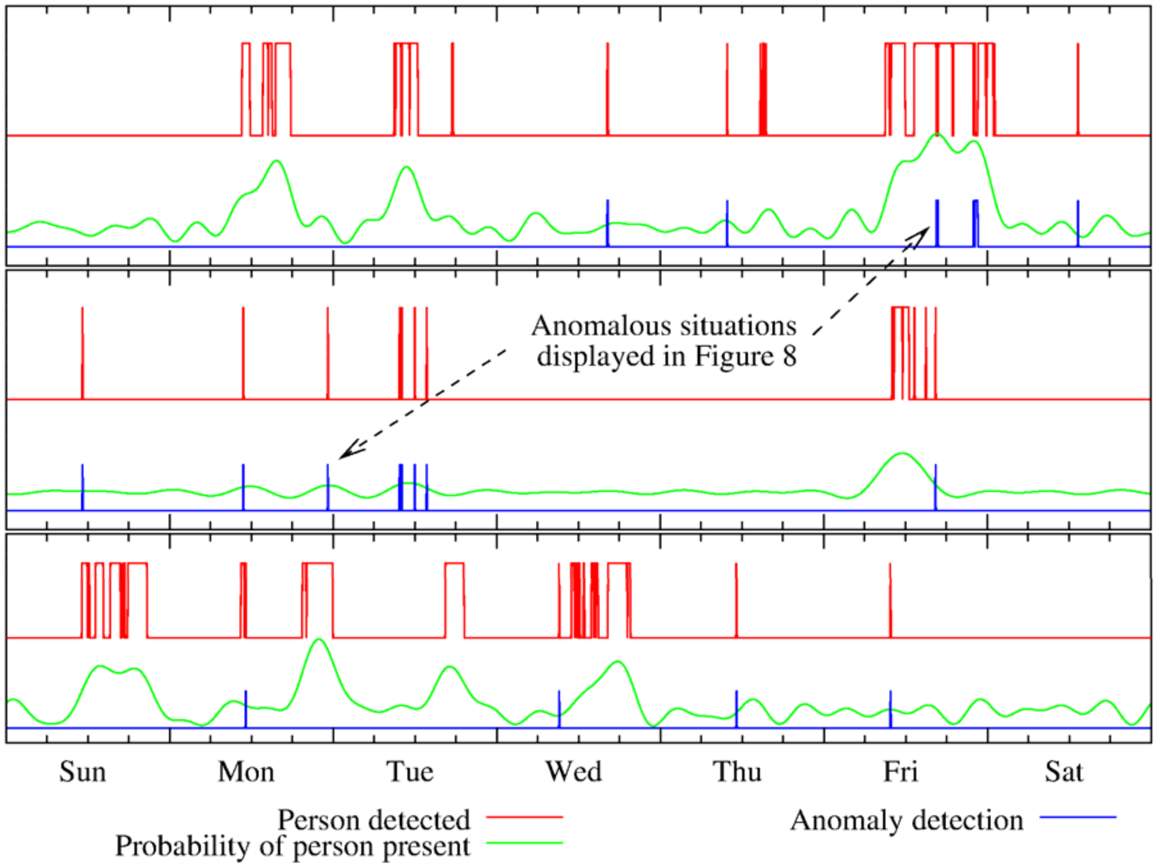
Questions?

Example 4: Anomaly detection

- the robot uses it’s 3D camera to detect people at the designated locations
- the FREMEN is run over the detection results and dynamic models of people presence at individual places are obtained
- anomaly detected if model-based prediction at 95% confidence level does not match the observation

Krajnik et al: Spectral Analysis for Long-Term Robotic Mapping, ICRA 2014 (to appear)

Example 4: Anomaly detection

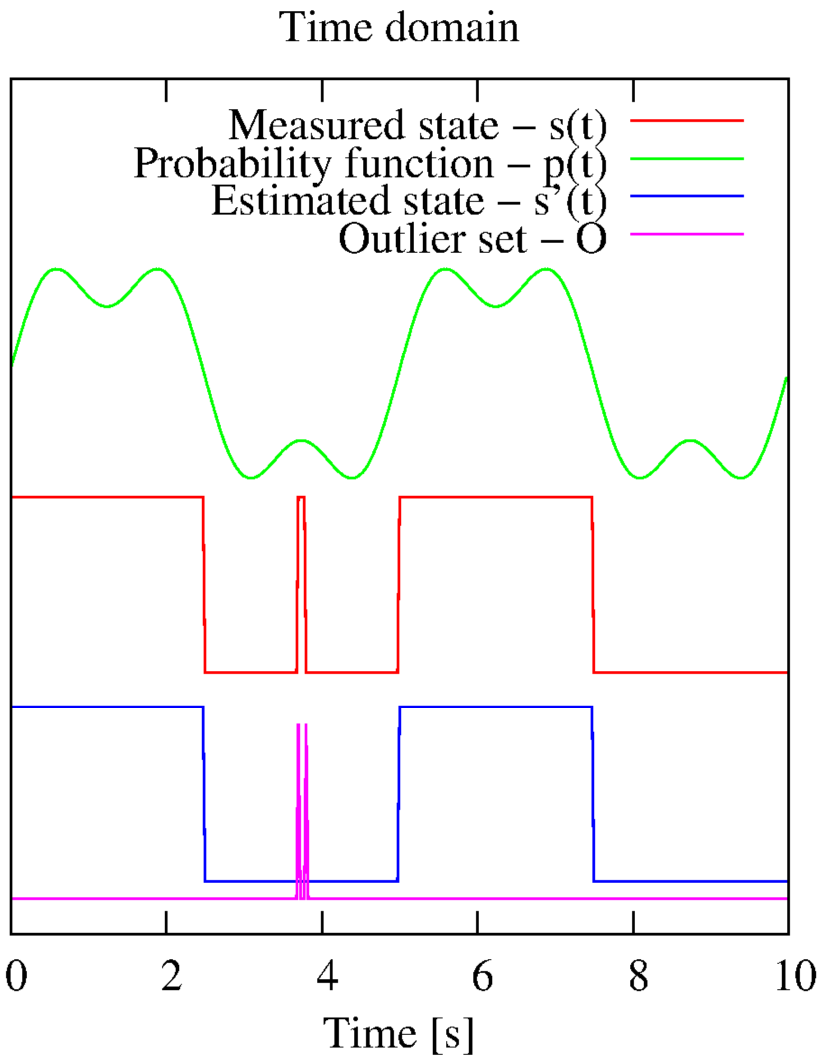


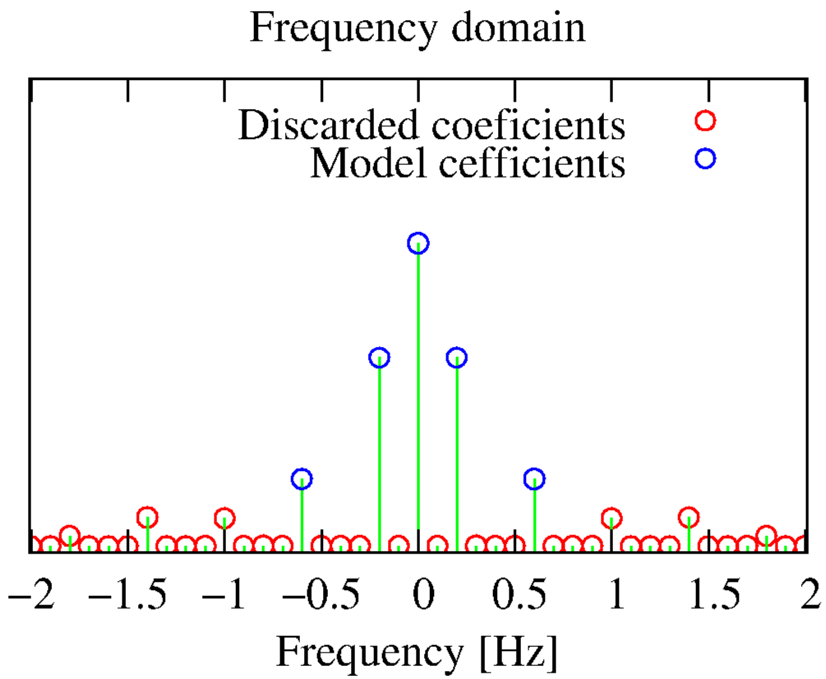
Krajnik et al: Spectral Analysis for Long-Term Robotic Mapping, ICRA 2014 (to appear)

Example 1: 3D occupancy grids

A robot builds 3D occupancy grids, calculates spectral model of occupancy of each cell

FREquency **M**ap **EN**hancement





abs(P):	{ 196, 46, 23 }
arg(P):	{ 0, 1.57, 1.57 }
Frequencies:	{ 0, 0.2, 0.6 }
Outlier set O:	{ 3.7, 3.8 }

Text representation of the actual model

Krajnik et al: Spectral Analysis for Long-Term Robotic Mapping, ICRA 2014 (to appear)

Example 2: 3D occupancy grids

A mobile robot builds 3D occupancy grids

3 spatial and 1 temporal dimension (3+1D)

- let a mobile robot patrol in a lab for one week
- scanning 3 locations every 5 minutes
- build 3D occupancy grids of these locations
- run the FREMEN over individual map cells of the occupancy grids
- perform reconstruction, compare with measurements
- model error decreased from 3% (static) to 1%

Krajnik et al: Spectral Analysis for Long-Term Robotic Mapping, ICRA 2014 (to appear)