Artificial Intelligence in Robotics Mapping of changing environments - Part I: Visual Navigation in Changing Environments

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Traditional autonomy: Understanding of space

Self-localisation, motion planning and navigation

focus on metric scale, accuracy, consistency

Traditional autonomy: Understanding of space

After a few hours ...

lack of focus on robustness

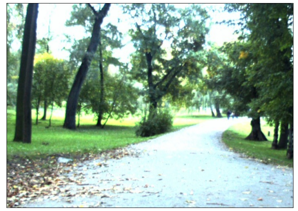
Long-term autonomous navigation

Target: 24/7 visual autonomous navigation
Environment: outdoor, forests, urban parks

Long-term operation: Environment changes

Oxford	*Churchill et al.*:	place-specific ‘experiences’
CMU	*Biswas et al.*:	static/dynamic separation
ETH	*Bürki et al.*:	map summarisation
QUT	*Sünderhauf et al.*:	appearance prediction
CTU	*Krajnik et al.*:	spatio-temporal models

Long-term operation: Environment changes



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Visual Navigation

Standard pipeline:

1. Extract image features,
2. find correspondences,
3. determine pose,
4. add new feats to map,
5. calculate movement.

Problems:

1. Feature deficiency,
2. environment change,
3. precision, complexity,
4. feature persistence,
5. real-time issues.

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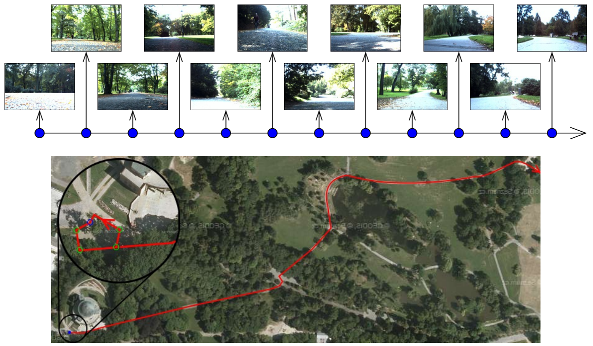
Teach and repeat navigation

- manually guide the robot along a given path,
- robot stores its odometry,
- robot stores image features,
- robot replays its odometry,
- while correcting its heading according to its visual memory.

Teach and repeat navigation

Image sequence indexed by position pics/along the learned path



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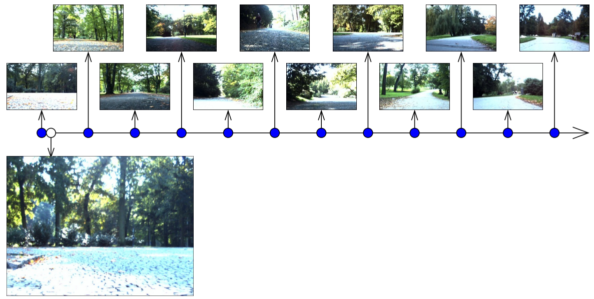
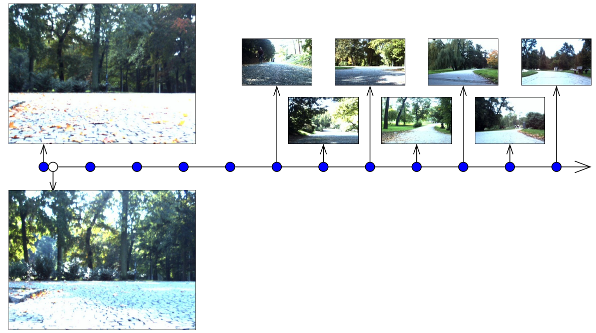


Image perceived by the robot during autonomous repeat

Teach and repeat navigation

Image sequence recorded during learning phase



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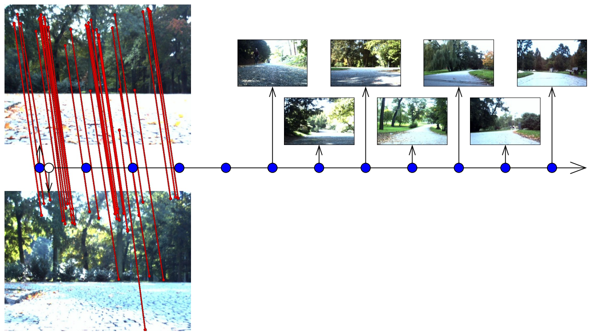

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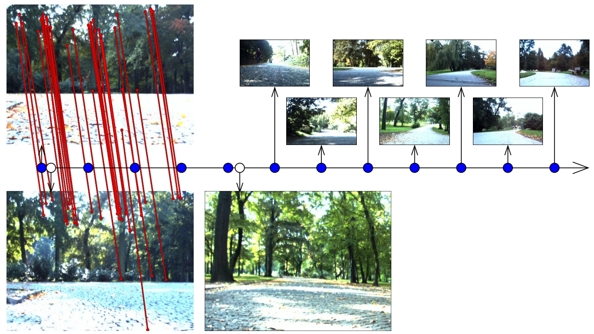

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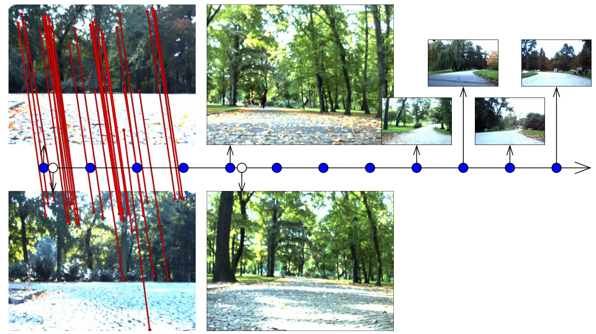

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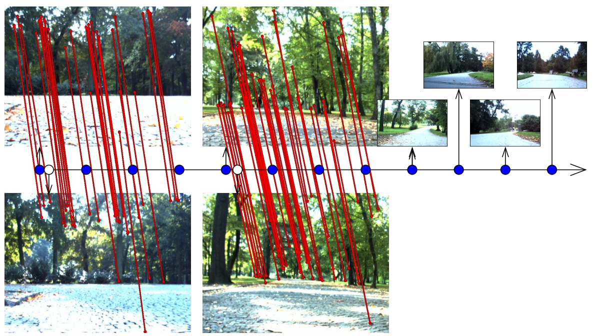

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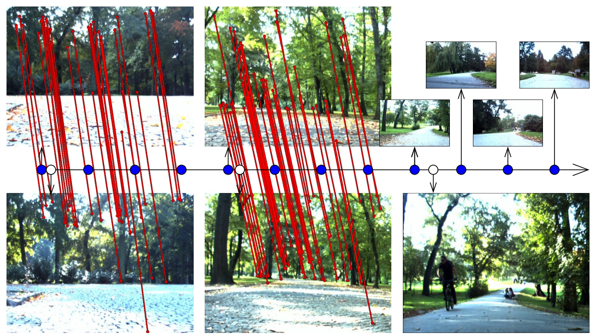

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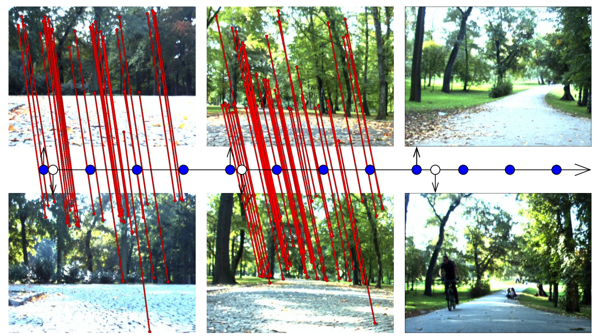
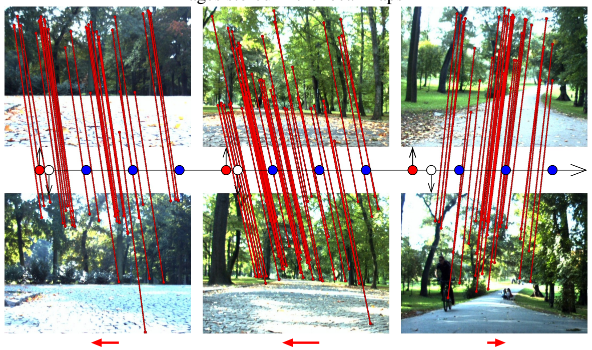


Image perceived by the robot during autonomous repeat

Teach and repeat navigation

Images stored in the local maps



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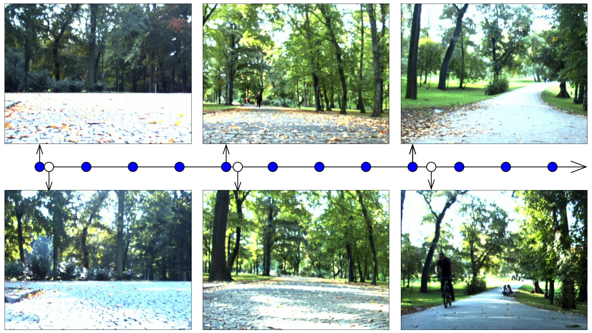

Image perceived by the robot during autonomous repeat

Not everything changes: learning stable features

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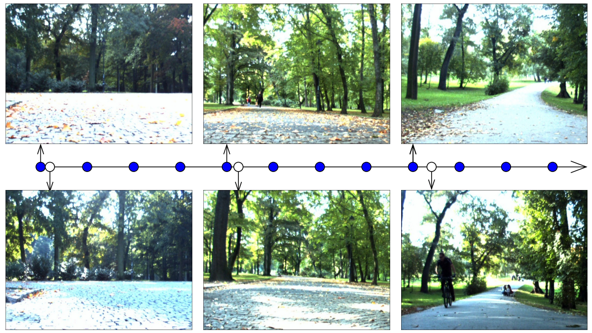


Image perceived by the robot during autonomous repeat

Not everything changes: learning stable features

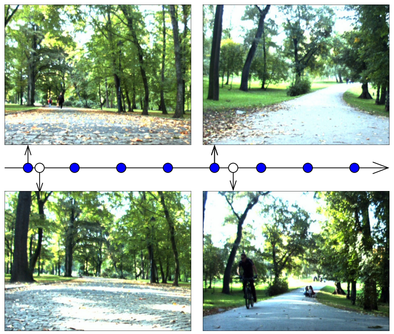
Typical features are robust to :

– viewpoint,
– scale,
– rotation,
– illumination.

Long–term teach–T&R requires robustness to :

– illumination,
– seasonal factors

Learned images



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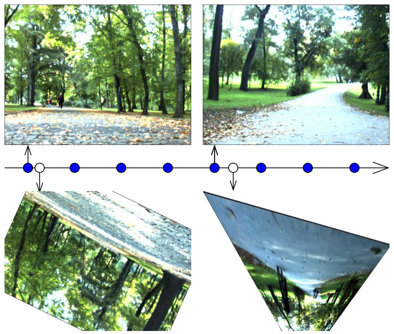

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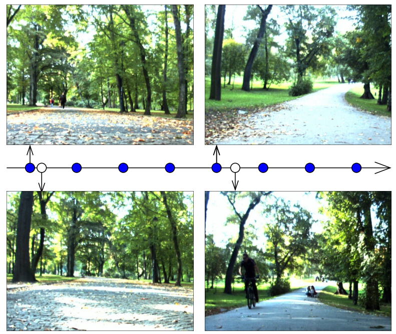

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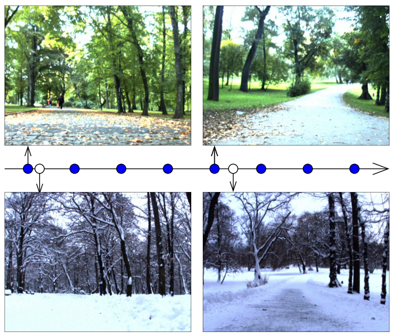


Perceived images

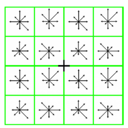
Not everything changes: learning stable features

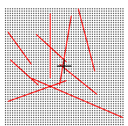
n-D vector describing local brightness gradients

- SIFT - typically best-performing, baseline method
- SURF - faster approximation of SIFT

Binary string describing brightness difference

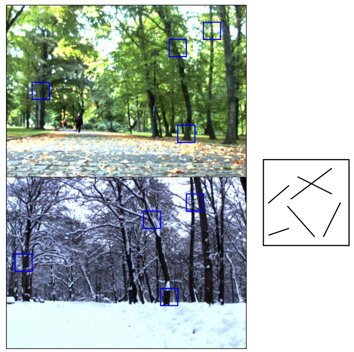
- BRIEF - binary comparisons, low viewpoint invariance,
- ORB - scale and rotation invariant BRIEF
- BRISK - scale and rotation invariant, symmetric positions
- GRIEF - BRIEF with comparison positions trained





Not everything changes: learning stable features

BRIEF Binary Robust Independent Elementary Features



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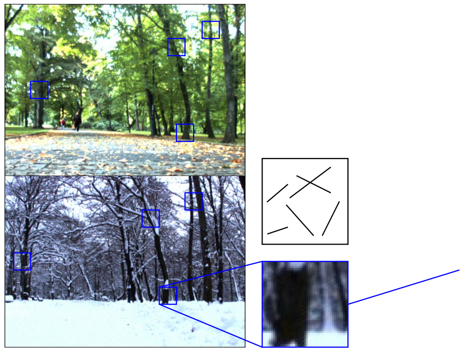

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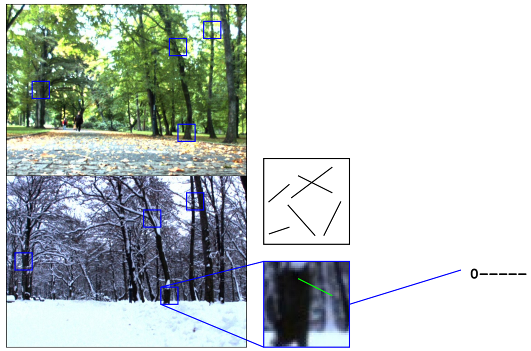

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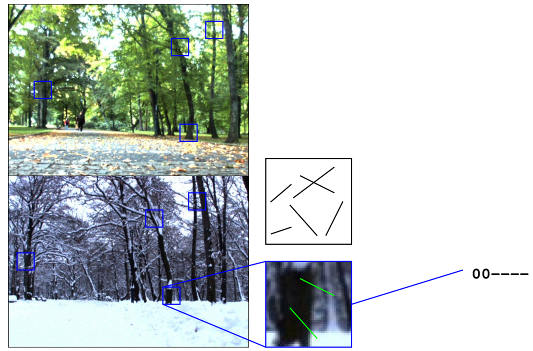

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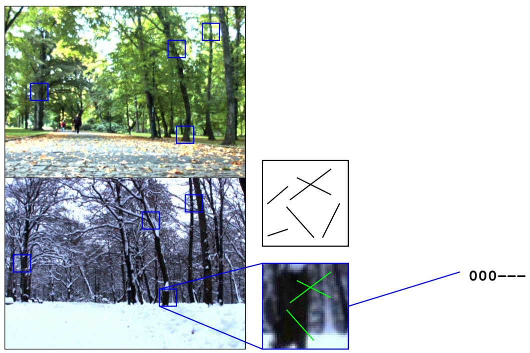

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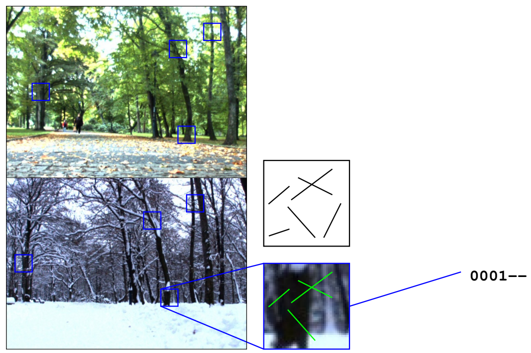

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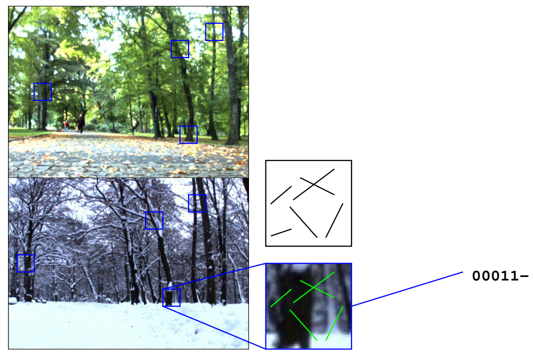

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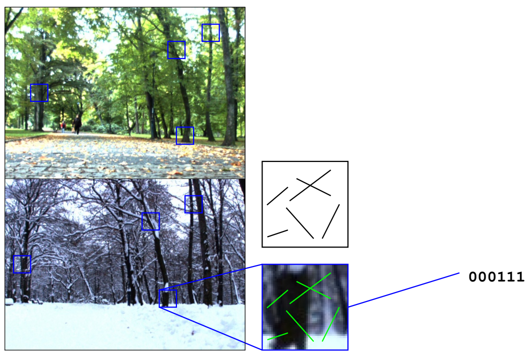
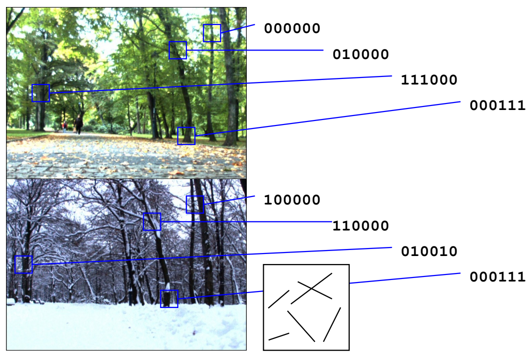


Not everything changes: learning stable features

Matching: Hamming distance of binary strings



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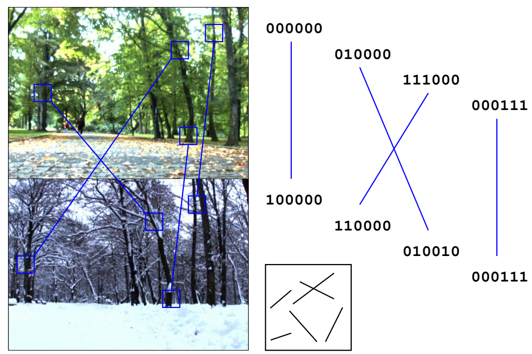
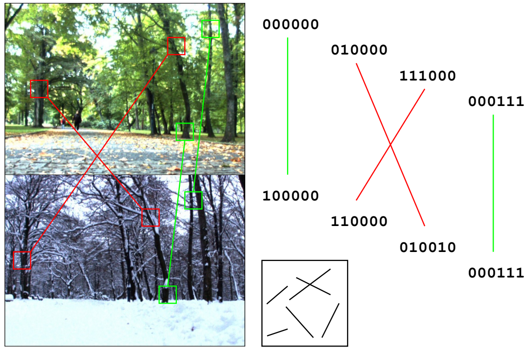


Not everything changes: learning stable features

Idea: rank the individual comparisons



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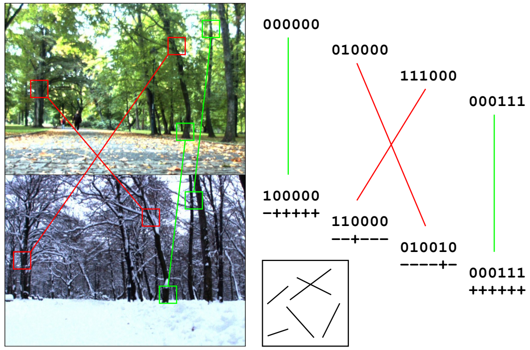

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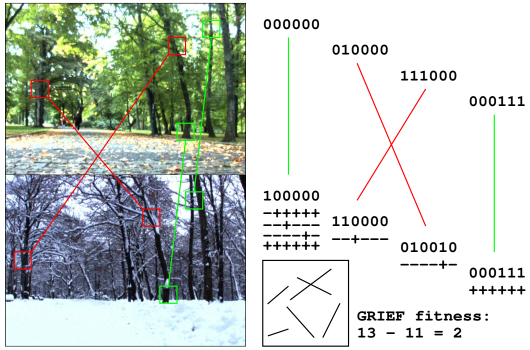

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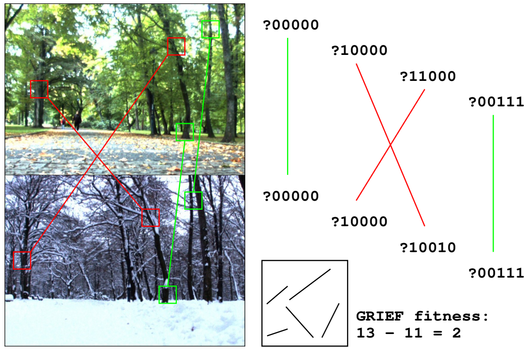

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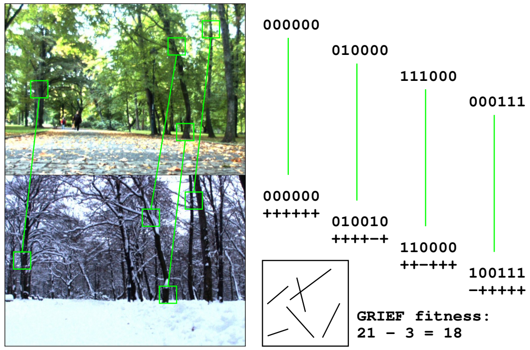

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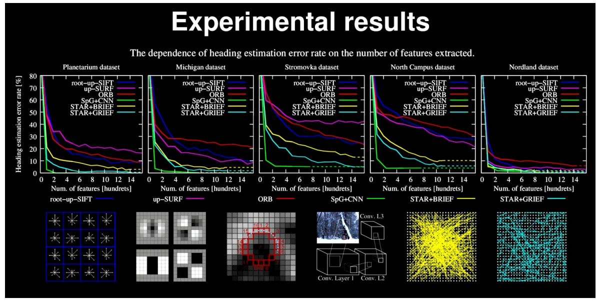


Not everything changes: learning stable features

Idea: **Not everything changes, and you can learn persistent features**

Training scheme is described in:

- T.Krajnik et al.: Image Features for Visual T&R Navigation in Changing Environments. RAS 2017.
- H.Nan et al.: Learning Place-And-Time-Dependent Binary Descriptors for Long-Term Visual Localization. ICRA 2018

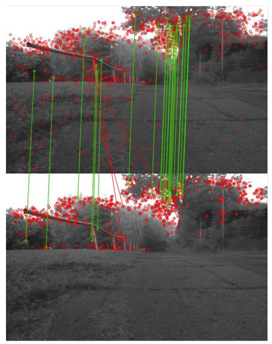
All code available at **http://github.com/gestom/grief**

Some changes are gradual, you can adapt your map

Two sources of uncertainty:
a) localisation, perception
b) environment change

Map management strategy:
- use the oldest map, robust to a)
- use the newest map, robust to b)

Some changes are gradual, you can adapt your map



Perform gradual map adaptation by ranking the map features:

- assign scores to features,
- check each feature match for geometrical consistency,
- increase score if consistent,
- decrease score if inconsistent,
- leave it not matched,
- remove the worst-scoring features,
- substitute with new ones.

Some changes are repetitive, we can learn patterns

Oxford	*Churchill et al.*:	place-specific ‘experiences’
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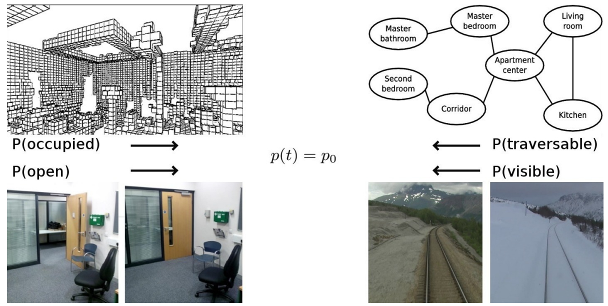
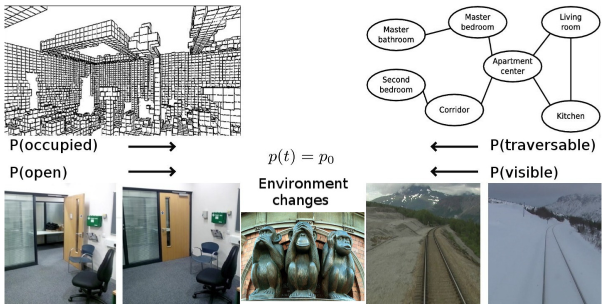


$p(t) = p_0$

Some changes are repetitive, we can learn patterns



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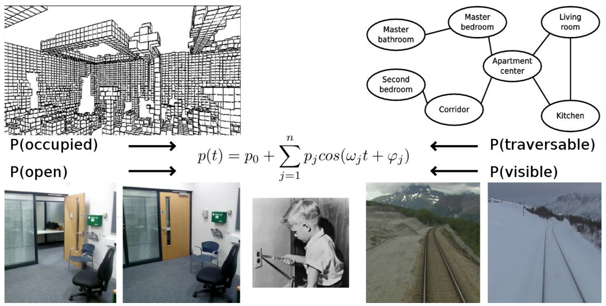

$$p(t) = p_0 + \sum_{j=1}^{n} p_j cos(\omega_j t + \varphi_j)$$

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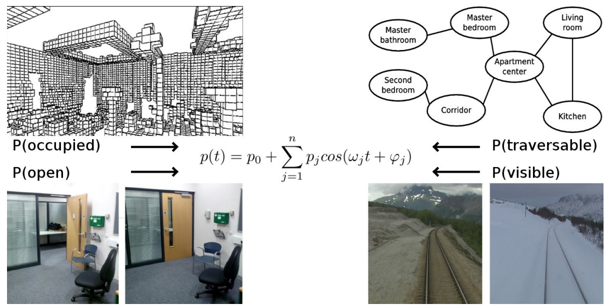
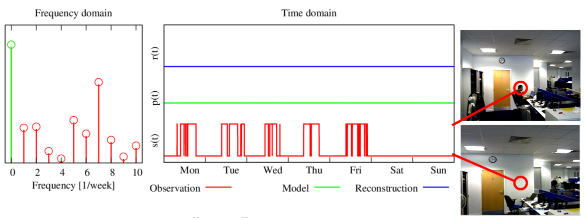


$$p(t) = p_0 + \sum_{j=1}^{n} p_j cos(\omega_j t + \varphi_j)$$

FreMEn: Frequency Map Enhancement

Continuous observation of an image feature

Static model:
$s'(t)$ matches the observations in 74% of cases

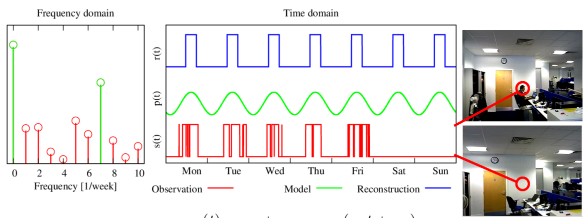


$p \quad = p_0$

FreMEn: Frequency Map Enhancement

Continuous observation of an image feature

Dynamic model with one periodic process:
$s'(t)$ matches the observations in 80% of cases

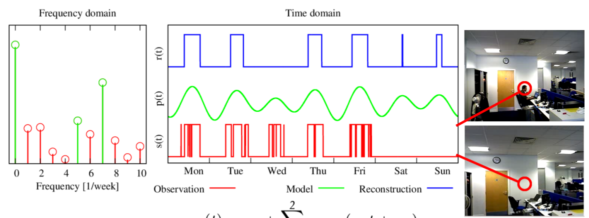


$p(t) = p_0 + \quad p_1 cos(\omega_1 t + \varphi_1)$

FreMEn: Frequency Map Enhancement

Continuous observation of an image feature

Dynamic model with two periodic processes:
$s'(t)$ matches the observations in 87% of cases

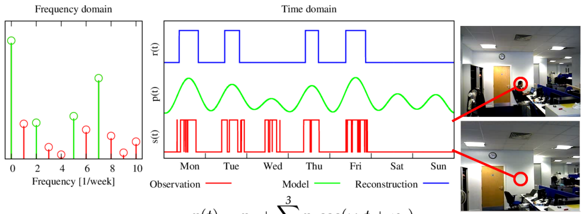


$$p(t) = p_0 + \sum_{j=1}^{2} p_j cos(\omega_j t + \varphi_j)$$

FreMEn: Frequency Map Enhancement

Continuous observation of an image feature

Dynamic model with n periodic processes:
$s'(t)$ matches the observations in $90\% - 95\%$ of cases



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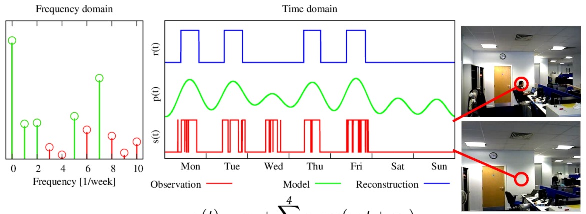

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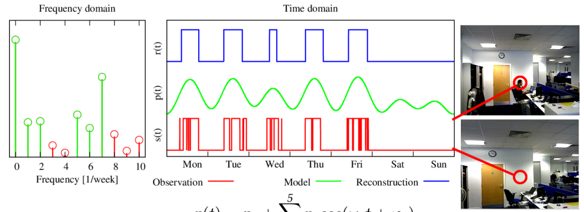
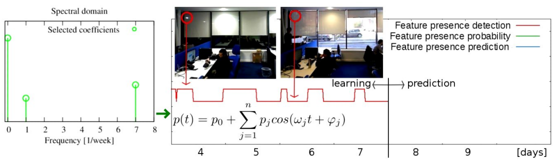


$$p(t) = p_0 + \sum_{j=1}^{5} p_j cos(\omega_j t + \varphi_j)$$

Frequency Map Enhanement principle

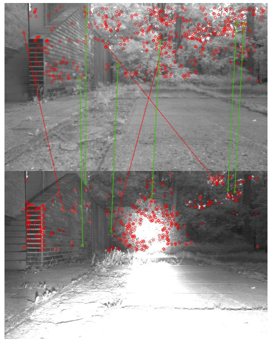
Frequency Map Enhancement (FreMEn)

Represents uncertainty of binary environment states in the frequency domain.
Can predict environment appearance at a given time.

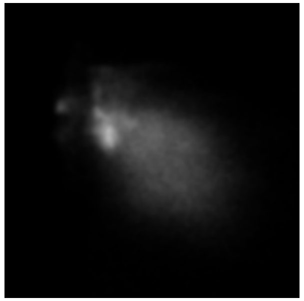


Krajnik, Fentanes, Cielniak, Dondrup, Duckett: **A frequency-based approach to long-term robotic mapping,** ICRA 2014

Some changes are consistent, and indicate objects



Form an accumulator



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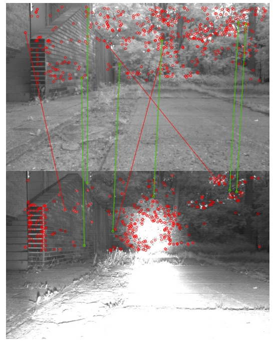
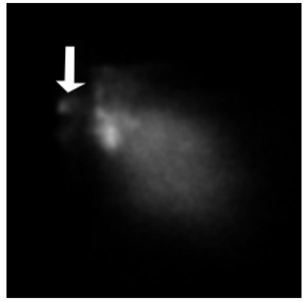


Find local maxima



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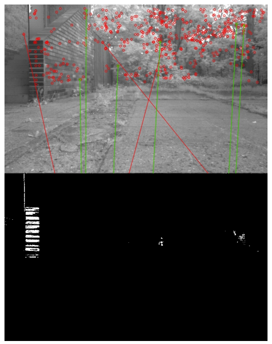
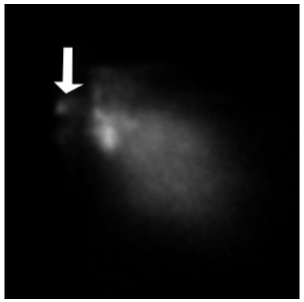
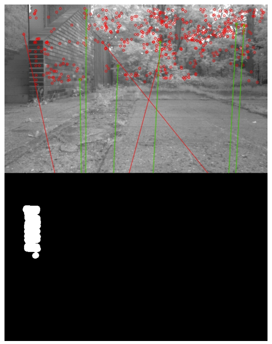


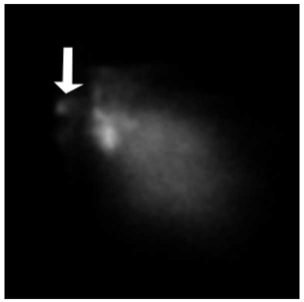
Reproject to images



Some changes are consistent, and indicate objects



Morphological ops.



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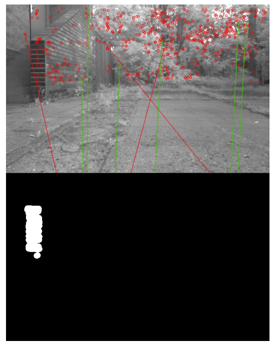
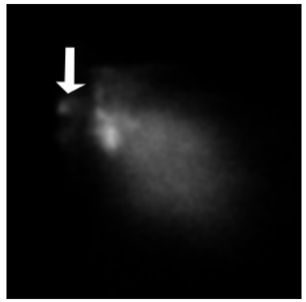


Feed masks to Mask-RCNN



What to remember from the first part of the lecture

Changes are source of valuable information [1,2].

Some changes are:

- **describable** and you can learn robust features [3],
- **gradual** and you can adapt to then [4],
- **repetitive** and you can learn their patterns [5],
- **consistent** and you can use them for auto-annotation [6],

References:
[1] Krajník et al.: Chronorobotics In IJCRAI 19 download link
[2] Kunze et al.: Artificial Intelligence for Long-term Autonomy IEEE RA-L 19
[3] Krajník et al.: Image Features for Visual T&R Navigation in Changing Environments RAS 17
[4] Halodova et al.: Predictive and adaptive maps for long-term visual navigation In IROS 19
[5] Krajník et al.: Fremen: Frequency map enhancement for LTA in changing environments IEEE T-RO 17
[6] Peconkova et al.: Unsupervised Learning of Landmarks for Vis.Nav. ... In PAIR 19

We strongly suggest to read [1] for an overview of the topic.

What to remember from the first part of the lecture

Changes are source of valuable information [1,2].

Some changes are:

- **describable** and you can learn robust features [3],
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Download:

BearNav system:	http://bearnav.eu
GRIEF Image features:	http://github.com/gestom/grief
Frequency Map Enhancement:	http://fremen.uk

Artificial Intelligence in Robotics
Mapping of changing environments
-
Part II: Spatio-temporal representations of the environment dynamics

Tom Krajník
Czech Technical University in Prague

Dec 2019

Traditional autonomy: Understanding of space

Self-localisation, motion planning and navigation

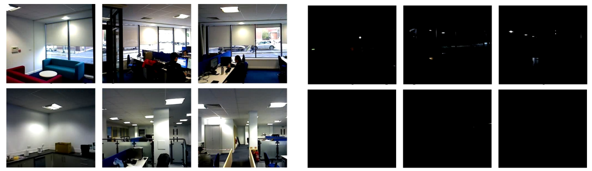
focus on metric scale, accuracy, consistency

Traditional autonomy: Understanding of space

After a few hours ...

lack of focus on robustness

Mid-term autonomy: Understanding that environment changes



Memorising and suppressing changes:

Oxford	*Churchill et al.*:	experience-based approach
Örebro	*Lowry et al.*:	condition-invariant appearance
CMU	*Biswas et al.*:	static/dynamic separation
ETH	*Bürki et al.*:	map summarisation

Mid-term autonomy: Understanding that environment changes

Memorising and suppressing changes:

Oxford	*Churchill et al.*:	experience-based approach
Örebro	*Lowry et al.*:	condition-invariant appearance
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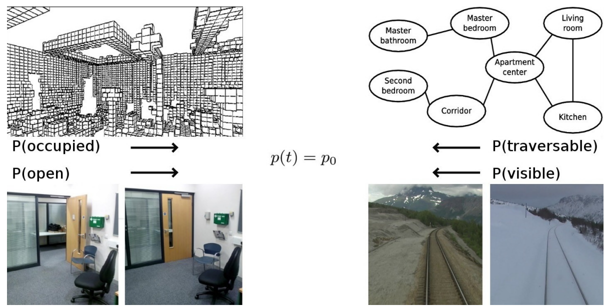
ETH	*Bürki et al.*:	map summarisation

Long-term autonomy: Understanding how environment changes

Obtaining information from the changes observed:

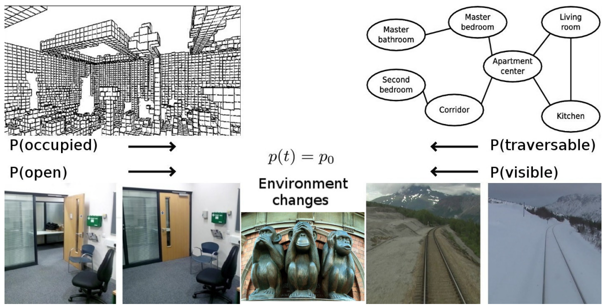
long-term operation	$\rightarrow$	observation of changes
observed changes	$\rightarrow$	spatio-temporal models
spatio-temporal model	$\rightarrow$	prediction of future states
prediction of future states	$\rightarrow$	improved long-term operation

Towards Spatio-Temporal Domain Modeling

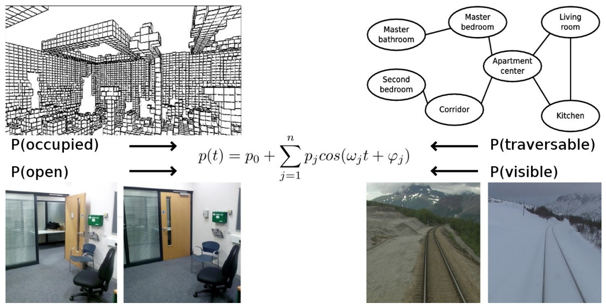


$p(t) = p_0$

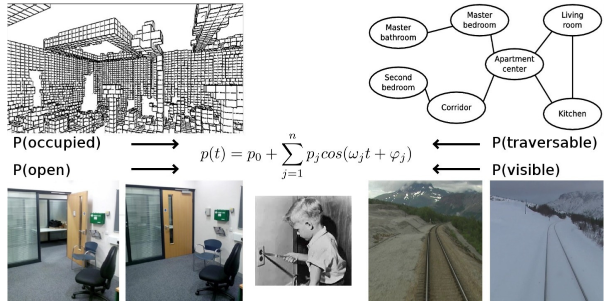
Towards Spatio-Temporal Domain Modeling



Towards Spatio-Temporal Domain Modeling



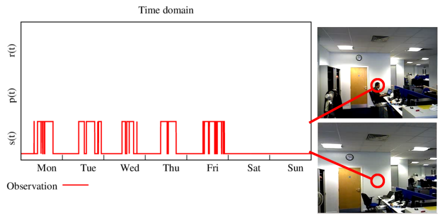
Towards Spatio-Temporal Domain Modeling



Example: Modeling a single state

Week-long model of a single feature

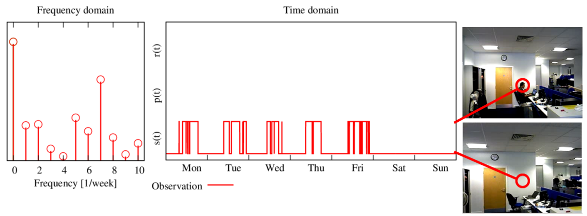
Data gathering:
Establish a binary function of time $s(t)$



Example: Modeling a single state

Week-long model of a single feature

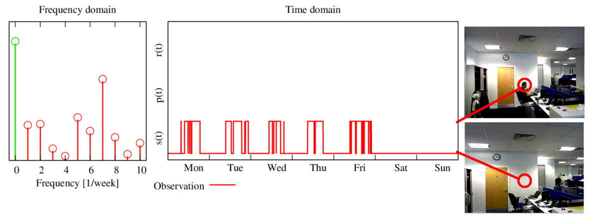
Fourier analysis:
Calculate frequency spectrum of $s(t)$



Example: Modeling a single state

Week-long model of a single feature

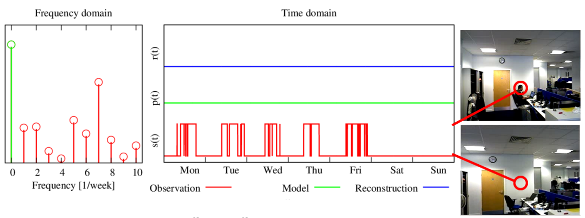
Component selection:
Select the most prominent spectral component(s)



Example: Modeling a single state

Week-long model of a single feature

Static model with one component with zero frequency:
$s'(t)$ matches the observations in 74% of cases

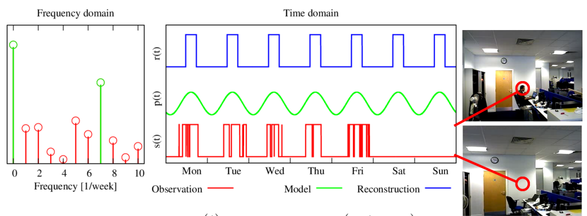


$$p \quad = p_0$$

Example: Modeling a single state

Week-long model of a single feature

Dynamic model with one periodic process:
$s'(t)$ matches the observations in 80% of cases

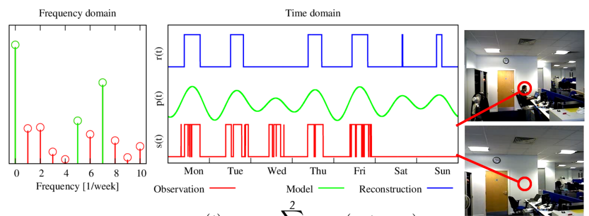


$$p(t) = p_0 + \quad p_1 cos(\omega_1 t + \varphi_1)$$

Example: Modeling a single state

Week-long model of a single feature

Dynamic model with two periodic processes:
$s'(t)$ matches the observations in 87% of cases

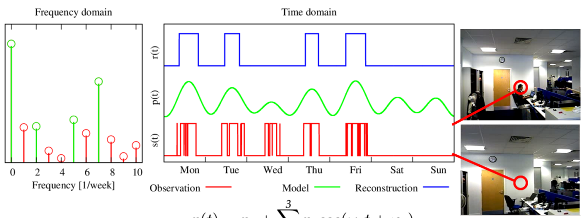


$$p(t) = p_0 + \sum_{j=1}^{2} p_j cos(\omega_j t + \varphi_j)$$

Example: Modeling a single state

Week-long model of a single feature

Dynamic model with n periodic processes:
$s'(t)$ matches the observations in $90\% - 95\%$ of cases



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

Example: Modeling a single state

Week-long model of a single feature

Dynamic model with n periodic processes:
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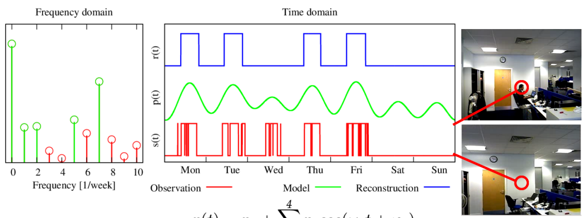

$$p(t) = p_0 + \sum_{j=1}^{4} p_j cos(\omega_j t + \varphi_j)$$

Example: Modeling a single state

Week-long model of a single feature

Dynamic model with n periodic processes:
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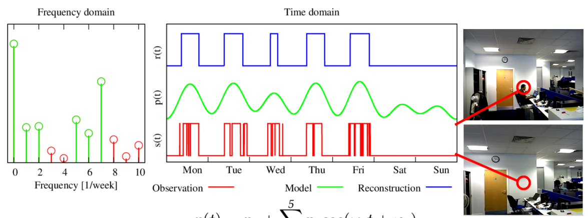
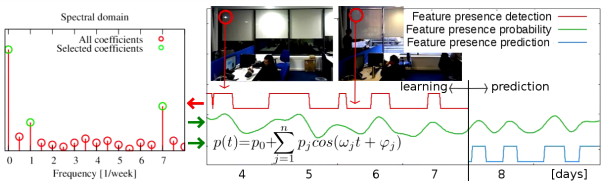


$$p(t) = p_0 + \sum_{j=1}^{5} p_j cos(\omega_j t + \varphi_j)$$

Video 1: Feature-based topological localization



Frequency-enhanced feature map for visual localisation:

- The observations of image feature visibility (centre,red) are transferred to the spectral domain (left).
- The most prominent components of the model (left,green) constitute an analytic expression (centre,bottom) that represents the probability of the feature being visible at a given time (green).
- This is used to predict the feature visibility at a time when the robot performs self-localisation (blue).

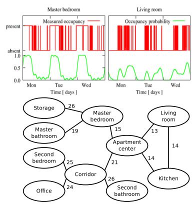
Object search scenario

Task: Find a person in shortest time possible.
Topological map, spectral-based model of room occupancies.

Spatial:
- 1 person
- 9 locations

Temporal:
- 16 weeks
- every minute

Figure: The CASAS-Aruba environment.



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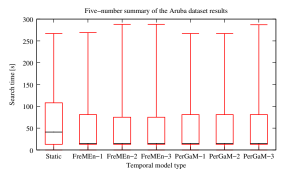
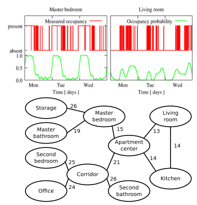


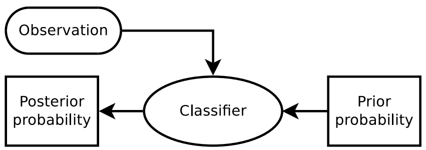
Figure: Time to find a person in the 'Aruba' flat.



Temporal context for activity recognition

Task: Classify person activity.

$$p(activity|observation) = \frac{p(observation|activity)}{p(observation)} p(activity)$$



Classification pipeline.

Temporal context for activity recognition

Task: Classify person activity.

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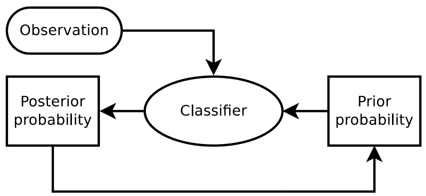
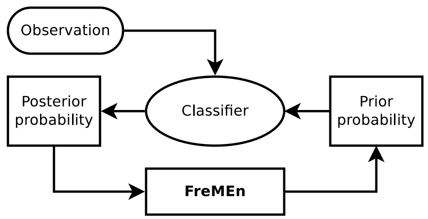


Classification pipeline + learning priors.

Temporal context for activity recognition

Task: Classify person activity.

$$p(activity|observation, t) = \frac{p(observation|activity)}{p(observation, t)} p(activity, t)$$



Classification pipeline + temporal priors.

Temporal context for activity recognition

Task: Classify person activity.
Use FreMEn-aided temporal models as priors.

$p(activity, t|observation) \sim p(observation|activity)p(activity, t)$

Household:
- 9 locations
- 12 activities

Office:
- 10 locations
- 10 activities

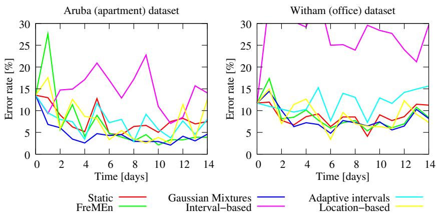


Figure: Error rate of activity recognition.

SPEctral Robotic Mapping

The approach allows for
- conversion of static models into dynamic ones,
- environment state and appearance prediction.

However, it requires regular and frequent observations,

$$S(k) = \frac{1}{N}\sum_{n=1}^{N} s(nT)e^{-2\pi jkn/N} \quad k \in \mathbb{N}$$

- which results in long, tedious and brittle learning,
- after which the model cannot be updated.

FREquency Map ENhancement

The approach allows for
- conversion of static models into dynamic ones,
- environment state and appearance prediction.

Allowing sparse and non-uniform observations,

$$S(\omega_k) = \frac{1}{N}\sum_{n=1}^{N} s(t_n)e^{-j\omega_k t_n} \quad \omega_k \in \Omega$$

- means that we can deal with irregular observations,
- and learn incrementally during operation.

Frequency Map Enhancement (FreMEn)

Can build spatio-temporal models **incrementally** from **sparse** and **irregular** observations. Allows **on-the-fly** learning.

Addition of a new measurement:

$\mu \leftarrow \frac{1}{n+1}(n\mu + s(t))$,			mean probability
$\alpha_k \leftarrow \frac{1}{n+1}(n\alpha_k + s(t)\,e^{-jt\omega_k})$	$\forall \omega_k \in \omega$,		state spectrum
$\beta_k \leftarrow \frac{1}{n+1}(n\beta_k + e^{-jt\omega_k})$	$\forall \omega_k \in \omega$,		observation spectrum
$n \leftarrow n+1$,			num of observations

Performing predictions:

$\gamma_k \leftarrow \alpha_k - \mu\,\beta_k$	predictive spectrum
$\gamma_{1..m} \leftarrow \operatorname{argmax}\lvert\gamma_k\rvert$	m components γ_k with highest abs. value
$p(t) = \mu + \sum_{j=1}^{m}\lvert\gamma_j\rvert\cos(\omega_j t + \arg(\gamma_j))$	actual prediction

Topological path planning

Decide the best time to navigate to a particular location.
Topological map with FreMEn edge traversability.

Spatial:
- 14 nodes
- 26 edges

Temporal:
- two months
- $\sim$ 10$\times$ per day

Nav. success rate:
- Static: 60%
- FreMEn: 90%

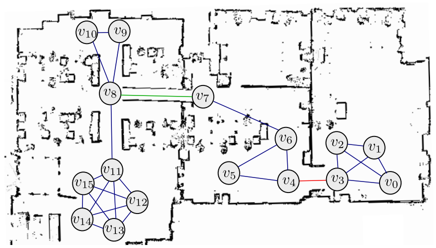


Figure: Topological/metric map overlay of the LCAS offices.

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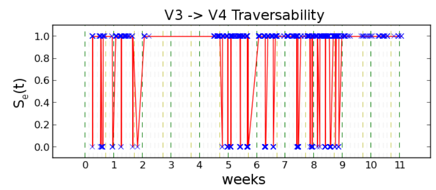

Edge V3->V4: Navigation success over time.

Topological path planning

Decide the best time to navigate to a particular location.
Topological map with FreMEn edge traversability.

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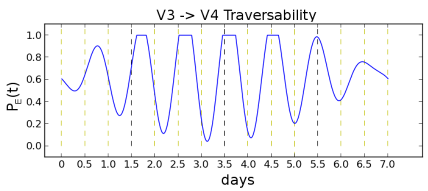

Edge V3->V4: FreMEn model for one week.

Topological path planning

Decide the best time to navigate to a particular location.
Topological map with FreMEn edge traversability.

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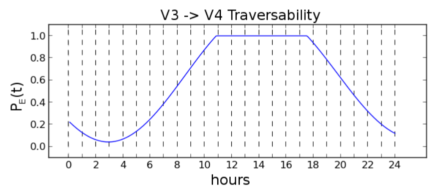
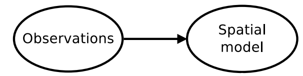


Edge V3->V4: FreMEn model for Thursday

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Mapping pipeline:

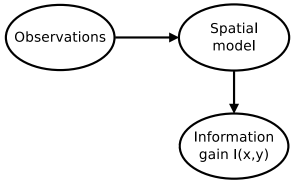


Observations gathered during routine operation

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Spatial exploration pipeline:

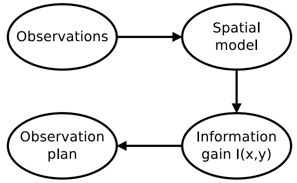


Robot decides **where** to perform observations

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Spatial exploration pipeline:

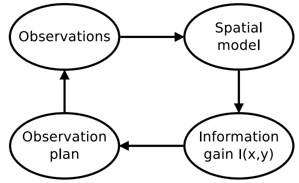


Robot decides **where** to perform observations

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Spatial exploration pipeline:

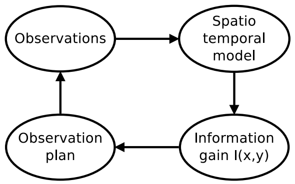


Robot decides **where** to perform observations

Towards Spatio-Temporal Exploration

Create and maintain accurate spatial-temporal models.

Spatio-temporal exploration pipeline:



Robot decides **where** and **when** to perform observations

Towards Spatio-Temporal Exploration

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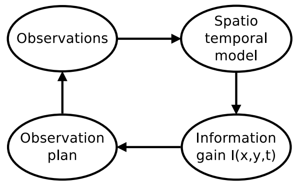
Spatio-temporal exploration pipeline:



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Towards Spatio-Temporal Exploration

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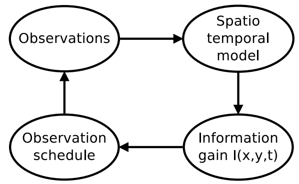
Spatio-temporal exploration pipeline:

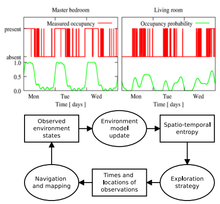


Robot decides **where** and **when** to perform observations

Information-theoretic spatio-temporal exploration

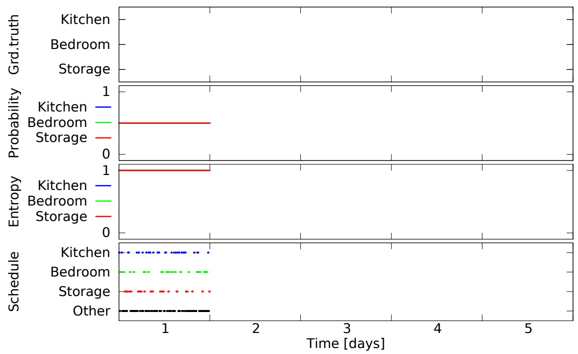
Create and maintain accurate spatio-temporal models.
Decide **where** and **when** to perform observations
Probability p(t) → Entropy H(t) → Prob. of observation o(t)
'Next Best Time and Location'

Figure: The CASAS-Aruba environment.



Spatio-temporal exploration

Decide **where** and **when** to go to make observations.
Spatio-temporal entropy + information-gain-based methods.



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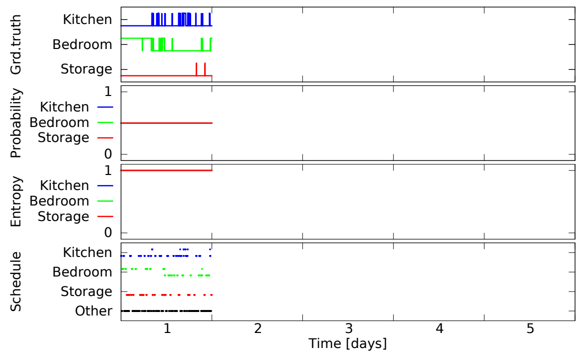

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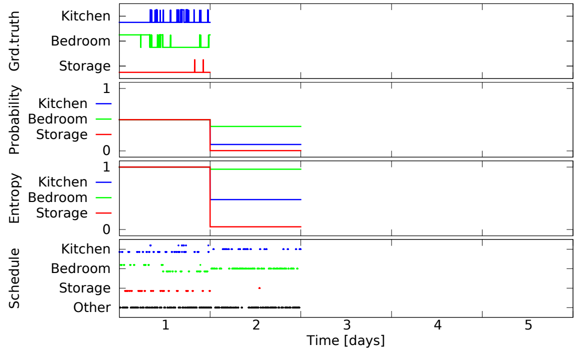

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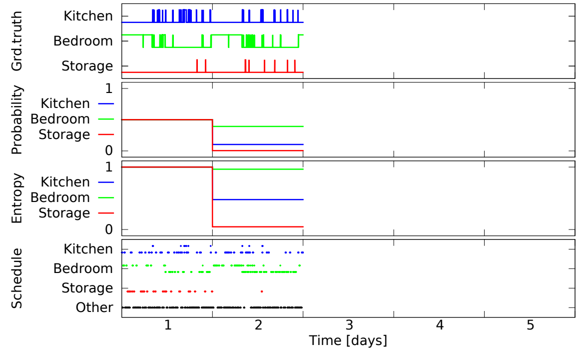

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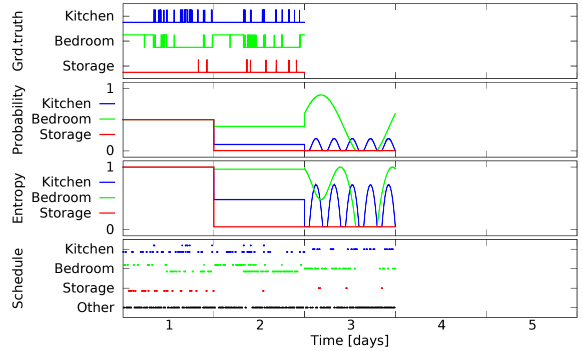
Decide **where** and **when** to go to make observations.
Spatio-temporal entropy + information-gain-based methods.



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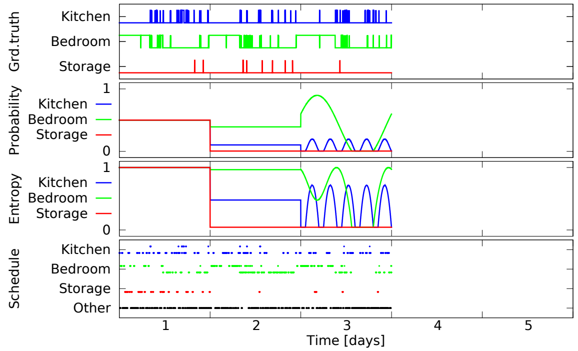

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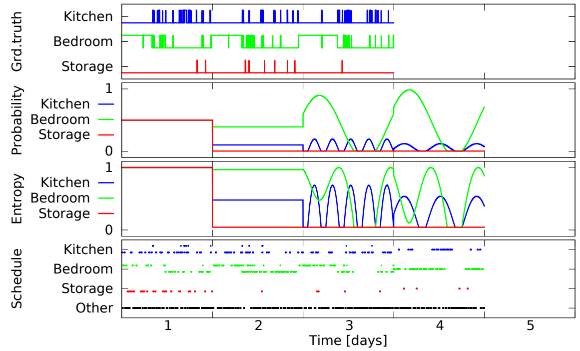

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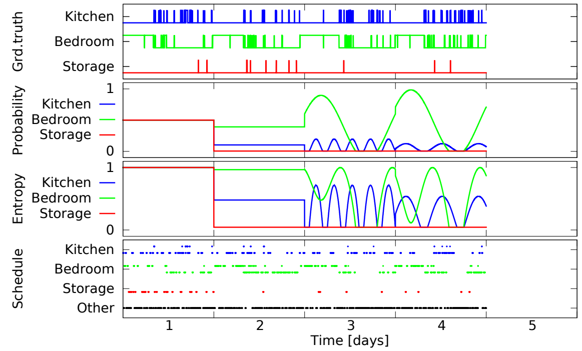

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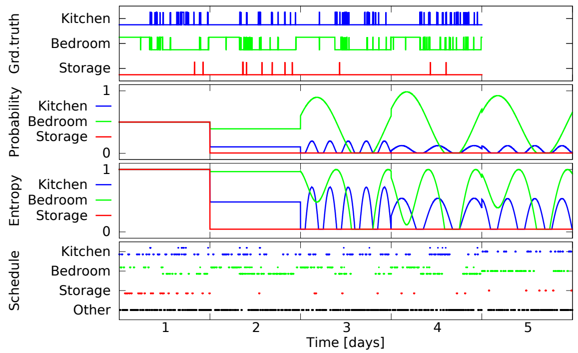

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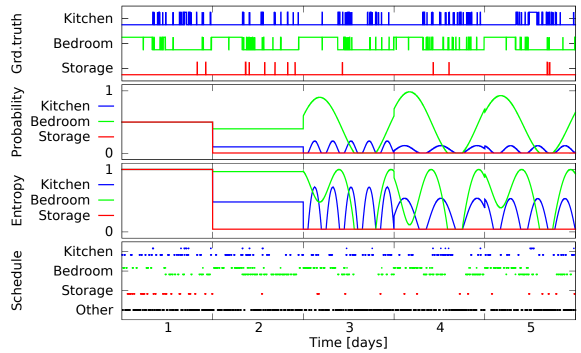
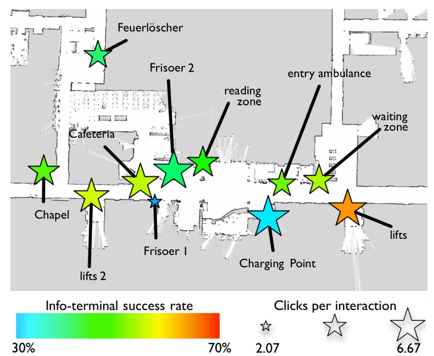


Mobile Infoterminal - exploration/exploitation

Decide the best time and location to provide an info-terminal service in a hospital. Maximise number of interactions.



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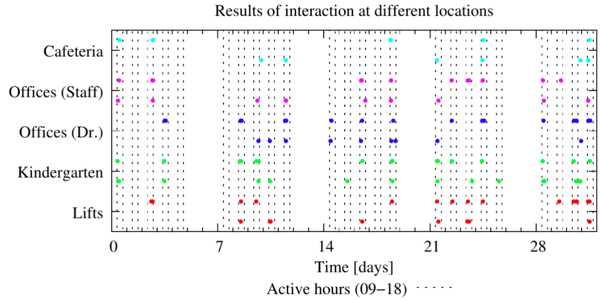

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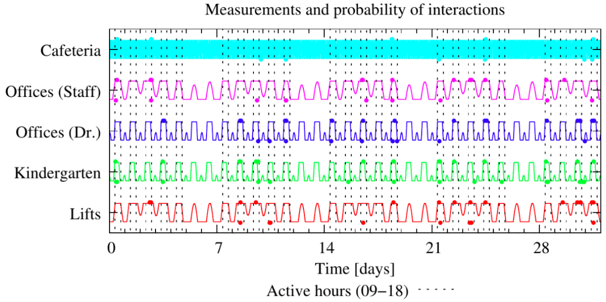

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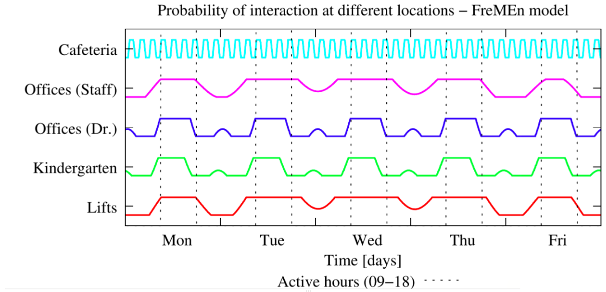
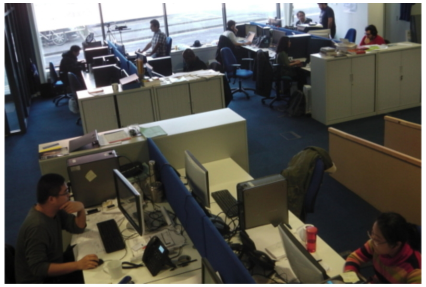


4D Spatio-Temporal Exploration

Spatio-temporal Information-driven Next Best View.
FreMEn 3D grid + spatio-temporal entropy + next best path



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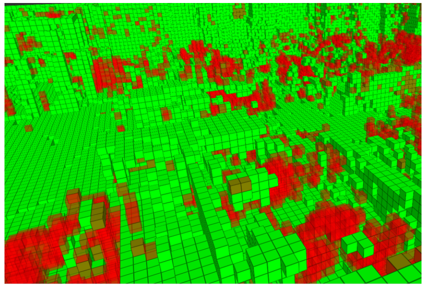

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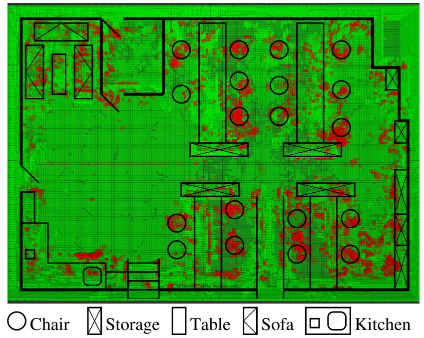
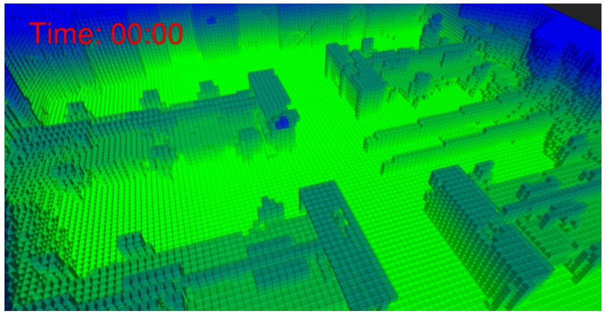


Video 2: 4D maps build by a FreMEn-based exploration system



To predict the grid state for a particular time, each cell contains a temporal model. Approx. 10^6 cells resulted in memory issues.

From discrete to continuous models

FreMEn is powefull, but it can model only:

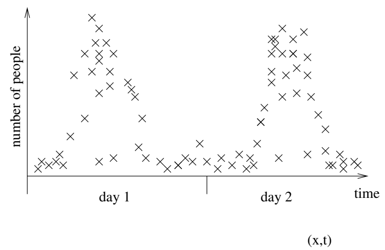
- Bernoulli distributions, i.e. probabilities of binary states,
- discrete models, which might be memory inefficient,
- events with durations comparable to the period length,
- independent components

Warped Hypertime can represent:

- arbitrary distributions, e.g. number of people, robot velocity,
- memory-efficient, continous models,
- arbitrarily long events and changes,
- respects spatio-temporal continuity

Warped Hypertime - continuous models

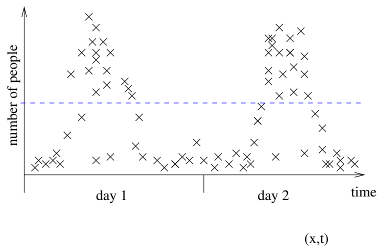
Example: modelling the number of people within a given area



Observe data over time,

Warped Hypertime - continuous models

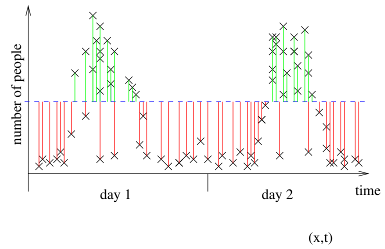
Example: modelling the number of people within a given area



establish some time-unavare model,

Warped Hypertime - continuous models

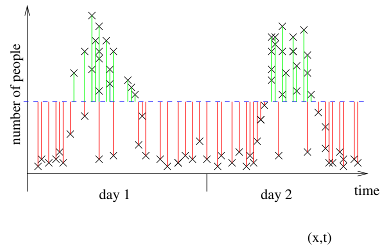
Example: modelling the number of people within a given area



establish model error over time $\epsilon(t)$,

Warped Hypertime - continuous models

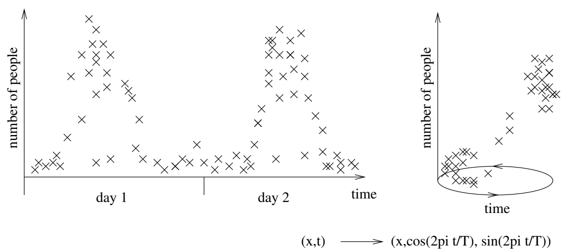
Example: modelling the number of people within a given area



use FreMEn to find periodicity T in $\epsilon(t)$,

Warped Hypertime - continuous models

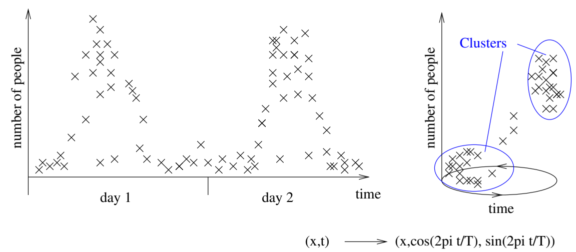
Example: modelling the number of people within a given area



project 1D time in ‘2D warped hypertime’

Warped Hypertime - continuous models

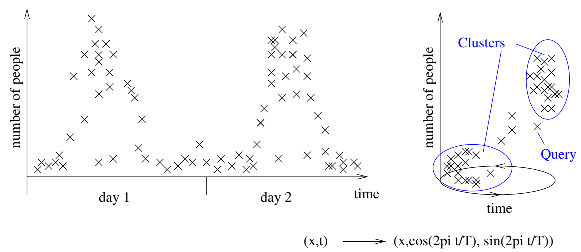
Example: modelling the number of people within a given area



create a model of the data distribution (k-means, EM-GMM),

Warped Hypertime - continuous models

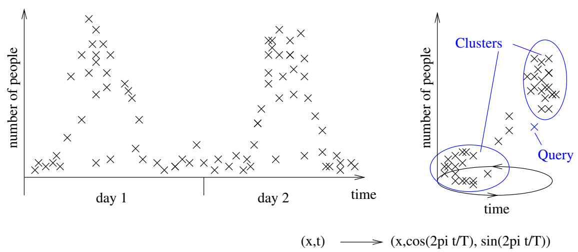
Example: modelling the number of people within a given area



repeat (add 2 temporal dimensions per observed periodicity).

Warped Hypertime - continuous models

Example: modelling the number of people within a given area



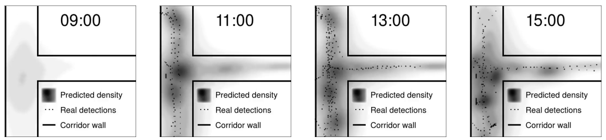
Predict probability of future distribution of x.

Video 3: Predicting future presence of people

Predicting future density of pedestrians

- pedestrian tracker detects people at x, y at time t,
- Warped Hypertime adds 4 temporal dimensions
- $[x, y] \rightarrow [x, y, \cos(2\pi\frac{t}{T_0}), \sin(2\pi\frac{t}{T_0}), \cos(2\pi\frac{t}{T_1}), \sin(2\pi\frac{t}{T_1})]$
- 9 clusters characterise spatio-temporal density of people

Prediction of people density

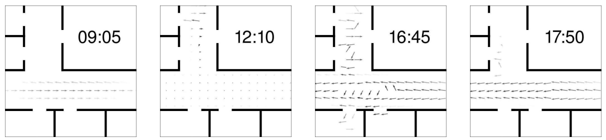


Video 4: Predicting future pedestrian flows

Prediction of pedestrian flows

- pedestrian tracker provides x, y, ϕ, v at time t,
- Warped Hypertime adds 4 temporal dimensions
- $[x, y, \phi, v, \cos(2\pi\frac{t}{T_0}), \sin(2\pi\frac{t}{T_0}), \cos(2\pi\frac{t}{T_1}), \sin(2\pi\frac{t}{T_1})]$
- 13 clusters characterise intensity, velocity and directions

Prediction of pedestrian flows



What to remember from the lecture

- explicit representation of the temporal domain improves the efficiency of robot operation in long-term scenarios [1]
- one can convert static representations into models that represent how the environment changes over time,
- by modeling the uncertainty in the spectral domain [2],
- by modeling the time in a multi-dimensional space [3].

References:

- [1] Krajník et al.: Chronorobotics: ... In IJCRAI 2020
- [2] Krajník et al.: FreMEn: ... IEEE T-RO 2017
- [3] Krajník et al.: Warped Hypertime ... IEEE RAL 2019

We strongly suggest to read [1] for an overview of the topic.