



Bio-inspiration for Deployed Autonomous Systems

The Good, the Bad, and the Unknowns

Professor Michael Milford | Australian Research Council Future Fellow | Microsoft Research Faculty Fellow | Chief Investigator, Australian Centre for Robotic Vision
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Overview



Introductions


Biologically-inspired Mapping and Navigation & Sensing



The Mystery of Navigational Grid Cells in the Brain

Translating Research to Industry Autonomous Vehicles



 michael.milford@qut.edu.au Twitter: @maththrills <https://www.youtube.com/milfordrobotics> <http://www.tinyurl.com/milfordm> <https://goo.gl/rczsls>

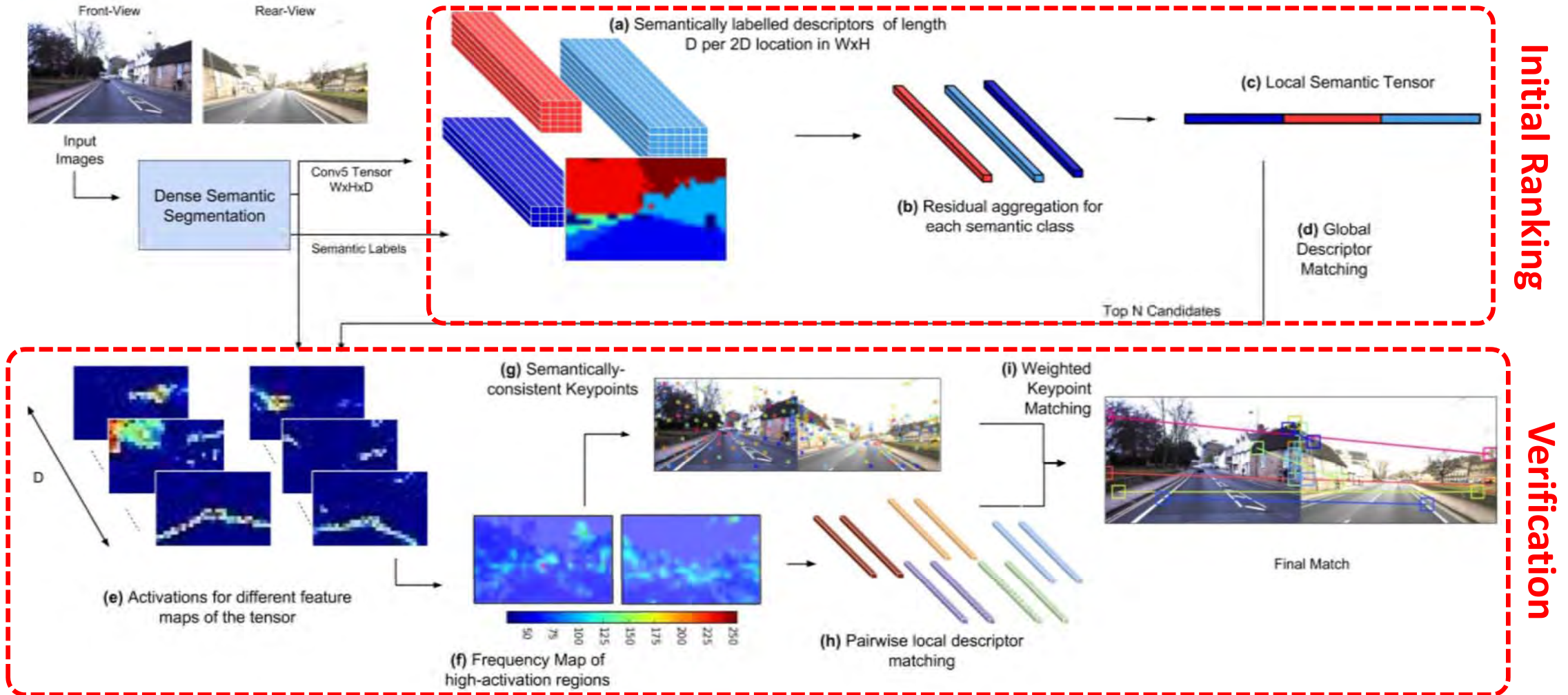
Today's talk will only cover a small fraction of our research and activities

Please reach out to chat:

autonomous vehicles | neuroscience-
inspired tech | robotics | computer vision |
active navigation | mapping and
localization | **machine and deep learning
inc. reinforcement learning** | artificial
intelligence | startups | STEM (Science
Technology Engineering Maths) education
| movie & fiction-based edutainment |
collaboration

Professor Michael Milford | Australian Research Council
Future Fellow | Microsoft Research Faculty Fellow | Chief
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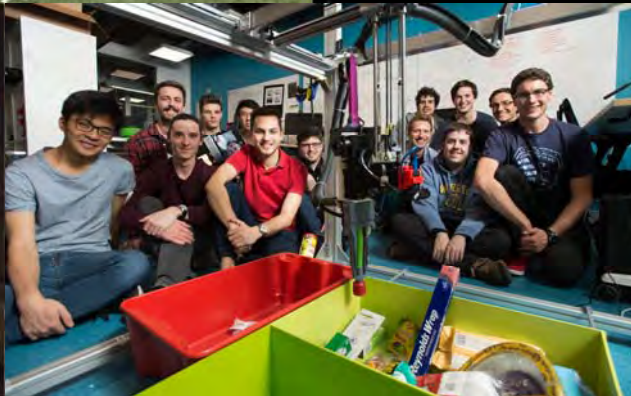
LoST? Appearance-Invariant Place Recognition for Opposite Viewpoints using Visual Semantics



Robotics and AI at QUT



Eyes Underground
A vision for mine safety



Extensive Outreach Engagement Consulting in AVs



تحدي دبي العالمي
للتفوق الذاتي القيادة
DUBAI WORLD CHALLENGE
FOR SELF-DRIVING TRANSPORT
2018 | 2023



Where to go for more information... (high level)

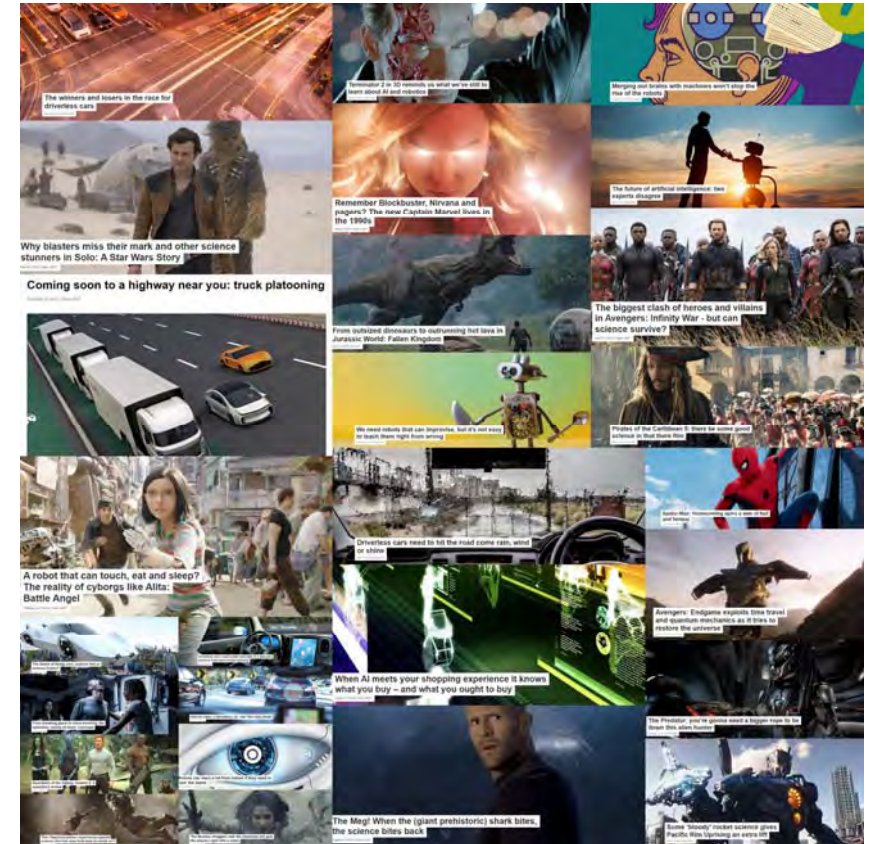
IEEE Spectrum June 2017



Username:
MilfordRobotics

Engineers Australia Create Magazine Nov 2018

The Conversation and other media outlets



Publications and Key Survey/Review Papers

Google Scholar: <http://scholar.google.com/citations?user=TDSmCKgAAAAJ>

IEEE TRANSACTIONS ON ROBOTICS, VOL. 32, NO. 1, FEBRUARY 2016

Visual Place Recognition: A Survey

Stephanie Lowry, Niko Sünderhauf, Paul Newman, Fellow, IEEE, John J. Leonard, Fellow, IEEE, David Cox, Peter Corke, Fellow, IEEE, and Michael J. Milford, Member, IEEE

Abstract—Visual place recognition is a challenging problem due to the vast range of ways in which the appearance of real-world places can vary. In recent years, improvements in visual sensing capabilities, an ever-increasing focus on long-term mobile robot autonomy, and the ability to drive on state-of-the-art research in other disciplines—particularly recognition in computer vision and animal navigation in neuroscience—have all contributed to significant advances in visual place recognition systems. This paper presents a survey of the visual place recognition research landscape. We start by introducing the concepts behind place recognition—the role of place recognition in the animal kingdom, how a “place” is defined in a robotics context, and the major components of a place recognition system. Long-term robot operations have revealed that changing appearance can be a significant factor in visual place recognition failures; therefore, we discuss how place recognition solutions can implicitly or explicitly account for appearance change within the environment. Finally, we close with a discussion on the future of visual place recognition, in particular with respect to the rapid advances being made in the related fields of deep learning, semantic scene understanding, and video description.

Index Terms—Visual place recognition, place recognition.

1 INTRODUCTION

VISUAL place recognition is a well-defined but extremely challenging problem to solve in the general case, given an image of a place, can a human, animal, or robot decide whether or not this image is of a place it has already seen? Whether referring to humans, animals, computers, or robots, there are some fundamental things a place recognition system must have

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Stephanie Lowry, Niko Sünderhauf, Paul Newman, John J. Leonard, David Cox, Peter Corke, and Michael J. Milford, “Visual Place Recognition: A Survey”, in *IEEE Transactions on Robotics and Automation*, 32 (1), 2016

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The limits and potentials of deep learning for robotics

Niko Sünderhauf¹, Oliver Brock², Walter Scheirer³, Raia Hadsell⁴, Dieter Fox⁵, Jürgen Leitner⁶, Ben Upcroft⁷, Pieter Abbeel⁸, Wolfram Burgard⁹, Michael Milford¹⁰ and Peter Corke¹

Abstract
The application of deep learning in robotics leads to very specific problems and research questions that are typically not addressed by the computer vision and machine learning communities. In this paper we discuss a number of robot-specific learning, training, and evaluation challenges for deep learning. We explain the need for better evaluation metrics, highlight the opportunity and unique challenges for deep robotic learning in simulation, and explore the spectrum between purely data-driven and model-driven approaches. We hope this paper provides a motivating overview of important research directions to overcome the current limitations and helps to fulfill the promising potentials of deep learning in robotics.

Keywords
 Robotics, deep learning, machine learning, robotic vision

1. Introduction
 A robot is an inherently active agent that interacts with the real world, and often operates in uncontrolled or detrimental conditions. Robots have to perceive, decide, plan, and execute actions, all based on incomplete and uncertain knowledge. Mistakes can lead to potentially catastrophic results that will not only endanger the success of the robot's mission, but can even put human lives at risk, e.g. if the robot is a driverless car.

The application of deep learning in robotics therefore motivates research questions that differ from those typically addressed in computer vision: How much trust can we put in the predictions of a deep learning system when misclassifications can have catastrophic consequences? How can we estimate the uncertainty in a deep network's predictions and how can we fuse these predictions with prior knowledge and other sensors in a probabilistic framework? How well does deep learning perform in realistic unconstrained open-set scenarios where objects of unknown class and appearance are regularly encountered?

If we want to use data-driven learning approaches to generate motor commands for robots to move and act in the world, we are faced with additional challenging questions: How can we generate enough high-quality training data? Do we rely on data solely collected on robots in real-world scenarios or do we require data augmentation through simulation? How can we ensure the learned policies transfer well

to different situations, from simulation to reality, or between different robots?

This leads to further fundamental questions: How can the structure, the constraints, and the physical laws that govern robotic tasks in the real world be leveraged and exploited by a deep learning system? Is there a fundamental difference between model-driven and data-driven problem solving, or are these rather two ends of a spectrum?

This paper explores some of the challenges, limits, and potentials for deep learning in robotics. The invited speakers and organizers of the workshop on *The Limits and*

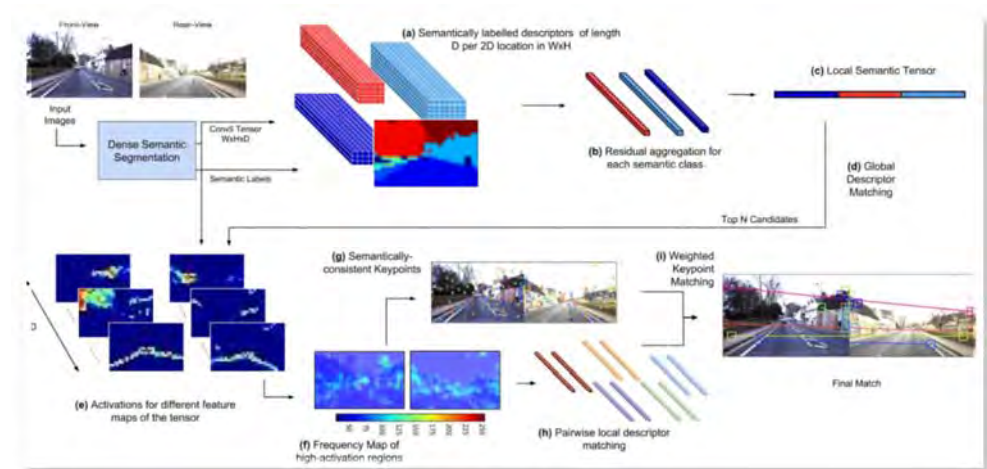
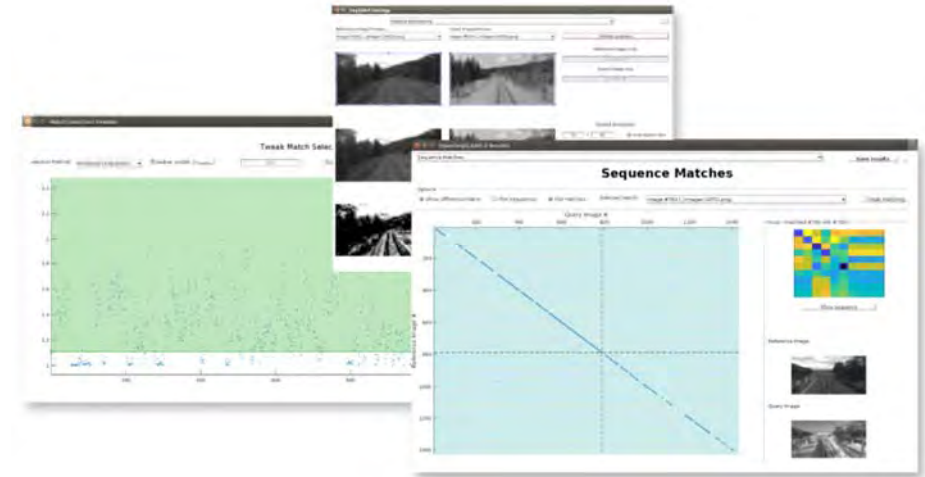
¹Australian Centre for Robotic Vision, Queensland University of Technology (QUT), Brisbane, Australia
²Robotics and Biology Laboratory, Technische Universität Berlin, Germany
³Department of Computer Science and Engineering, University of Notre Dame, IN, USA
⁴DeepMind, London, UK
⁵Pratt & Allen School of Computer Science & Engineering, University of Washington, WA, USA
⁶University of Oxford, Oxford, UK
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Niko Sünderhauf, Oliver Brock, Walter Scheirer, Raia Hadsell, Dieter Fox, Jürgen Leitner, Ben Upcroft, Pieter Abbeel, Wolfram Burgard, Michael Milford and Peter Corke, “The limits and potentials of deep learning for robotics”, in *International Journal of Robotics Research*, 37 (4-5), 2018

Open Source Code and Datasets

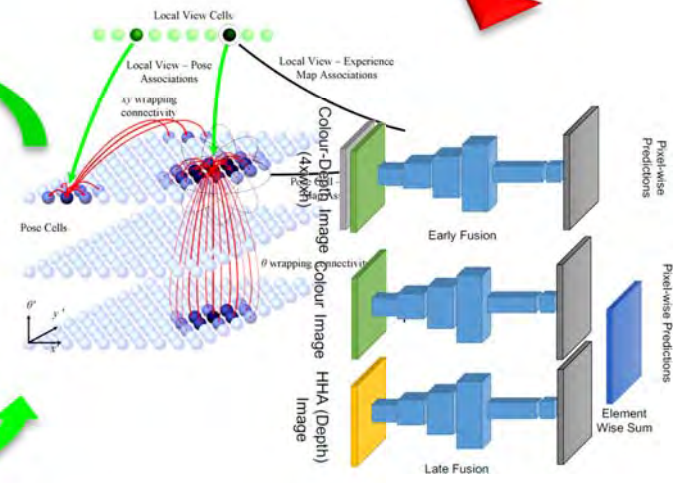
- **OpenSeqSLAM 2.0:** <http://seqslam.com/>
- **OpenSeqSLAM:** <https://openslam.org/openseqslam.html>
- **OpenRatSLAM:** <https://code.google.com/p/ratslam/wiki/RatSLAMROS>
- **OpenFABMAP** (also in OpenCV): <https://github.com/arenglover/openfabmap>
- **Learning to Navigate at Scale:** rl-navigation.github.io/deployable
- **Local Semantic Tensors:** <https://github.com/oravus/lostX>
- **Multi-Process Fusion:** <https://github.com/StephenHausler/Multi-Process-Fusion>
- **Look No Deeper: Recognizing Places from Opposing Viewpoints:** <https://github.com/oravus/seq2single>



“Understanding spatial and perceptual intelligence as a gateway to understanding, creating and applying general intelligence”



Research Philosophy



RatSLAM*: rat-inspired mapping and navigation

Key contributors

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Milford



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Wyeth



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Wiles



David
Prasser



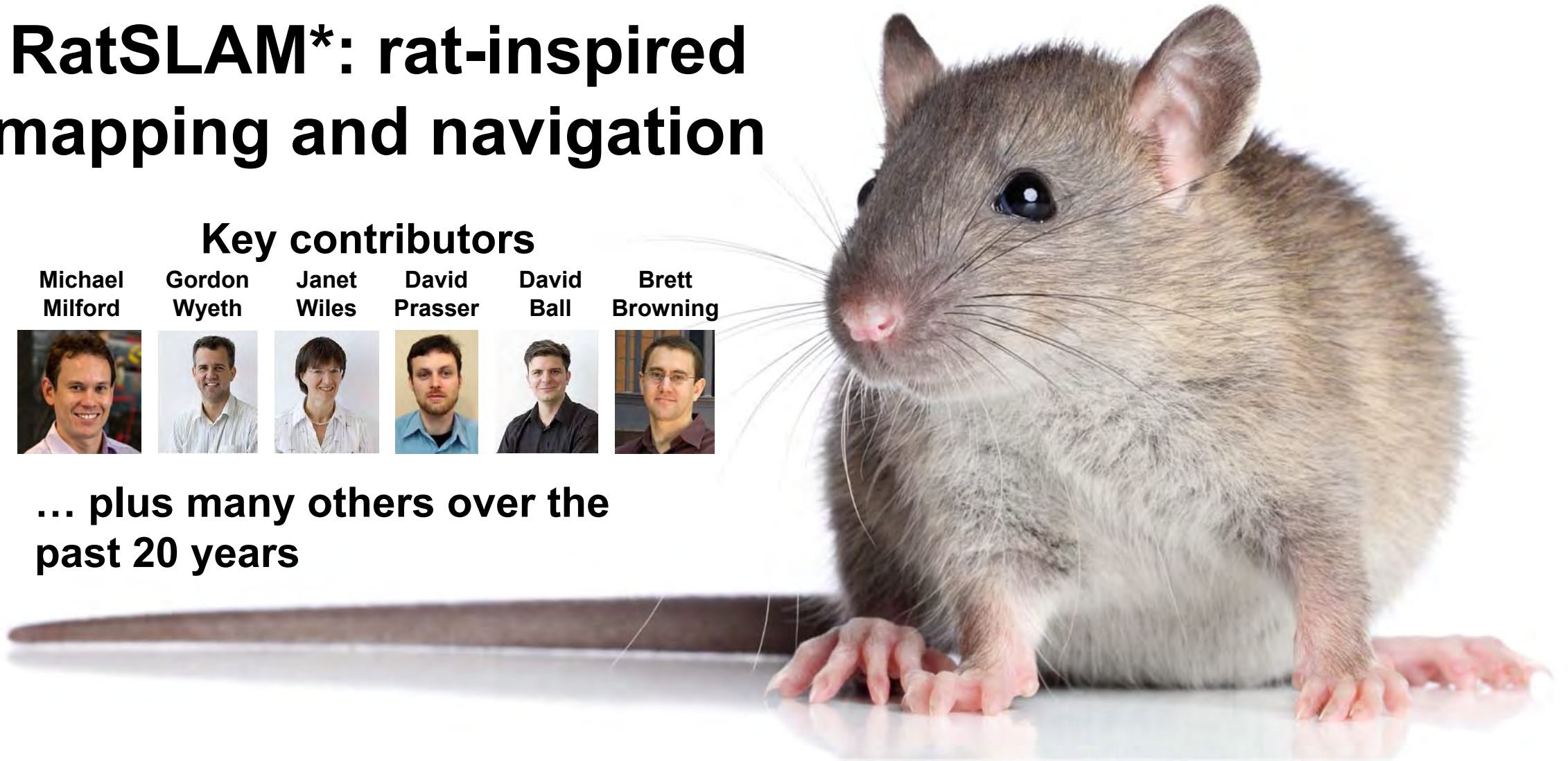
David
Ball



Brett
Browning

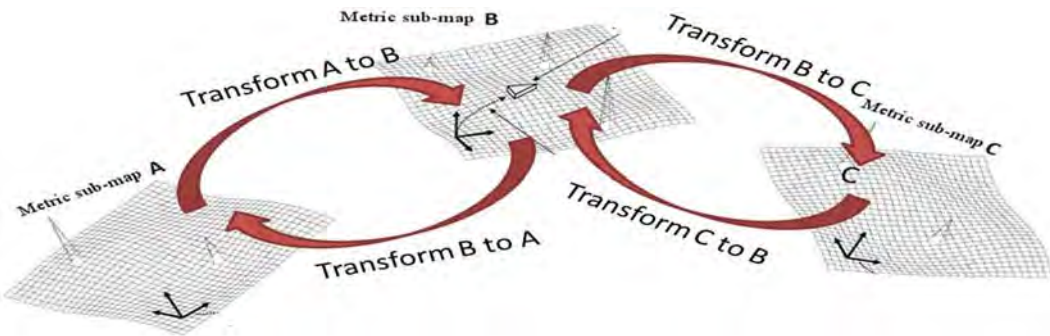
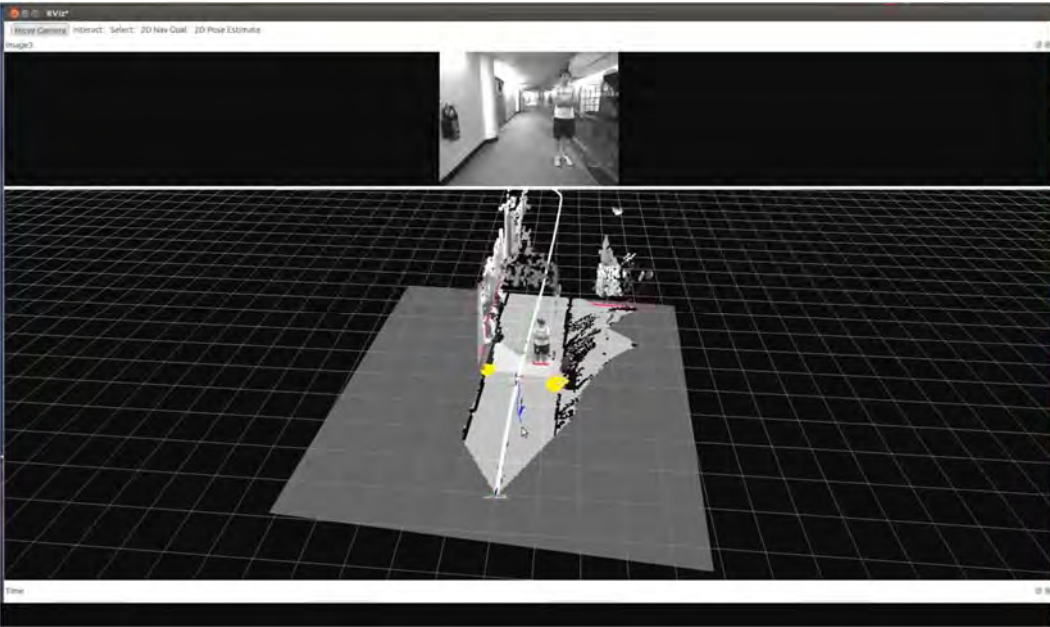


... plus many others over the
past 20 years



***SLAM** = **S**imultaneous **L**ocalisation **A**nd **M**apping

Spatial Mapping: Robotics versus Nature



Rats as inspiration



Well-characterized Sensing & Perception



Human vision



*Normally-pigmented
rats have blurry
dichromatic vision
with a little color*



*Albino rats may see a
very blurry, light-
dazzled world*

<http://www.ratbehavior.org/RatVision.htm>



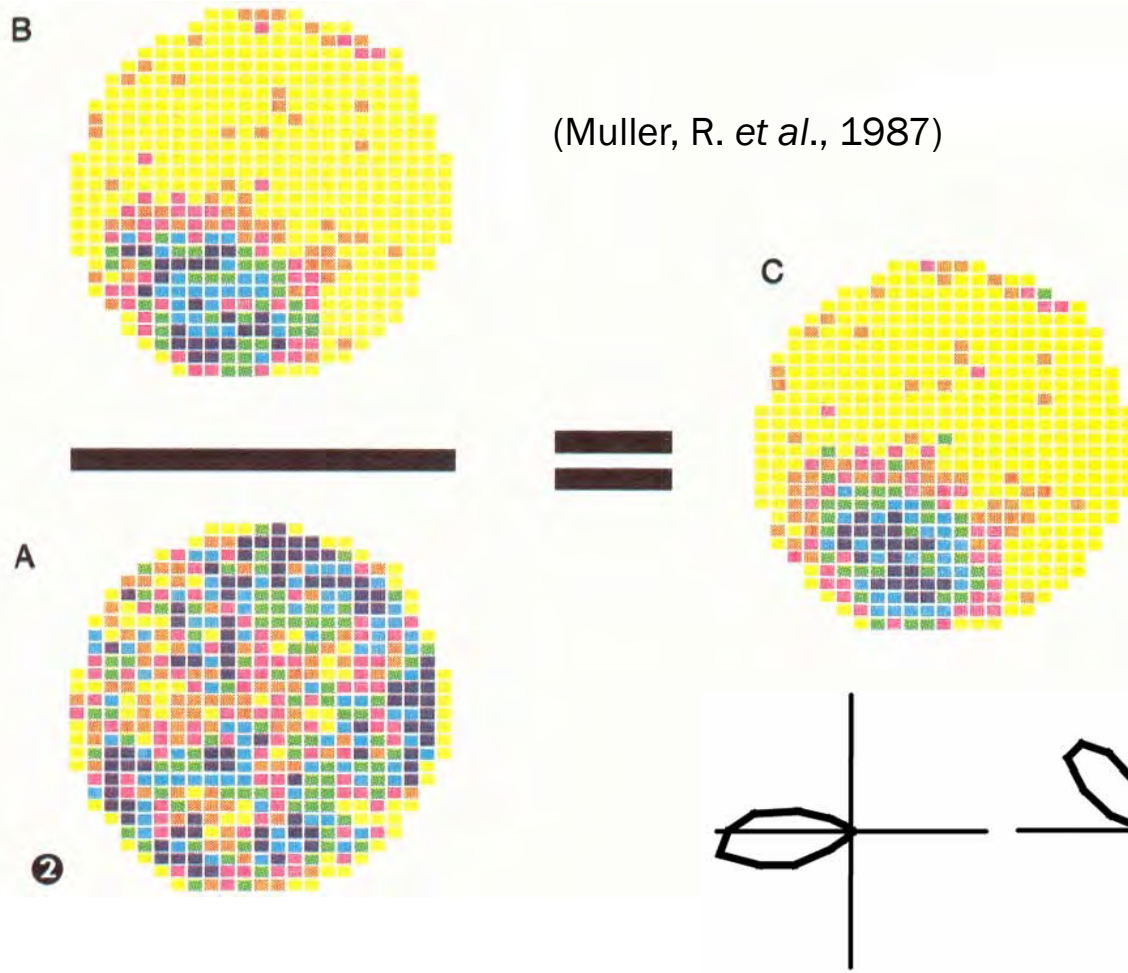
A **LED** is triggered when the firing rate of the place cell is above 10 Hz.



Source: www.gtec.at

Well-characterized Neural Navigation Systems

Place and Head-Direction Cells

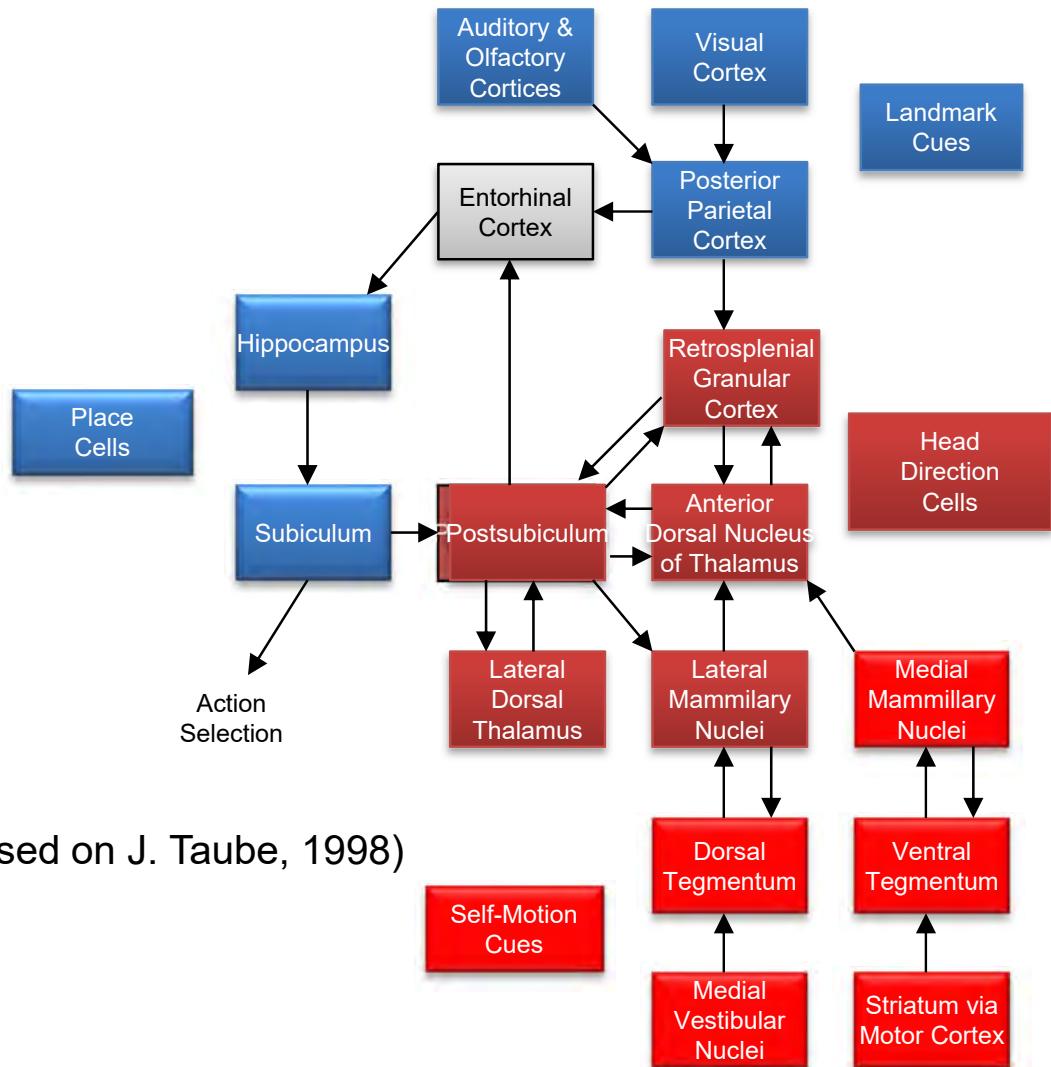


Cells that are perfect for encoding a robot's location (1971) and orientation (1984)

(Yoganarasimha, Yu and Knierim, 2006)

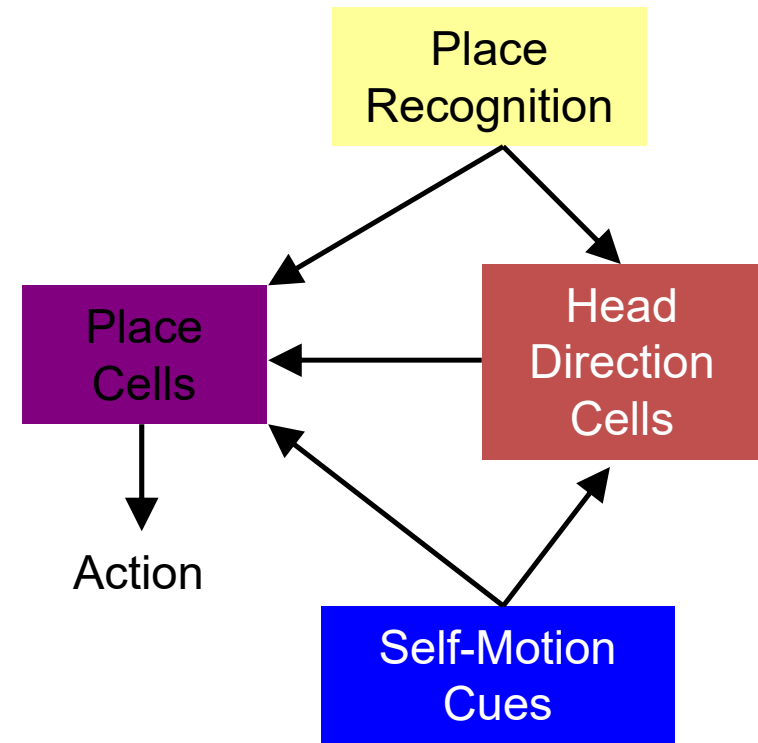
Modelling the Neural System?

Neuroscientist System Overview

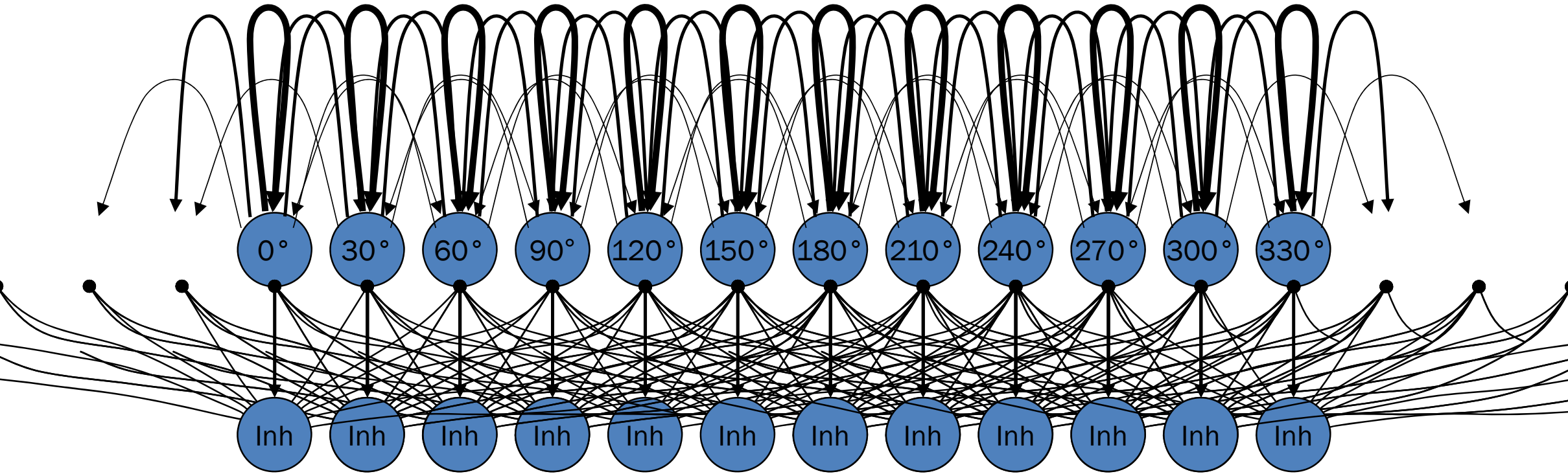


(based on J. Taube, 1998)

Robotist Abstraction RatSLAM Mark 1



Modelling with Continuous Attractor Networks (CAN)



An aerial, top-down view of a suburban neighborhood. The scene is filled with houses of various colors (red, orange, blue, grey) and sizes, interspersed with green lawns and trees. A network of dark grey roads with white dashed lines winds through the area. Several small, colorful cars (yellow, red, blue) are visible on the roads. The overall style is a clean, illustrative 3D perspective.

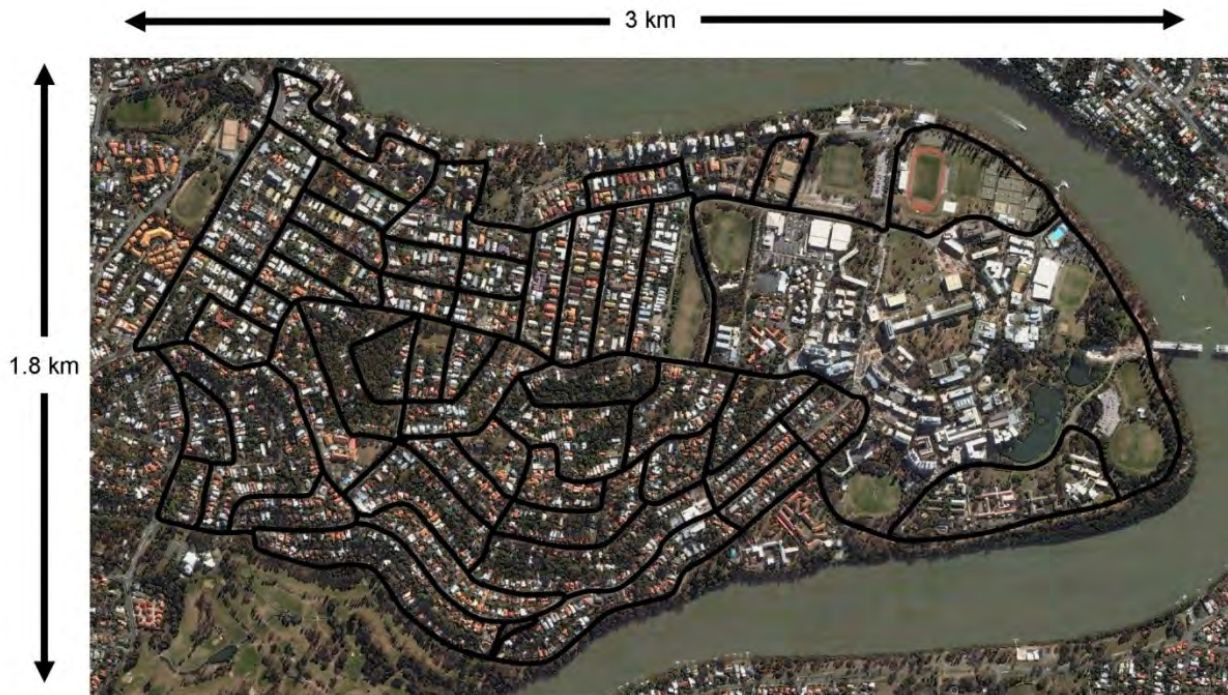
Key Mapping and Navigation Demonstrations

1) **Mapping a Suburb**

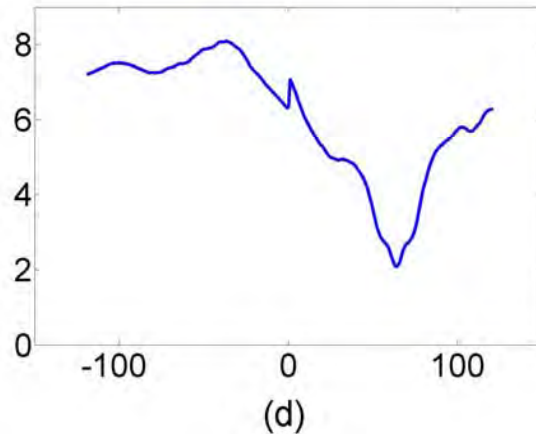
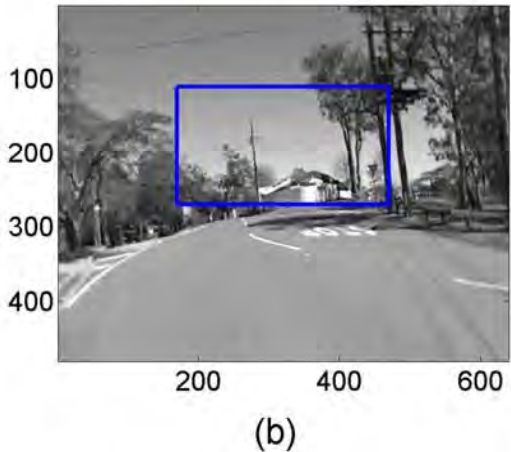
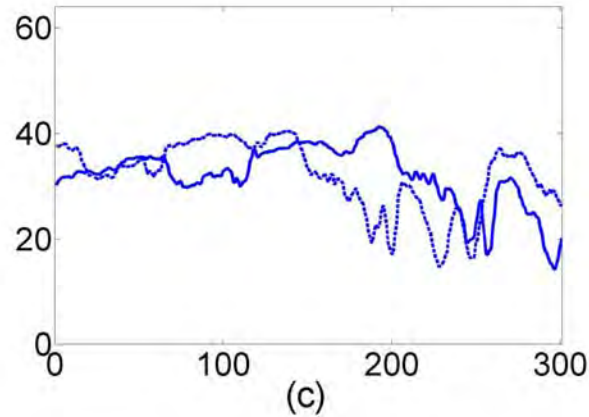
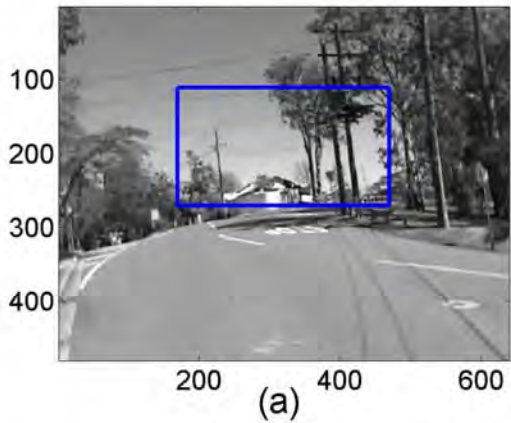
2) **Persistent Mapping and Navigation**

Mapping a Suburb

- Used vision for local view *and* odometry.
- Vision from built-in camera of a Mac iBook mounted on experimenter's car.
- Mapped 66 km over just under 2 hours.



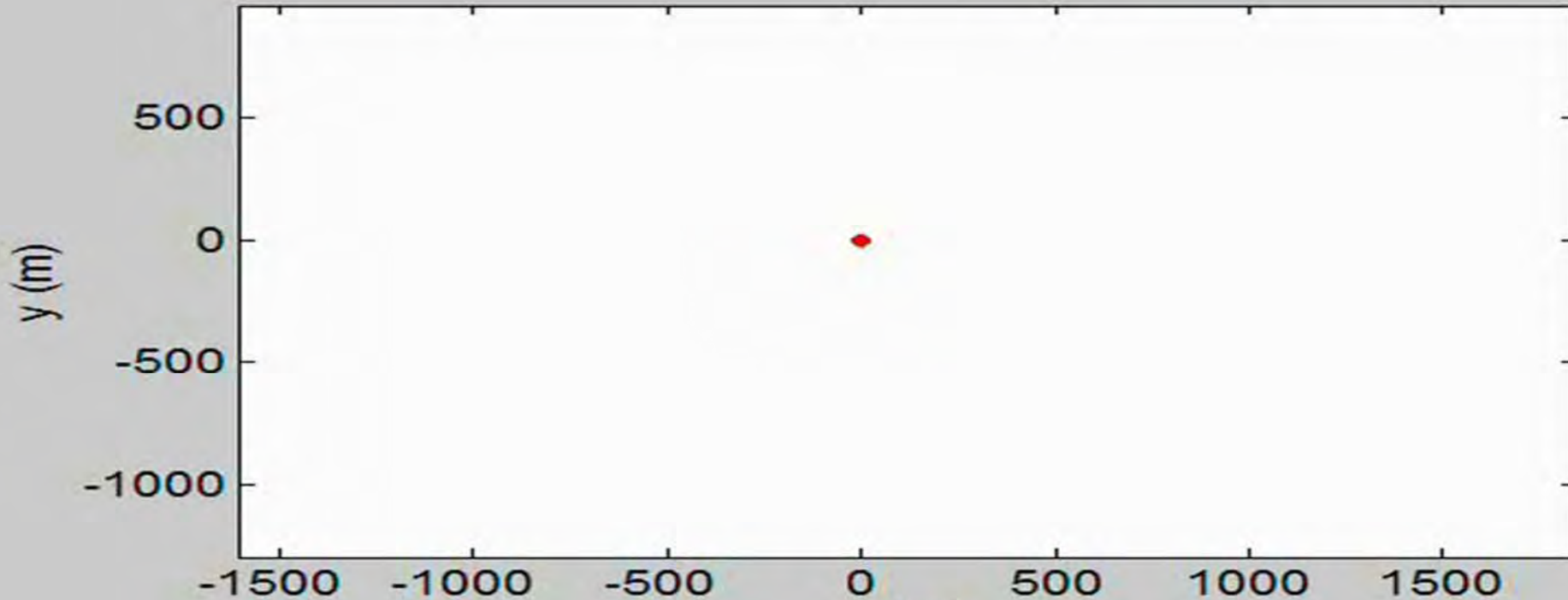
Visual Odometry and Place Recognition

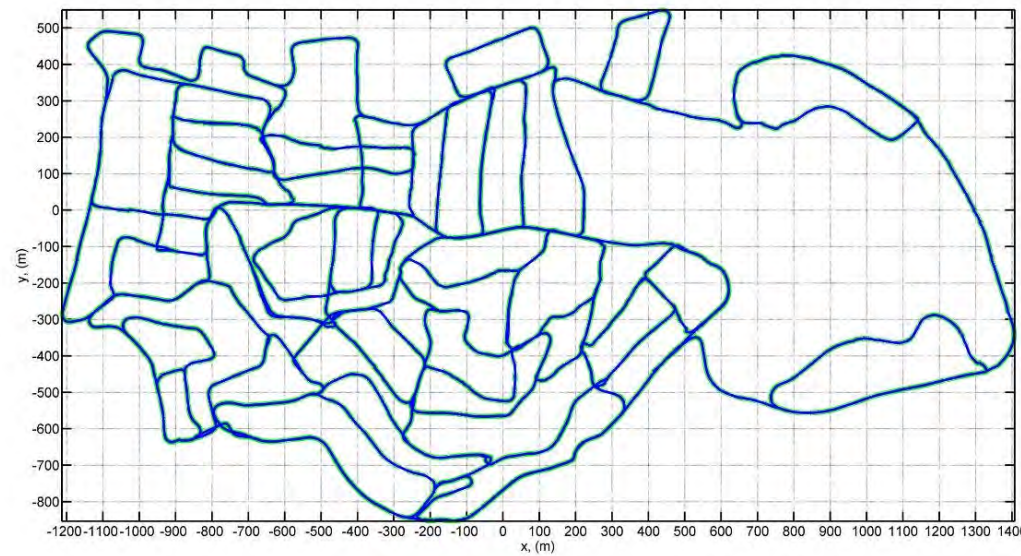


- Forward speed estimated from change in scanline intensity profile between current profile and rotated previous profile.
- Template matching based on profiles with rotation accounted.

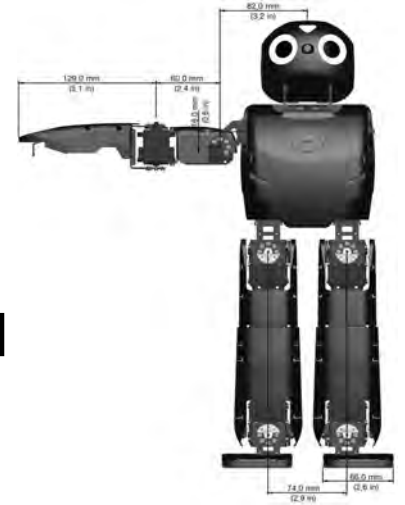
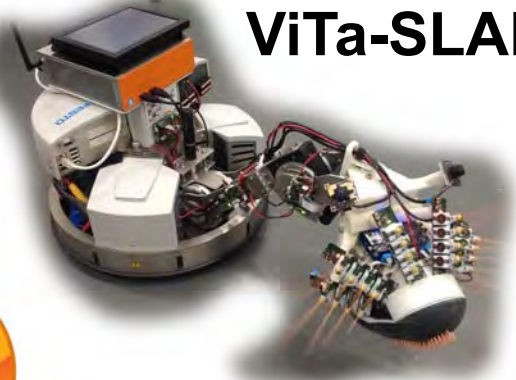
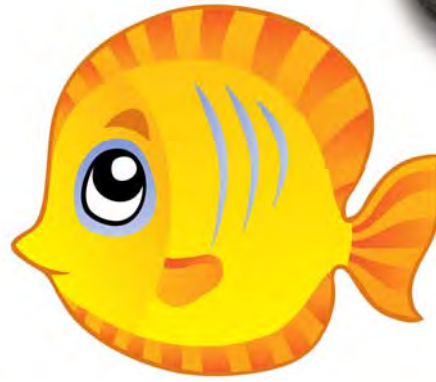
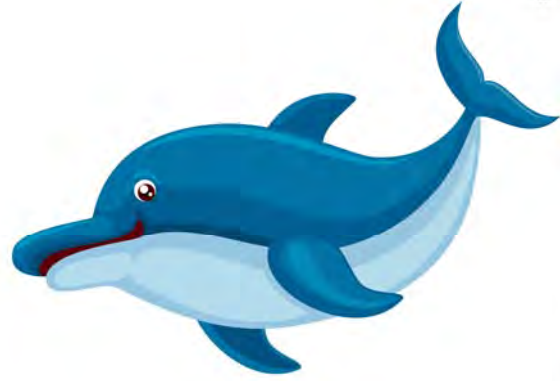
Mapping an Entire Suburb

Time: 1.0 s





CatSLAM* (Maddern et al) and many others...

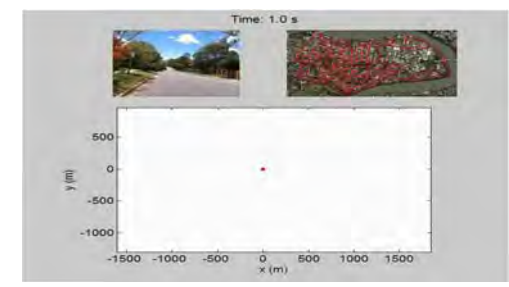
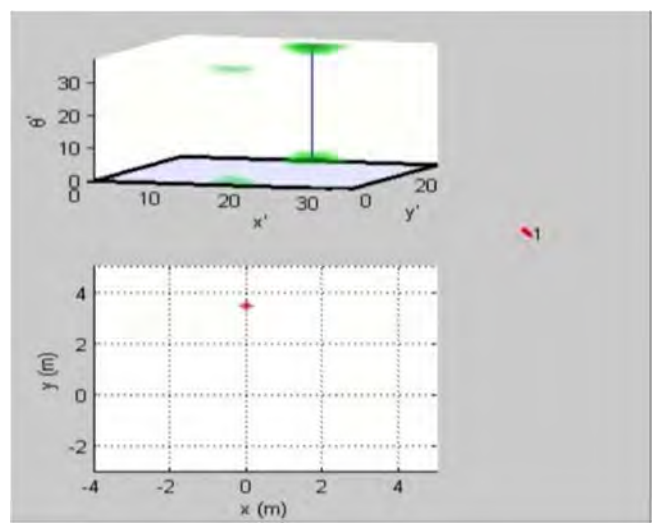
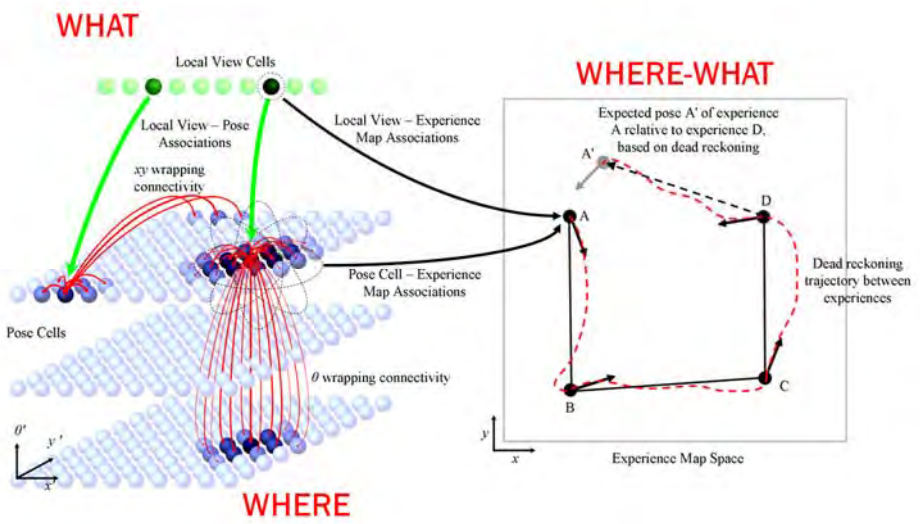
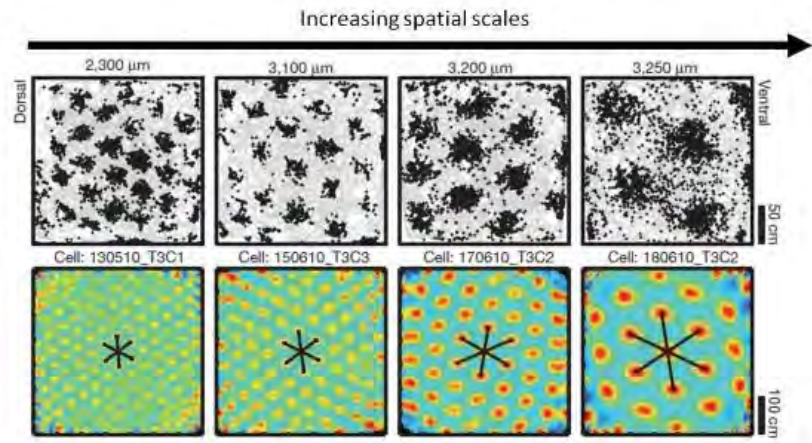


***CatSLAM is not biologically inspired**

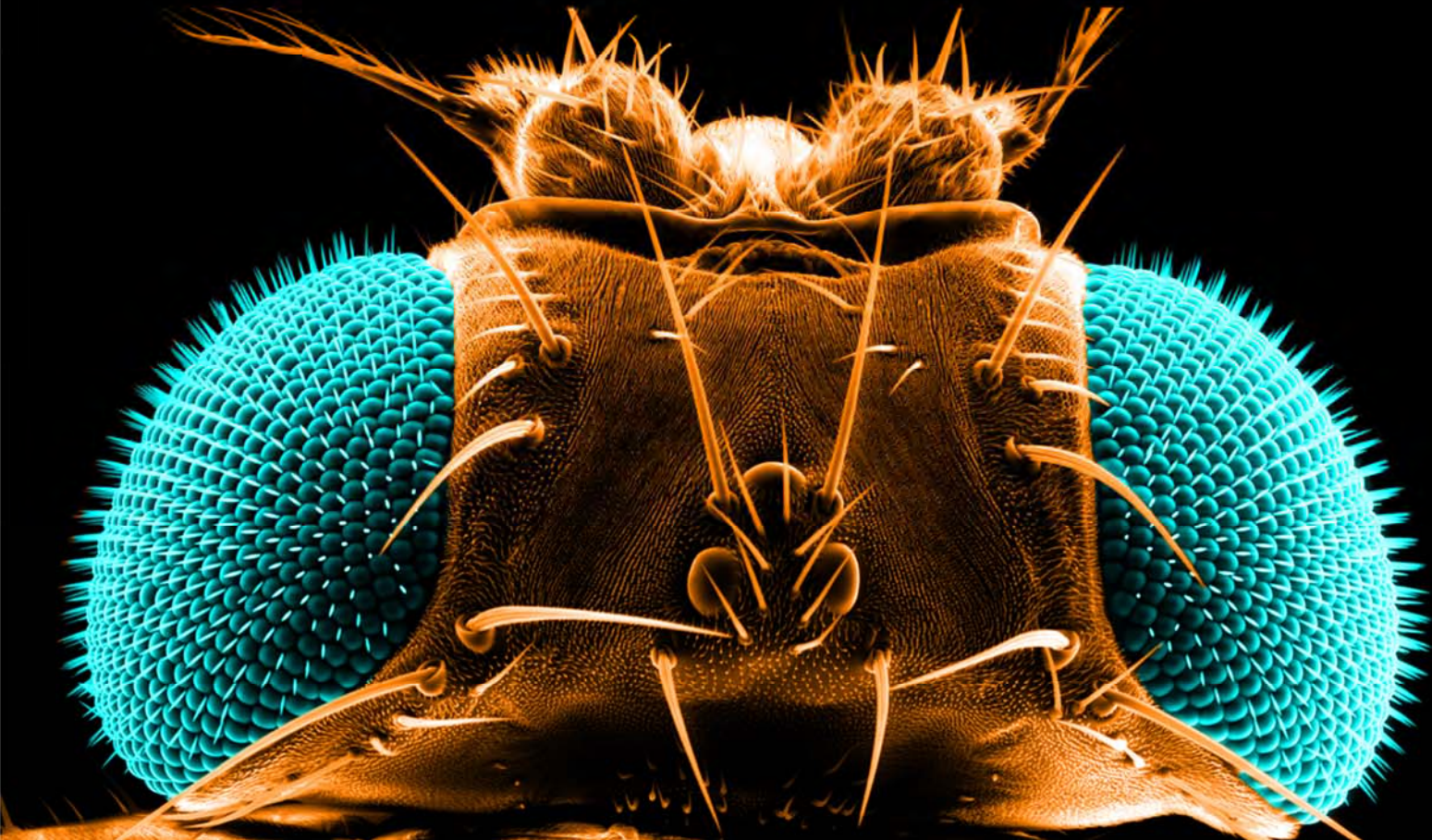
RatSLAM: Over a decade from neuroscience to deployment



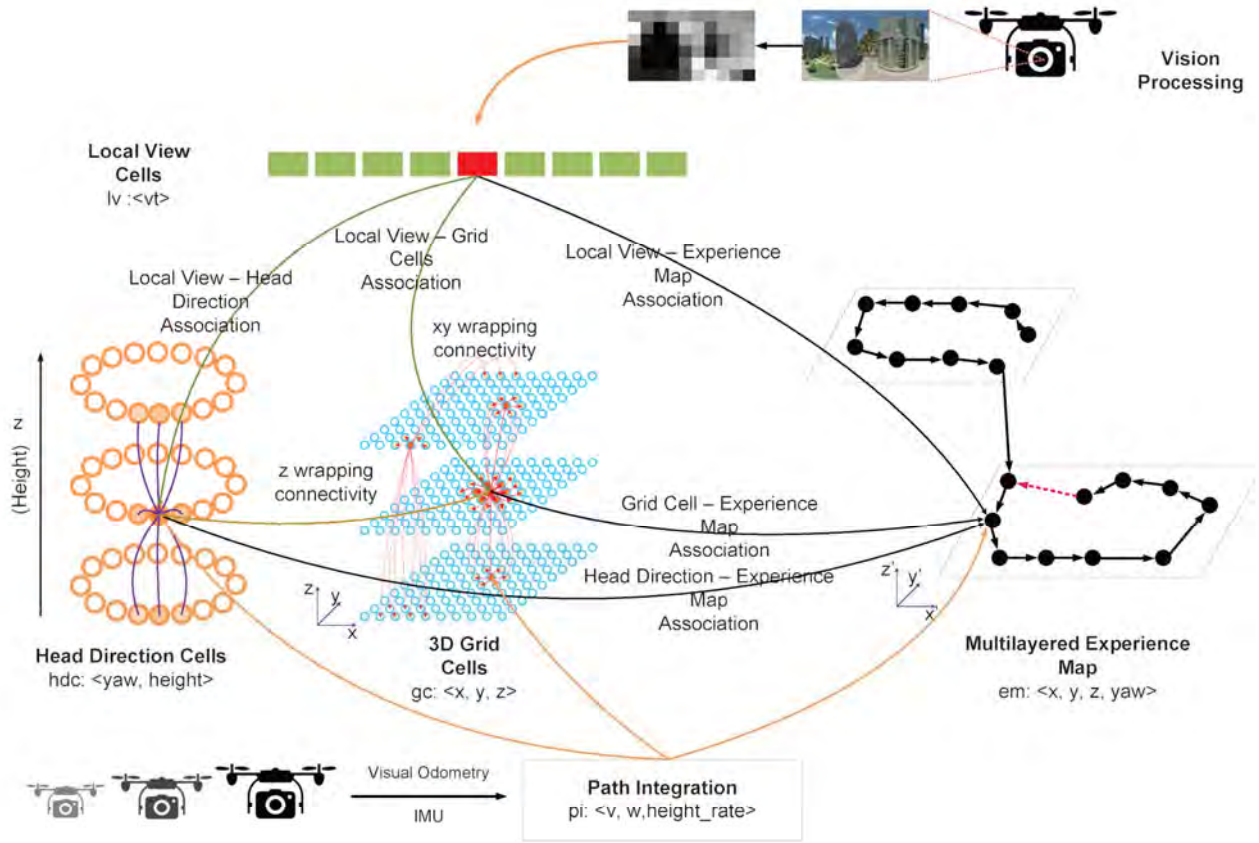
Attractor Connections



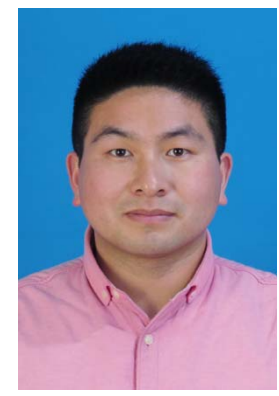
Recent & Ongoing Bio-inspired Research



NeuroSLAM: A Brain inspired 6-DOF SLAM System for 3D Environments

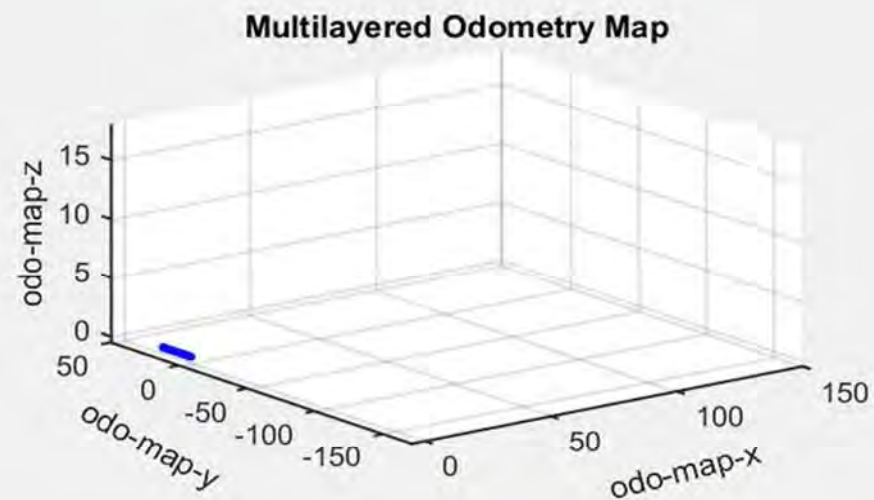
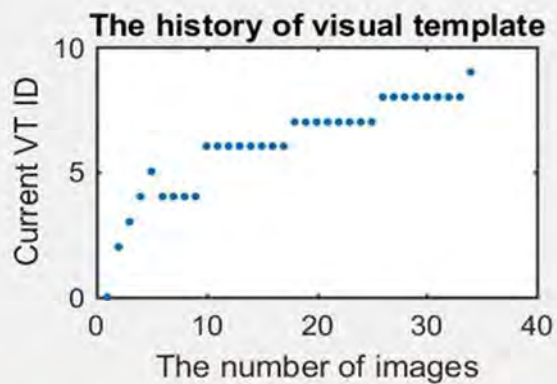
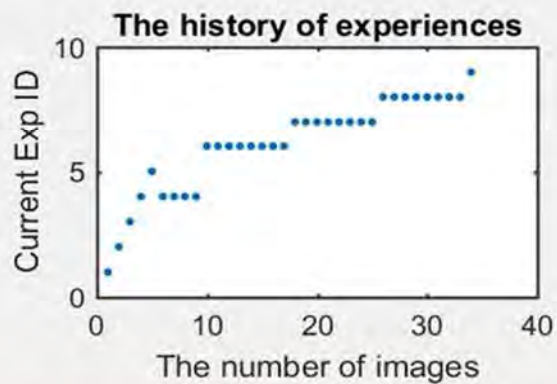
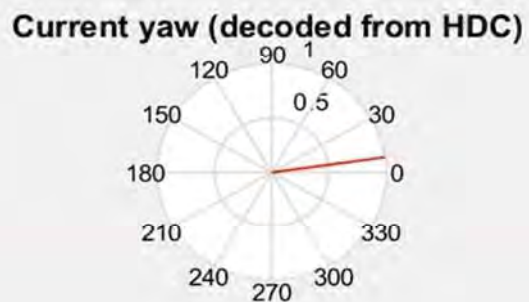
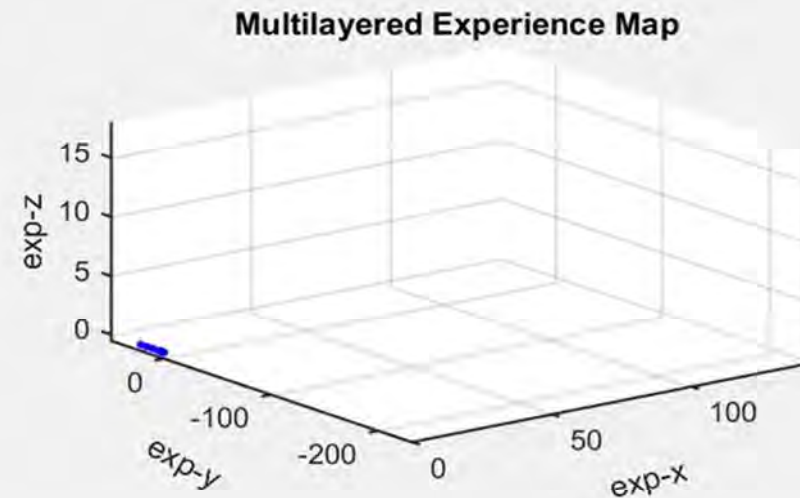
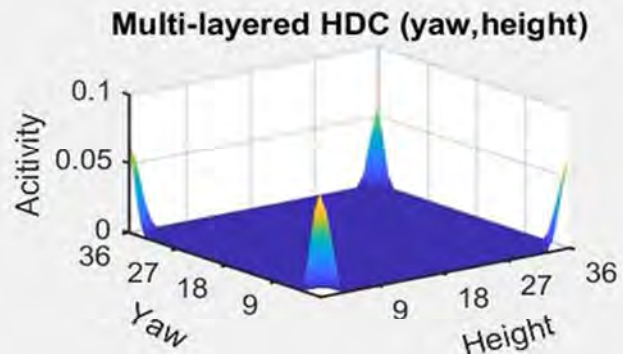
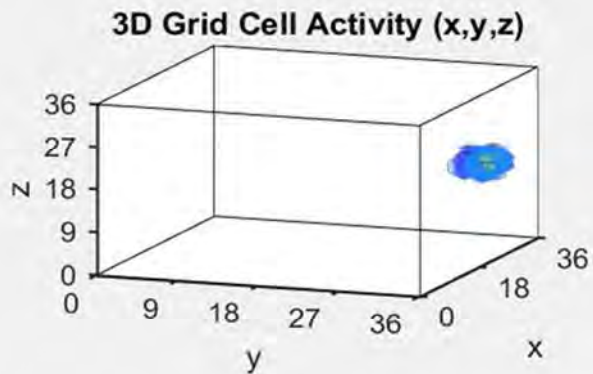


Fangwen Yu



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Fig. 1 NeuroSLAM architecture. The system consists of conjunctive pose cells combining the 3D grid cells and multilayered head direction cells, the multilayered experience map and vision modules. The conjunctive pose cell network performs path integration based on the local view cues and self-motion information. Local view cells encode distinct scenes in 3D environment. The self-motion information including translational velocity, altitude velocity and rotational velocity is estimated based on a lightweight 3D visual odometry system. The output from three components of the conjunctive pose cells, local view cells and 3D visual odometry drives the creation of a multilayered experience map, a hybrid spatial representation with topological, metric 3D graphical map of the 3D environment.




Winner of a Innovation Grand Prize at the 2019 International Collegiate Competition for Brain-inspired Computing run by Tsinghua University



Bio-inspired Sensing

Event Cameras






Towards Visual SLAM with Event-based Cameras

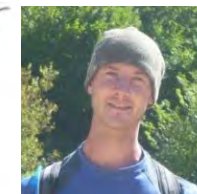
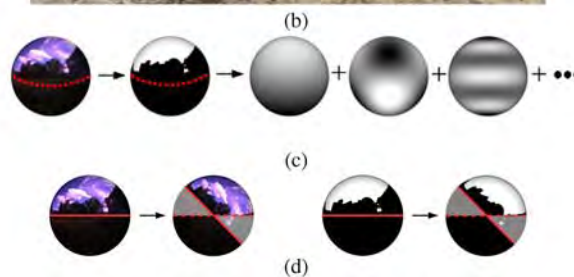
Michael Milford¹, Hanme Kim², Stefan Leutenegger² and Andrew Davison²

¹Australian Centre for Robotic Vision, Queensland University of Technology
²Department of Computing, Imperial College London
Corresponding author: michael.milford@qut.edu.au

In "The Problem of Mobile Sensors: Setting future goals and indicators of progress for SLAM" Workshop at *Robotics and Science Systems 2015*




UV-sensitive cameras



Tom Stone

Low light cameras

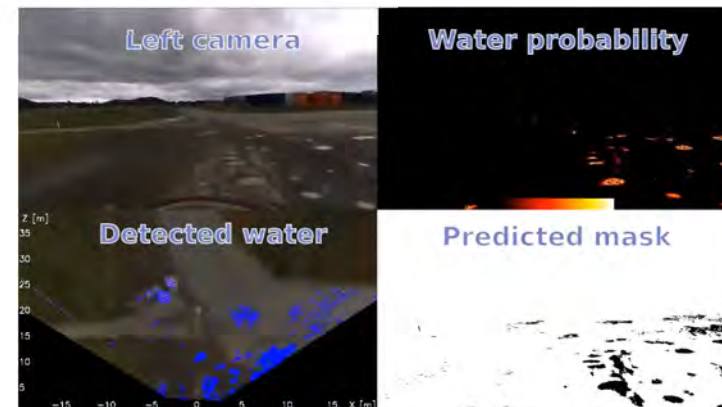


James Mount

Stereo Polarized Cameras




 Australian National University
Chuong Nguyen





How Bio-inspired Research Can Spur Breakthroughs

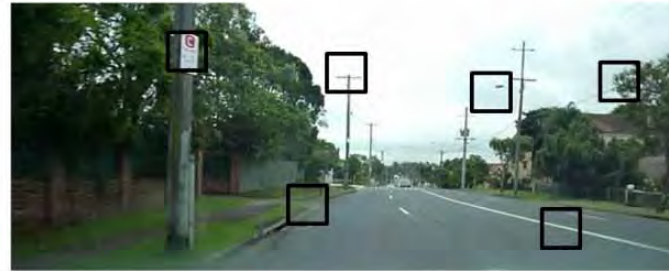
The Core Challenge

Place A



Same place, low similarity

Place A'

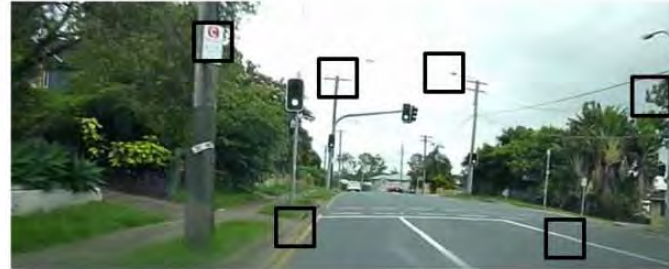


Place A

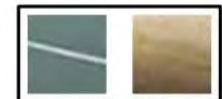
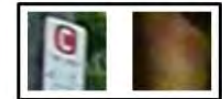


Difference place, high similarity

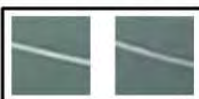
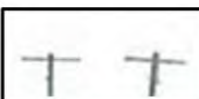
Place B



A-A'



A-B



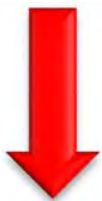
One of our core research foci

Some papers from 2018-2019

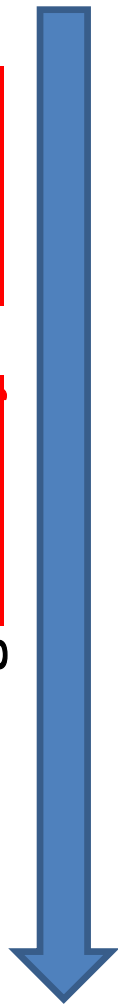


Stephanie Lowry, Niko Sünderhauf, Paul Newman, John J. Leonard, David Cox, Peter Corke, and Michael J. Milford, **“Visual Place Recognition: A Survey”**, in *IEEE Transactions on Robotics and Automation*, 32 (1), 2016

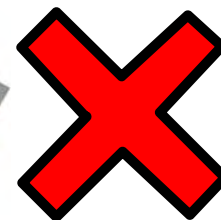
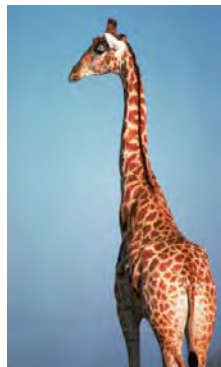
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Increasing selectivity & tolerance



Early stage



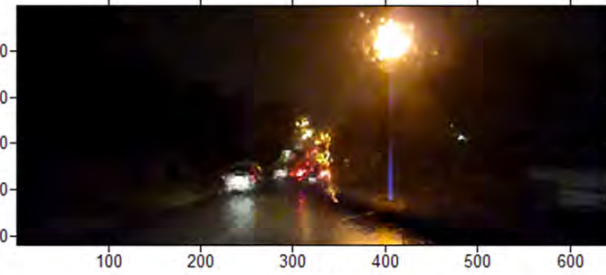
Later stage



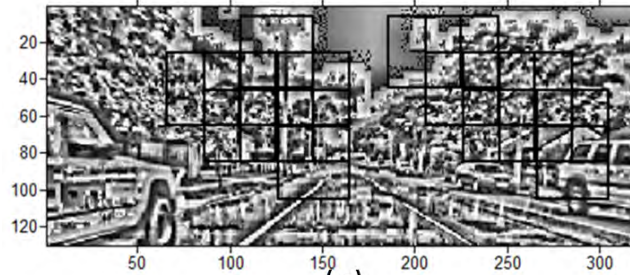
**Correctly
 confirmed
 match: true
 positive**



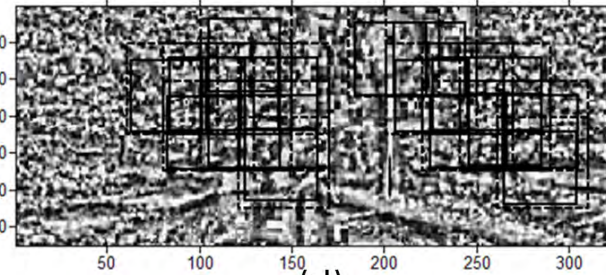
(a)



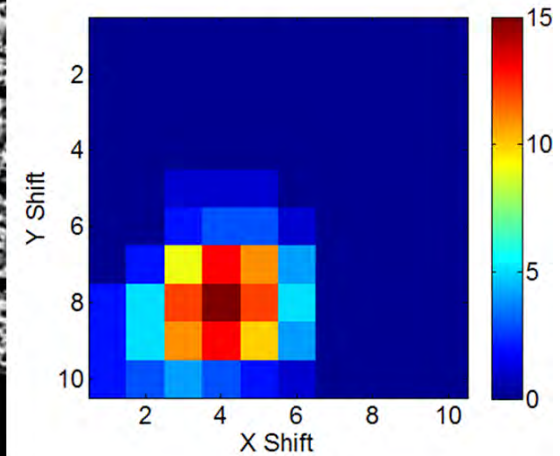
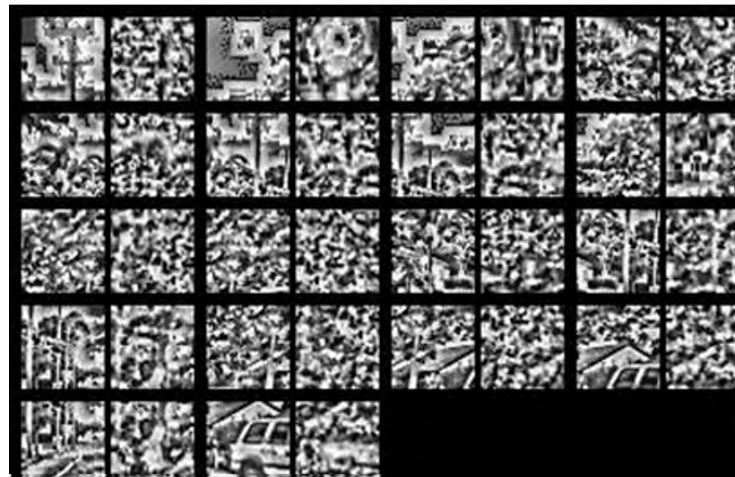
(b)



(c)



(d)

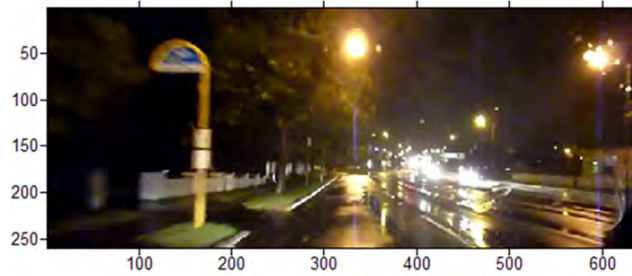


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- Michael Milford, Walter J. Scheirer, Eleonora Vig, Arren Glover, Oliver Baumann, Jason Mattingley, David D. Cox, "Condition-Invariant, Top-Down Visual Place Recognition," *IEEE International Conference on Robotics and Automation*, 2014

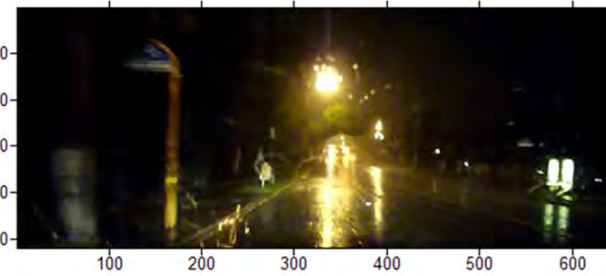
**Correctly
rejected match
hypothesis:
true negative**



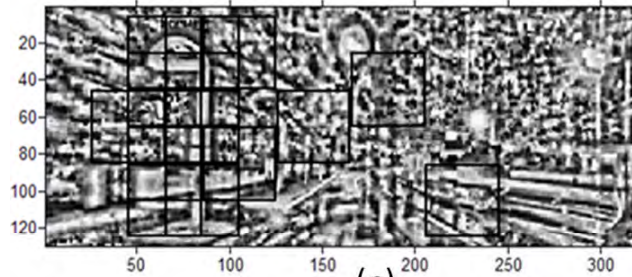
**Beat the Machine
Game**



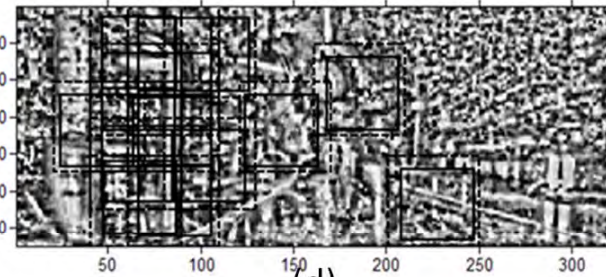
(a)



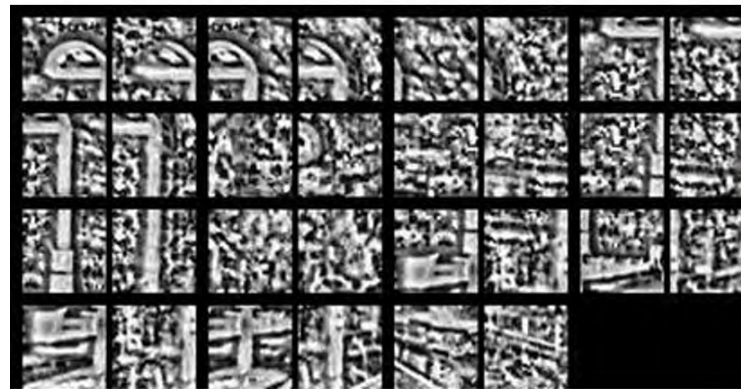
(b)



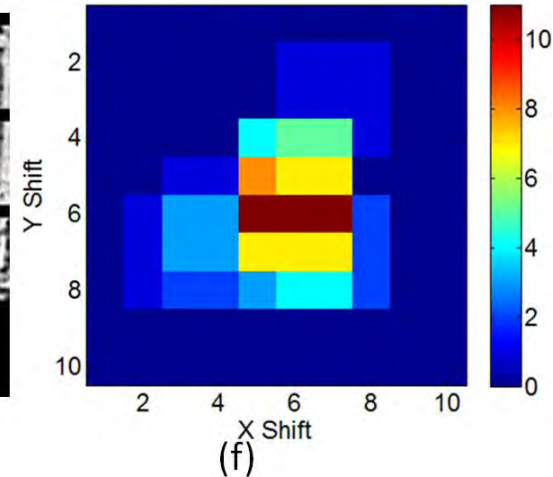
(c)



(d)



(e)



- Michael Milford, Eleonora Vig, Walter J. Scheirer, David D. Cox, "Vision-based Simultaneous Localization and Mapping in Changing Outdoor Environments", in *Journal of Field Robotics*, 31 (5), 2014.
- Michael Milford, Walter J. Scheirer, Eleonora Vig, Arren Glover, Oliver Baumann, Jason Mattingley, David D. Cox, "Condition-Invariant, Top-Down Visual Place Recognition," *IEEE International Conference on Robotics and Automation*, 2014



How SeqSLAM Came About

- Experimentation with spike train sequence generation
- Very low resolution images proven by prior RatSLAM bio-inspired work
- Attempting to generate self-sustaining spike trains in software, corresponding to image sequences
- Final SeqSLAM was an algorithmic, non-spiking simplification

	X_0				X_7			
Images			
Indexes	0	1	2	3	4	5	6	7
Bit 1	0	0	0	0	1	1	1	1
Bit 2	0	0	1	1	0	0	1	1
Bit 3	0	1	0	1	0	1	0	1

BTEL: A Binary Tree Encoding Approach for Visual Localization

Huu Le¹, Tuan Hoang², and Michael Milford³

Contact: Professor Michael Milford, michael.milford@qut.edu.au

¹Chalmers University of Technology, ²Singapore University of Technology and Design, ³QUT



The Nuances of Compression & Storage

- Early days of robotics: critical factors for deployment & feasibility
- Recent years: move towards focus on maximal recall / accuracy / precision / other performance
- All other things being equal, better compression & storage enables:
 - Cheaper, less bulky / power hungry compute hardware
 - On-board rather than off-board operations
 - Better absolute performance with no growth in compute

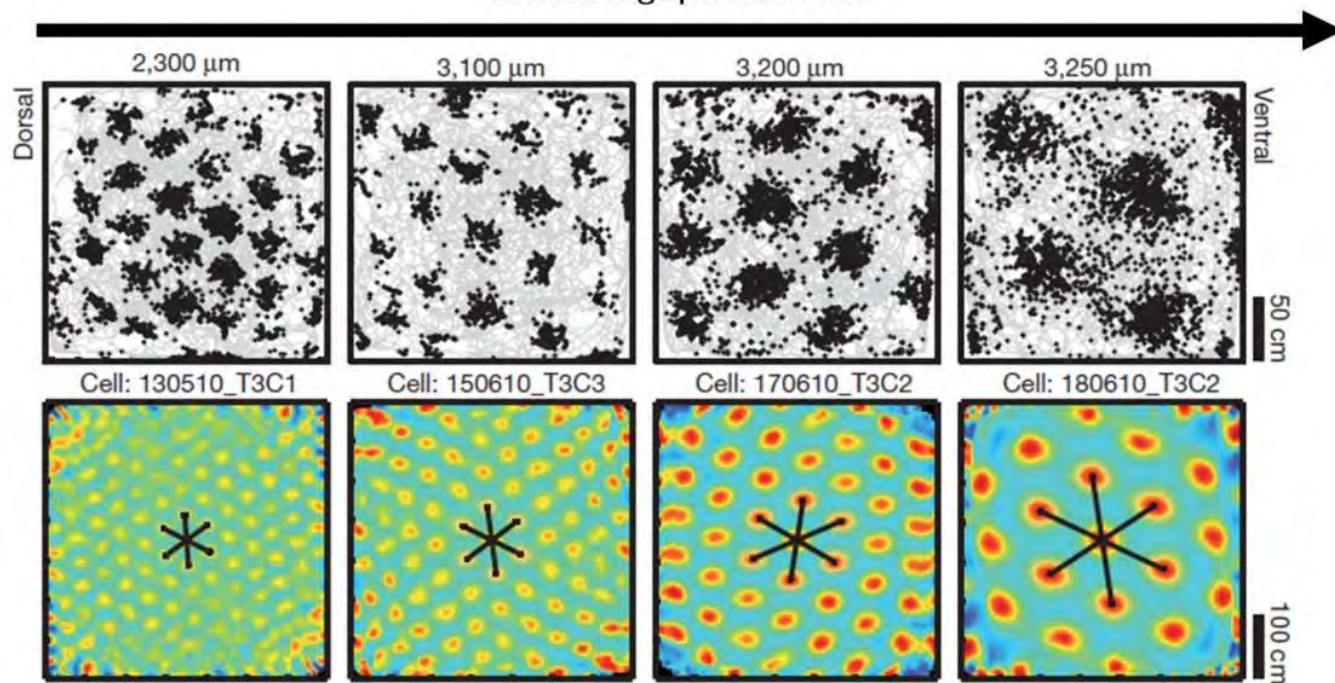
Absolute versus Scalability

- Much focus on absolute scalability
- But still at least linear growth
- Can we achieve sub-linear **storage** growth?
- Can we achieve this while maintaining competitive performance?
- Can we achieve sub-linear growth while maintaining compact **absolute** storage requirements?

Grid Cells (2004/2005)

- Multi-scale grid cell mapping. ~5+ scales, $\sqrt{2}$ scaling

Increasing spatial scales →

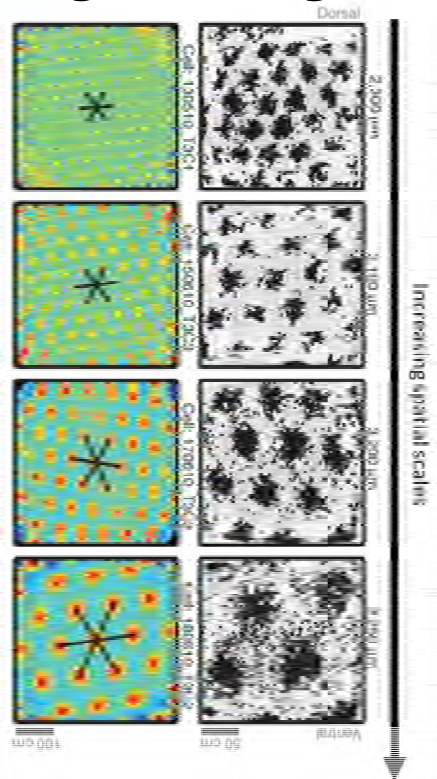


*2014 Nobel Prize for
Physiology or Medicine:
Edvard Moser, May-Britt
Moser and John O'Keefe*



[2] H. Stensola, T. Stensola, T. Solstad, K. Froland, M. Moser, and E. Moser, "The entorhinal grid map is discretized," *Nature*, vol. 492, pp. 72-78, 2012

A Mystery We've Been Investigating Thoroughly



- **Why have multiple scales?**
- **What scale ratio?**
- **How to set the scales?**
- **Interaction with all sensing modalities?**
- **What memory and computational advantages?**

H. Stensola, T. Stensola, T. Solstad, K. Froland, M. Moser, and E. Moser, "The entorhinal grid map is discretized," *Nature*, vol. 492, pp. 72-78, 2012

- Huu Le, Tuan Hoang, Michael J Milford, "BTEL: A Binary Tree Encoding Approach for Visual Localization", in *IEEE International Conference on Intelligent Robots and Systems*, 2019
- A Jacobson, Z Chen, M. Milford, *Biological Cybernetics*, 2018
- Litao Yu, Adam Jacobson, Michael J Milford, "Rhythmic Representations: Learning Periodic Patterns for Scalable Place Recognition at a Sub-Linear Storage Cost", in *IEEE Robotics and Automation Letters*, 2018
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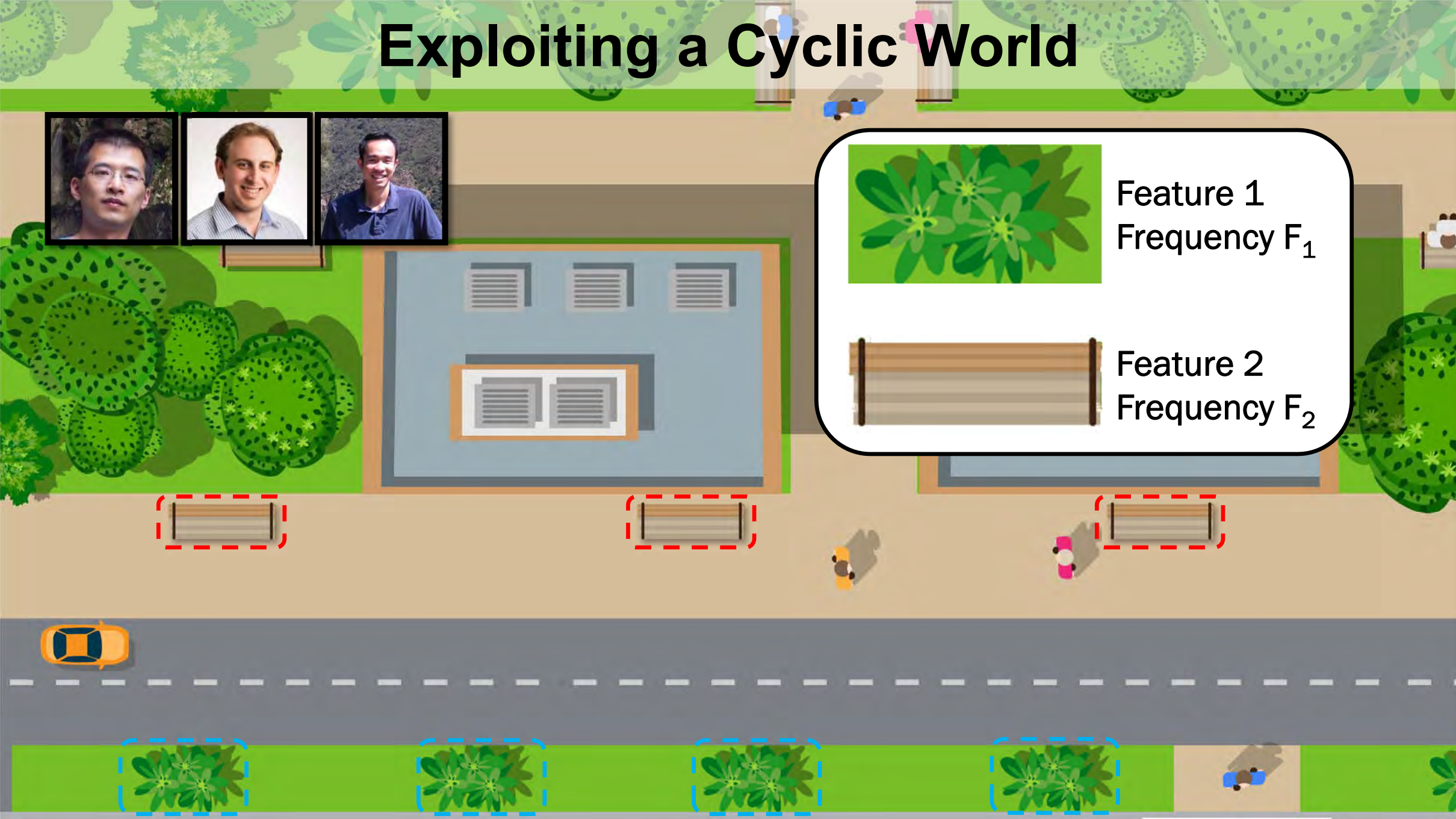
Exploiting a Cyclic World



Feature 1
Frequency F_1



Feature 2
Frequency F_2



Exploiting a Cyclic World

Place ID: 1 2 3 4 5 6 7 8

Feature 1: 0 1 0 1 0 1 0 1

Feature 2: 0 1 2 0 1 2 0 1 2

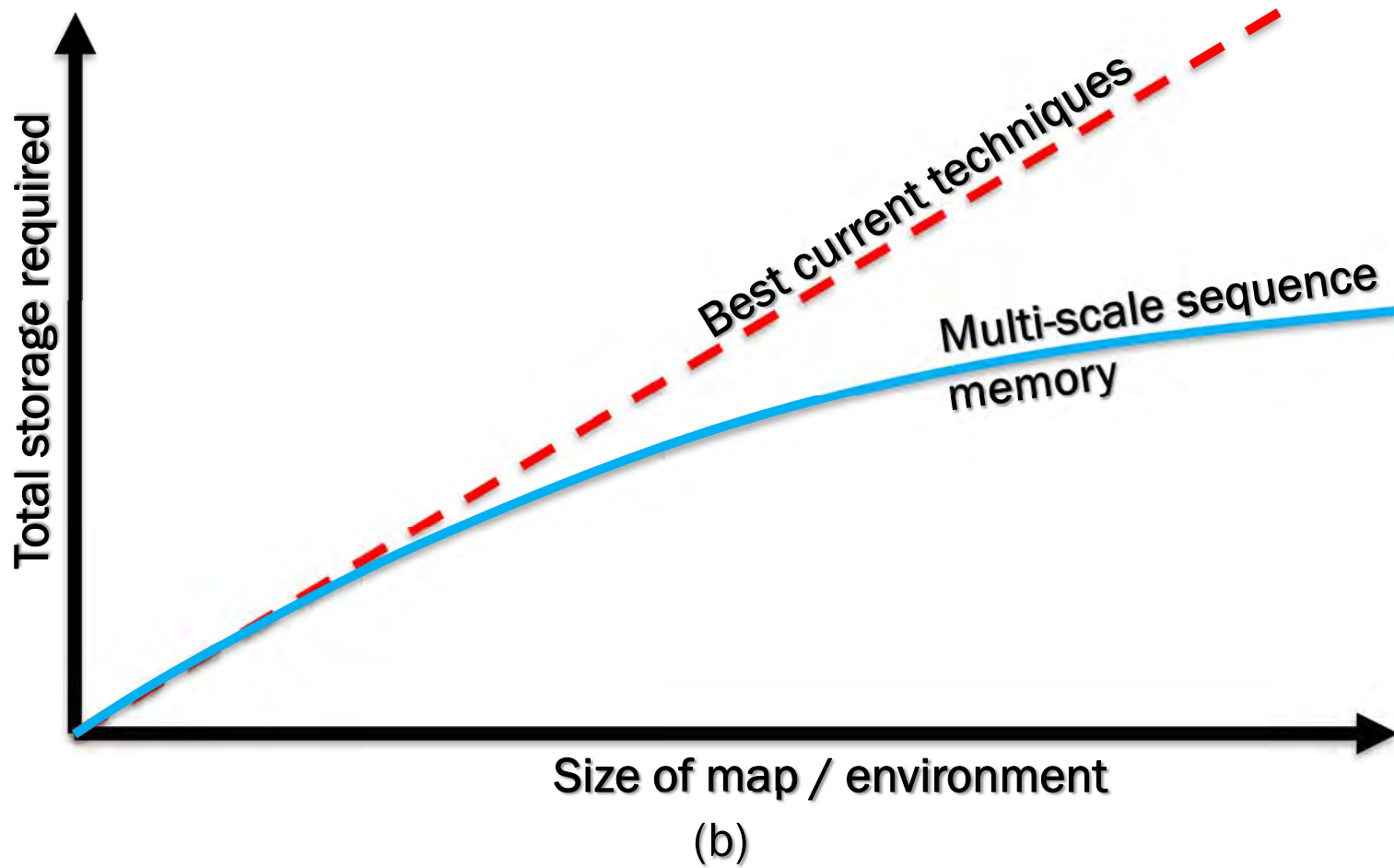
Memory collision

6 places, 5 units of storage

Feature 1: [0 1]

Feature 2: [0 1 2]

Real World Sub-Linear Dataset Compression



- Huu Le, Tuan Hoang, Michael J Milford, "BTEL: A Binary Tree Encoding Approach for Visual Localization", in *IEEE International Conference on Intelligent Robots and Systems*, 2019
- Litao Yu, Adam Jacobson, Michael J Milford, "Rhythmic Representations: Learning Periodic Patterns for Scalable Place Recognition at a Sub-Linear Storage Cost", in *IEEE Robotics and Automation Letters*, 2018
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Images			
Indexes	0	1	2	3	4	5	6	7
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BTEL: A Binary Tree Encoding Approach for Visual Localization

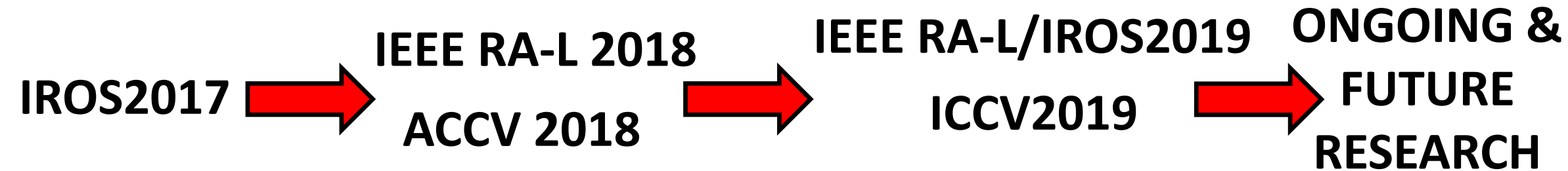
Huu Le¹, Tuan Hoang², and Michael Milford³

Contact: Professor Michael Milford, michael.milford@qut.edu.au

¹Chalmers University of Technology, ²Singapore University of Technology and Design, ³QUT



Future Work



- Co-investigating both **absolute storage compression** and **sub-linear scaling**
- Scaling up to **global-size datasets**

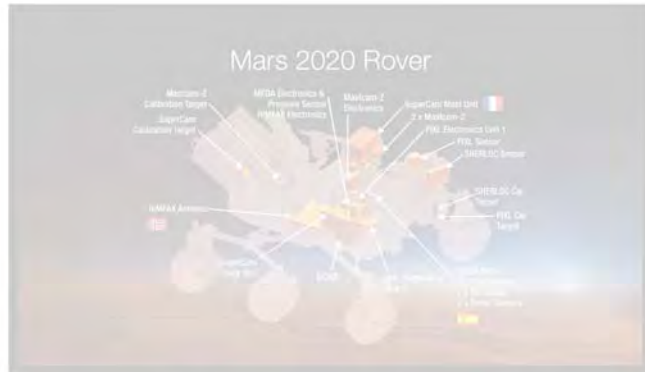


**Applications:
Industry and Government Projects**

Example Application Areas



Positioning Systems for Autonomous Mining Vehicles



Robust multimodal toolpoint positioning



How Automated Vehicles Will Interact With Road Infrastructure Now and in the Future



Robust hazard detection on construction and mining sites



Automating Analysis of Vegetation with Computer Vision: Cover Estimates and Classification



An Infinitely Scalable Learning and Recognition Network



Queensland Government



Automation-enabling positioning for underground mining



No drive in the park...

Clear images



Low light



Water



Dust

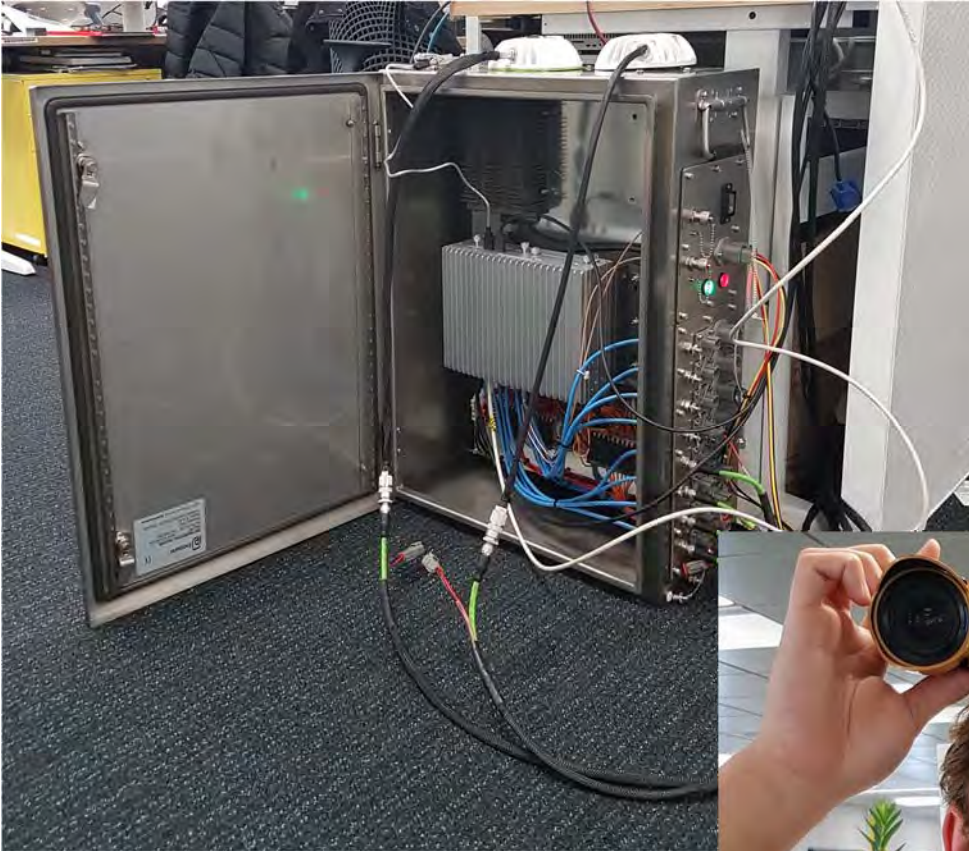


Glare



- Fan Zeng, Adam Jacobson, David Smith, Nigel Boswell, Thierry Peynot, Michael J Milford , "TIMTAM: Tunnel-Image Textually-Accorded Mosaic for Location Refinement of Underground Vehicles with a Single Camera", in *IEEE/RSJ International Conference on Intelligent Robots*, Macau, China 2019.
- Fan Zeng, Adam Jacobson, David Smith, Nigel Boswell, Thierry Peynot, Michael J Milford , "LookUP: Vision-Only Real-Time Precise Underground Localisation for Autonomous Mining Vehicles", in *IEEE International Conference on Robotics and Automation*, 2019.
- Adam Jacobson, Fan Zeng, David Smith, Nigel Boswell, Thierry Peynot, Michael J Milford , "Semi-Supervised SLAM: Leveraging Low-Cost Sensors on Underground Autonomous Vehicles for Position Tracking", in *IEEE/RSJ International Conference on Intelligent Robots*, Madrid, Spain 2018.

The Early Days...



“Octobox”



Cameras



Adam



SICK

NOT FOR PRODUCTION

192-16R

SICK

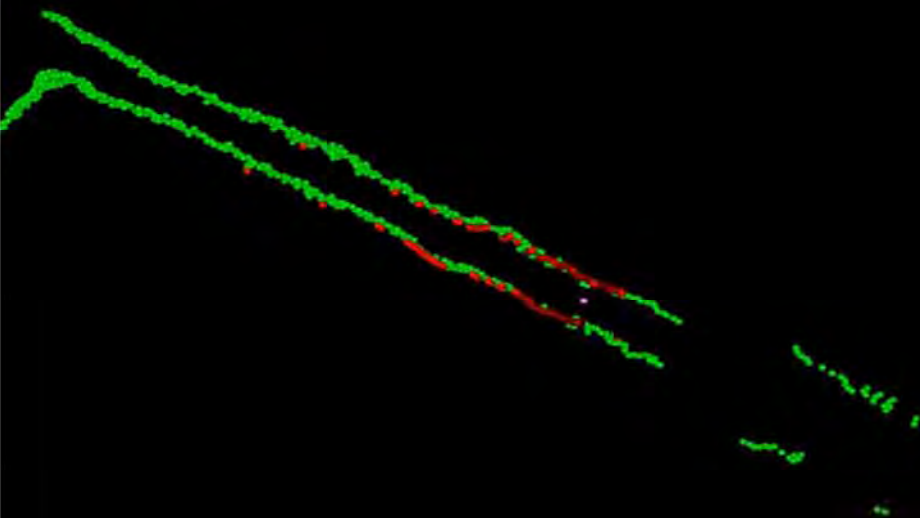
SICK

DV-2 #3

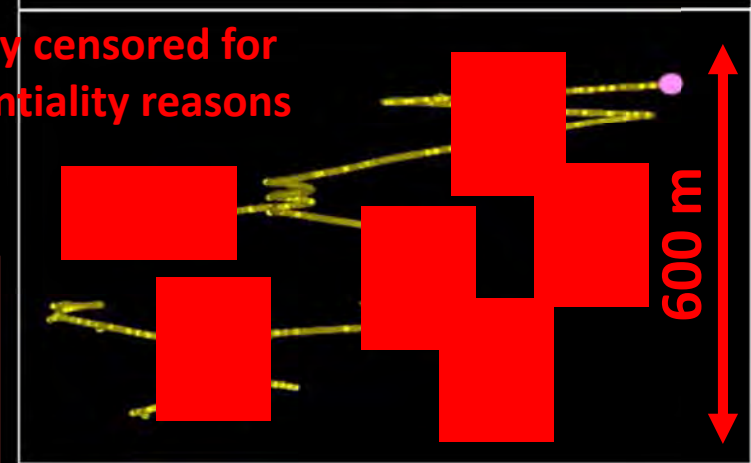






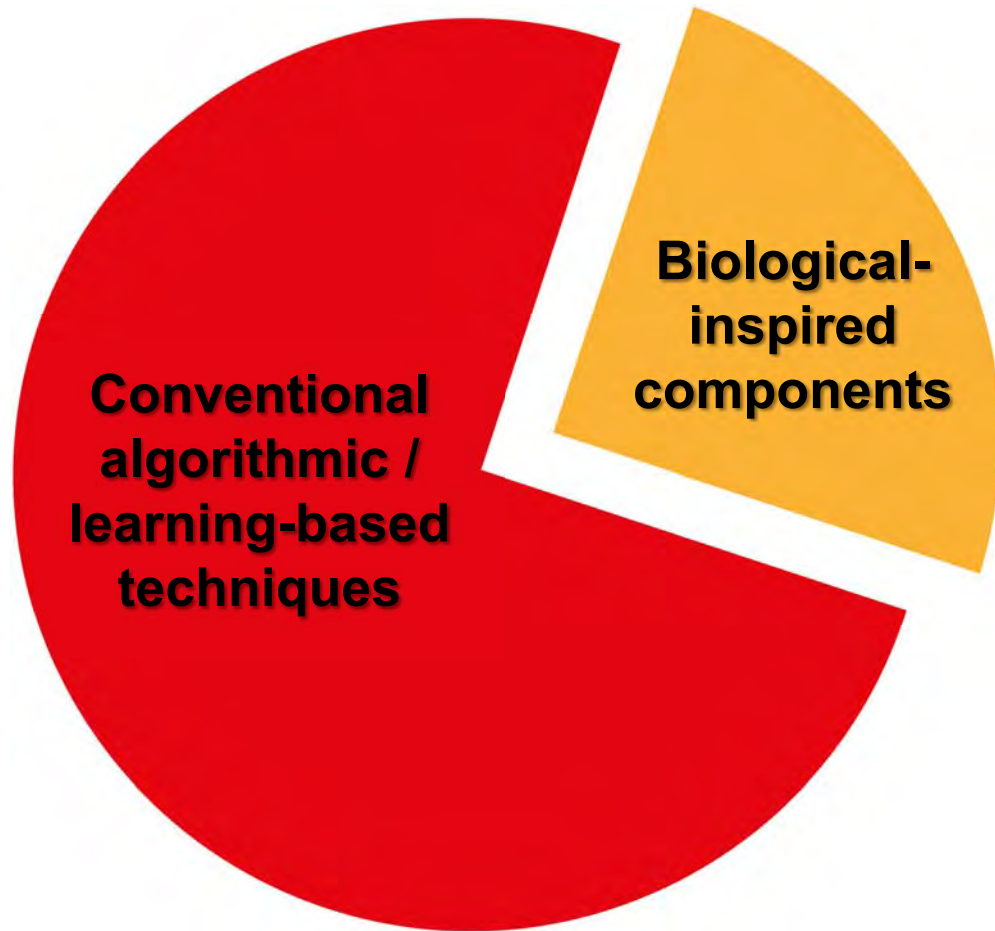


Partially censored for confidentiality reasons



- Fan Zeng, Adam Jacobson, David Smith, Nigel Boswell, Thierry Peynot, Michael J Milford , "TIMTAM: Tunnel-Image Textually-Accorded Mosaic for Location Refinement of Underground Vehicles with a Single Camera", in *IEEE/RSJ International Conference on Intelligent Robots*, Macau, China 2019.
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Going from biological inspiration to deployment



- Mixture of bio-inspired + conventional.
- Why?:
 - Sensor differences (both limited and opportunistic)
 - AI limitations
 - Embodiment differences
 - Different risk appetites
 - Provability

What Bio-inspiration Made it In

- Image processing techniques partially derived from bio-inspired research
- Short bespoke sequence-matching techniques
- Topological mapping techniques partially derived from bio-inspired research
- Image matching techniques derived from fundamental primate-inspired vision research several years ago



We are hiring!

Current and upcoming roles including PhDs, Postdocs,
Research Engineers, and Academic Roles

We work
here



E-mail: michael.milford@qut.edu.au

QUT

Collaboration Opportunities



Some groups we have published with or held joint grants with



- Access to unique or limited access datasets / sensors / compute
- Non-critical-path but important big picture research problems
- Co-authored publications
- Grants
- Consulting
- Part-time academic roles
- Student & researcher exchanges
- Intern programs
- Co-organization of workshops / conferences etc...



Thank you to our collaborators, and our funders, including:



Australian Government
Australian Research Council

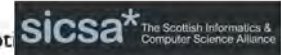


Microsoft
Research



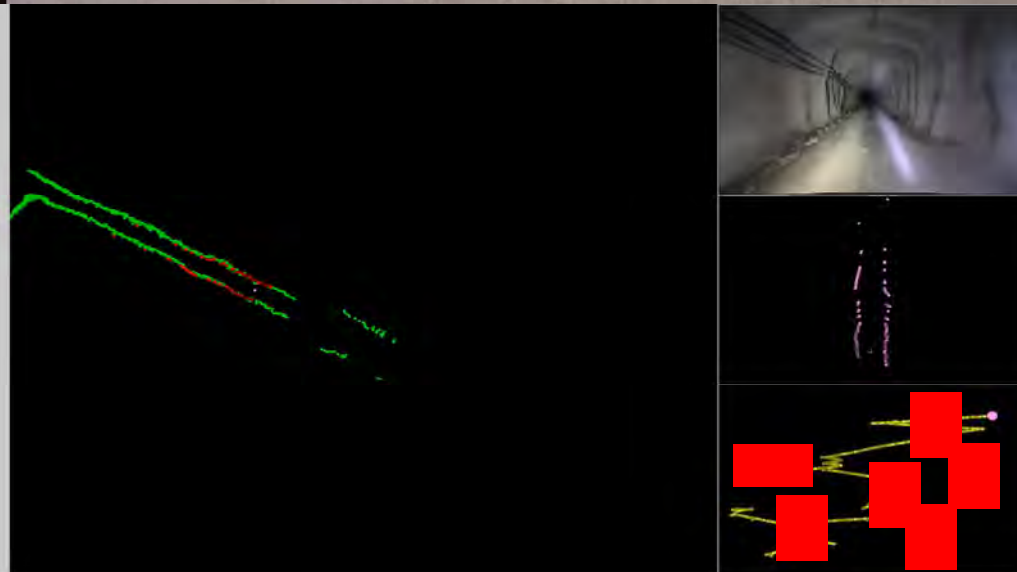
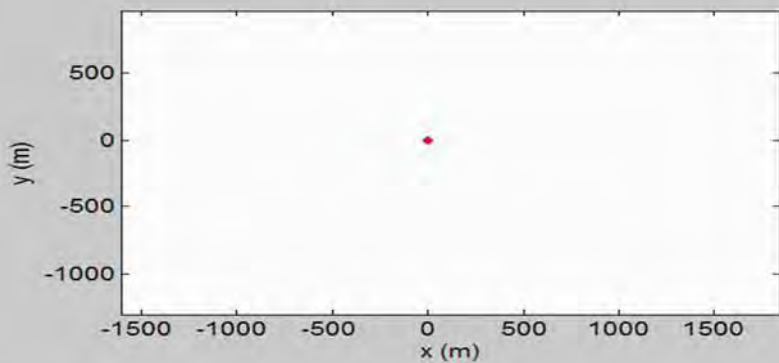
Queensland Government
Department of Transport and Main Roads

Queensland Government



Australian Government
Department of Defence
Science and Technology

Time: 1.0 s



Professor Michael Milford | Australian Research Council
Future Fellow | Microsoft Research Faculty Fellow | Chief
Investigator, Australian Centre for Robotic Vision
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 🐦 Twitter: @maththrills
 📺 YouTube https://www.youtube.com/milfordrobot
 🔗 http://www.tinyurl.com/milfordm
 🌐 Google https://goo.gl/rczslc