Combining Semantic Tagging and Support Vector Machines to Streamline the Analysis of Animal Accelerometry Data









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http://oztrack.org





Tracking cassowaries in Moresby

▶ Range National Park using GPS-based telemetry

▼ H	ome Range Calculator
Date	Range:
Fron	1:
To:	
Layer	Type:
01	Detections
01	[rajectory
01	Minimum Convex Polygon
OF	Peeled Convex Hull (95%)
OF	Peeled Convex Hull (50%)
0	Kernel UD (utilization distribution) 95%
0	Kernel UD (utilization distribution) 60%

Spatial Reference System:

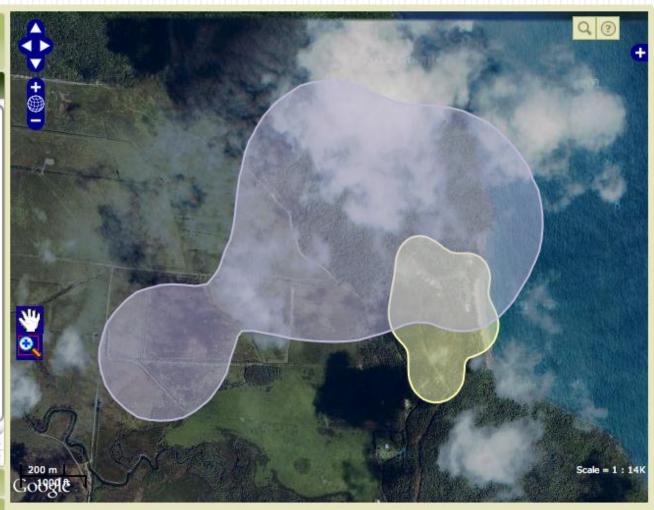
EPSG: 20355

EPSG: 20355

Ellipse Name: Australian Natl & S. Amer. 1969

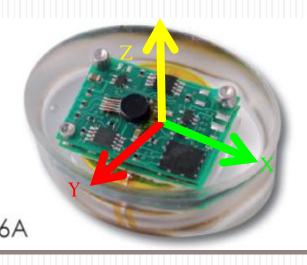
Calculate

- ▶ Help
- Project Menu





Combining Semar Machines to Stre Acc G6A



Vector nimal









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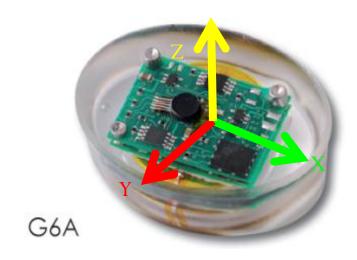


Overview

- Background
- Objectives
- Methodology
 - System Architecture
 - User Interface
 - Data Collection
 - Evaluation Result
- Conclusions & Future work

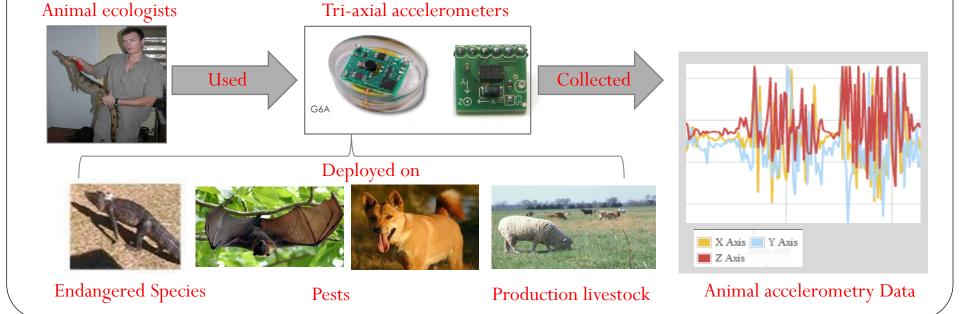
Data Collection-Device

- Devices parameters
 - A tri-axial accelerometer named G6A
 - Produced by CTL(Cefas Technology Limited)
 - 40mm*28mm*16.3mm
 - 16MB memory
 - 7.3g weight in air
 - Sampling rates
 - From 1Hz to 30Hz

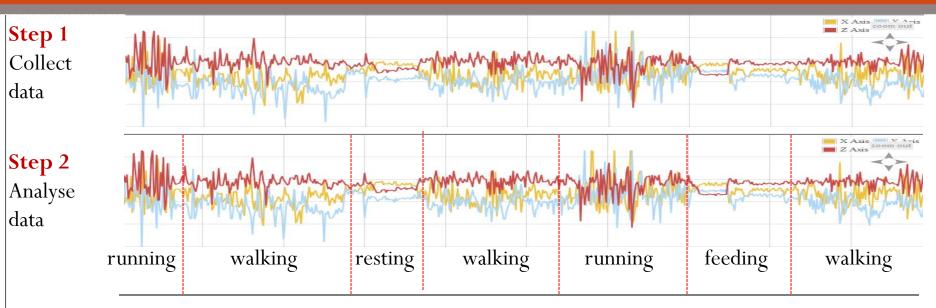


Background: accelerometer data

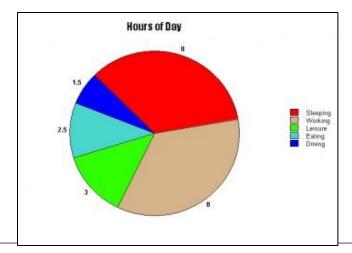
- Explosion in animal-attached accelerometers
 - To monitor animal movements and behaviour
- Collected an avalanche of raw tri-axial accelerometer data streams
 - Enable the identification of specific animals behaviours



Background: accelerometer data

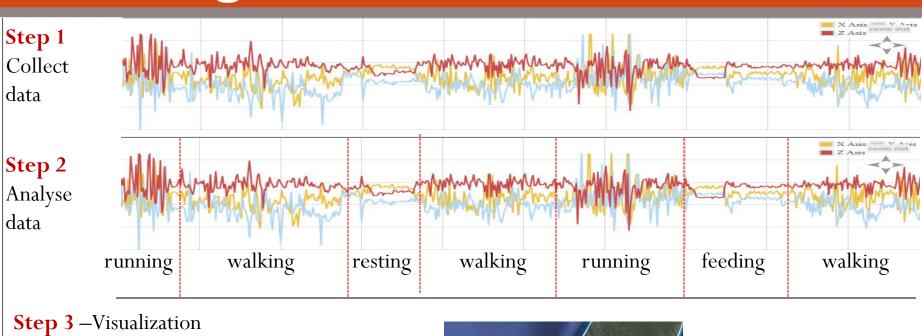


Step 3 – Visualization

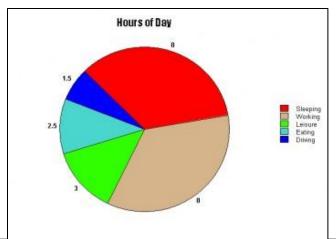


Understand animal health, energy consumption, food/water requirements

Background: accelerometer data









Understand animal health, energy consumption, food/water requirements

Background: challenges

- Limitations of raw 3D acceleromtery data streams
 - Numerical, unstructured, complex, imprecise, large volume
 - Poor data representation
- Problems
 - Massive volumes of complex data
 - Lack of automatic analysis
 - Lack of pattern recognition tools
 - Manual analysis
 - Onerous, time consuming, expensive
 - Poor quality, subjective
- Wild animal activities
 - Difficult to monitor and analyze

What is 87???

What is the measurement unit??							
	A	В	С	D	Е	F	G
1	07.06.07 19:00:00		87.001		14.06.07 13:		85.001
2	07.06.07 19:00:09		86.001	0	14.06.07 13:		85.001
♦ 3	07.06.07 19:00:18		87.001	•	14.06.07 13:		85.001
4	07.06.07 19:00:27		87.001		14.06.07 13:		85.001
5	07.06.07 19:00:36		89.001		14.06.07 13:		85.001
6	07.06.07 19:00:45		87.001		14.06.07 13:		83.001
7	07.06.07 19:00:54		87.001		14.06.07 13:		85.001
8	07.06.07 19:01:03		87.001		14.06.07 13:		85.001
9	07.06.07 19:01:12		87.001		14.06.07 13:		85.001
10	07.06.07 19:01:21		87.001		14.06.07 13:		83.001
11	07.06.07 19:01:30		87.001		14.06.07 13:		83.001

How to analyze???

How to improve???



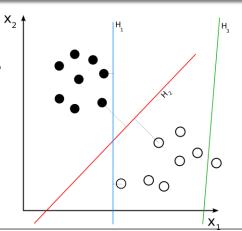
Possible solutions

- Semantic Tagging
 - attach meaningful descriptions
 - mark up events/activities
 - enrich data semantic meaning
 - collect expert domain knowledge

- Support Vector Machines
 - supervised machine learning models
 - support automatic classification

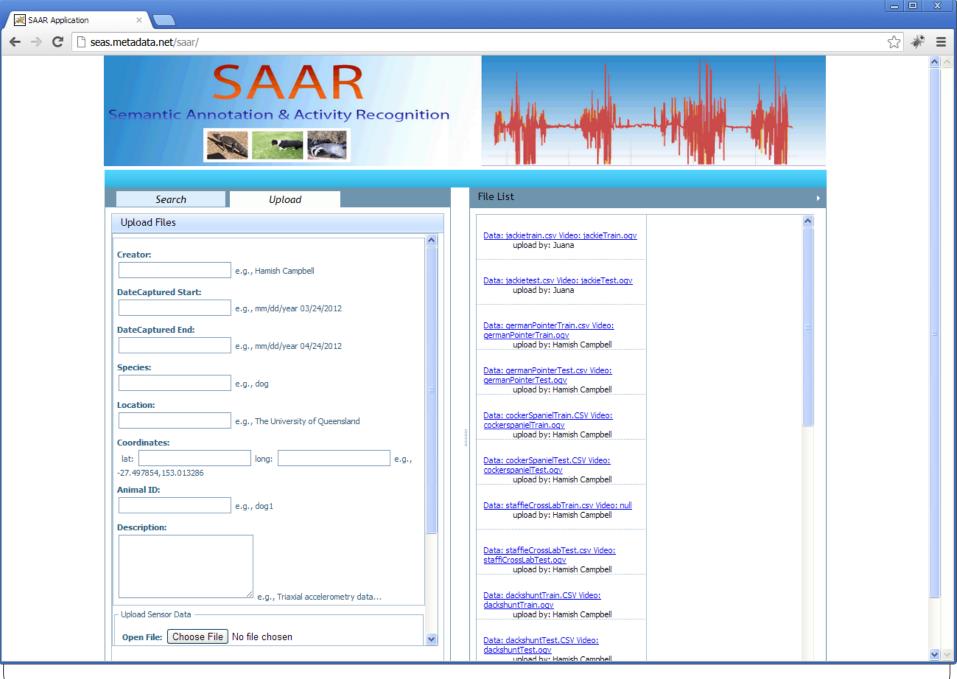
	A	В	С	D	Е	F	G
1	07.06.07 19:00:00		87.001		14.06.07 13:		85.001
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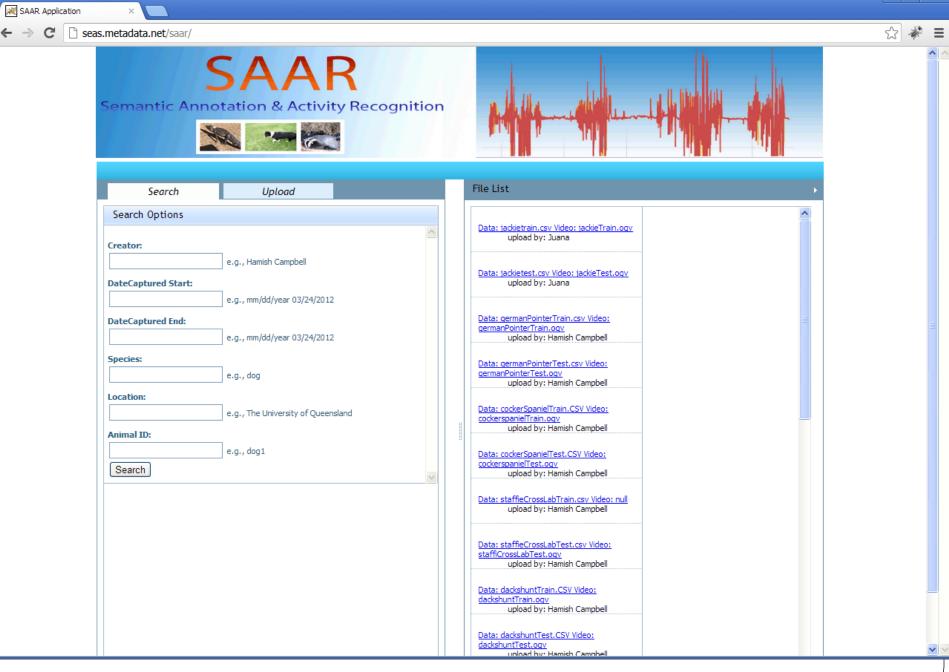


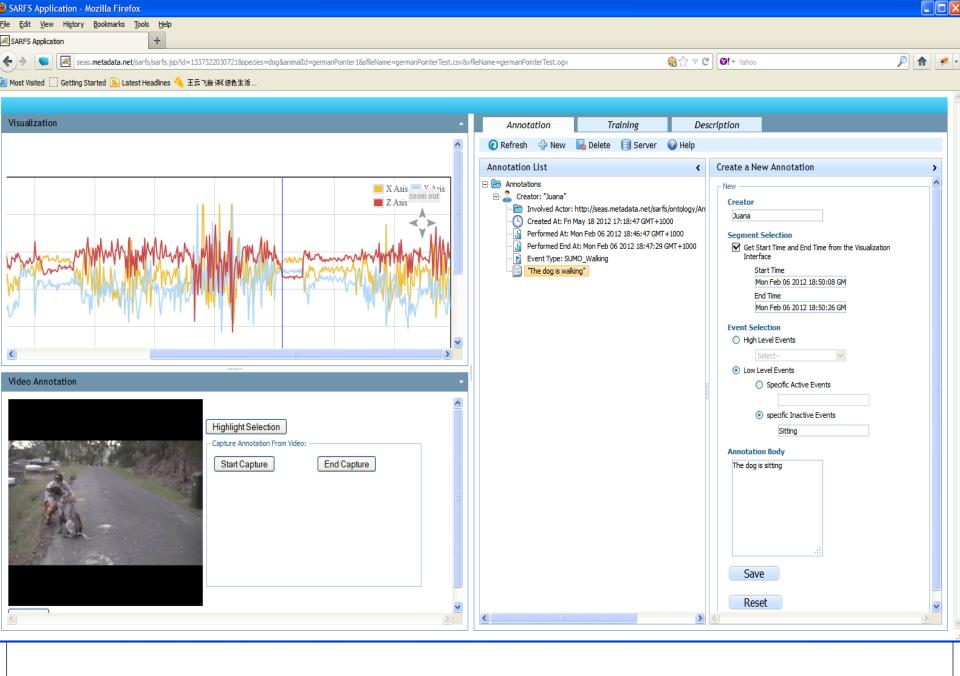
System objectives

- Web-based repository
 - To upload and share tri-axial accelerometer animal datasets
 - To search, retrieve and compare datasets
- Annotation services
 - Record, share and re-use expert knowledge on animal movements within tri-axial accelerometer data streams
 - Using terms from pre-defined ontologies
 - Analyze, tag and visualize 3D accelerometry datasets
 - Synchronized with video to compare with base truth
- Automated analysis services
 - Build activity recognition models by training classifiers using features extracted from preannotated training sets
 - To improve the quality of results generated by SVM-based activity recognition classifier
 - To enable the sharing, re-use and refinement of activity recognition classifiers developed for specific species, between scientists.
- Simple statistical visualisation of annotated data streams

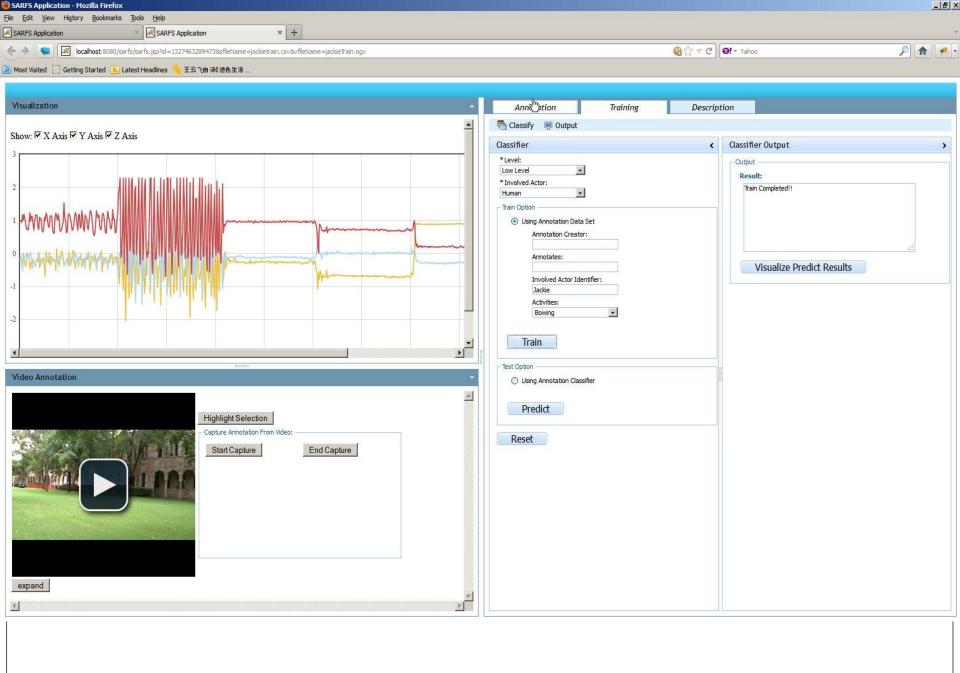


Screenshot of the SAAR upload user interface

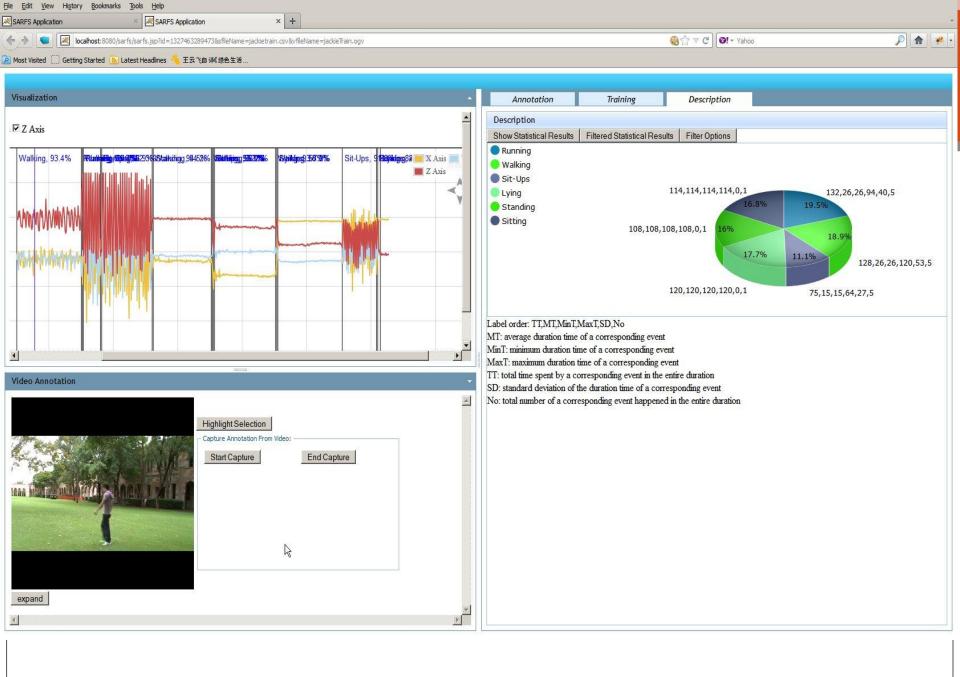




Screenshot of SAAR Plot-Video visualization interface and the annotation interface

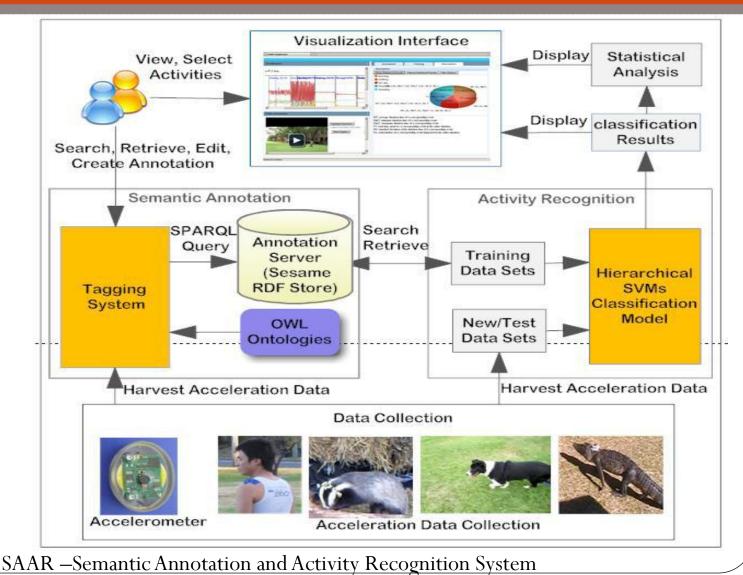


User interface when retrieving all the specific annotation to train a SVM activity classifier



Screenshot of the SAAR interface with human activity identification results

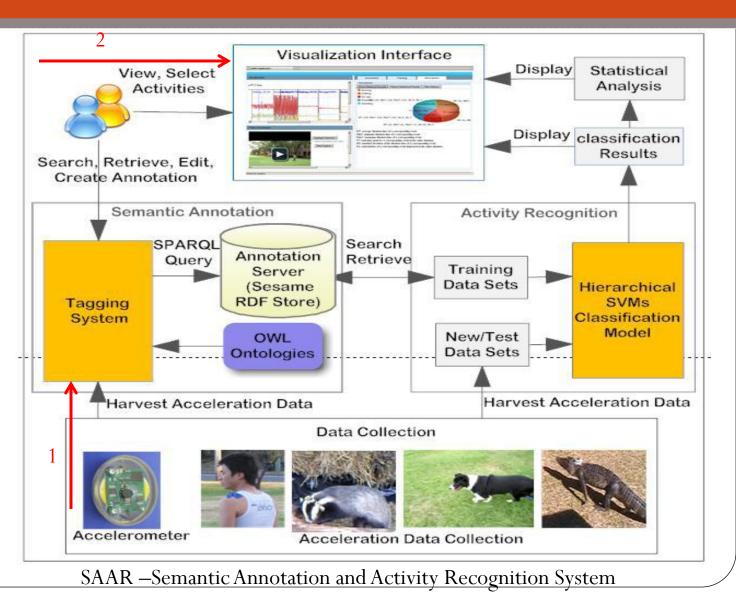
System Architecture



Visualisation

Step 2: display raw data and video in the visualization interface

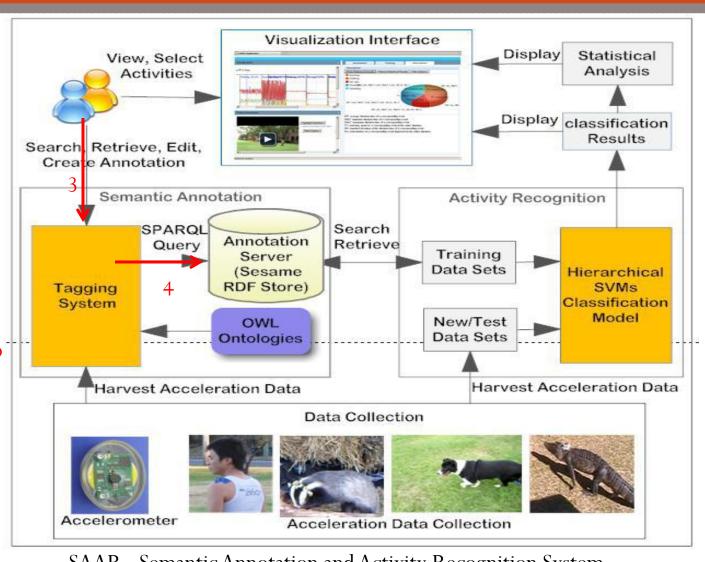
Step 1: upload raw data and videos



Annotation

Step 3: users create, search, retrieve, edit annotations

Step 4: created annotations marked up with ontologies, and then saved in the annotation server



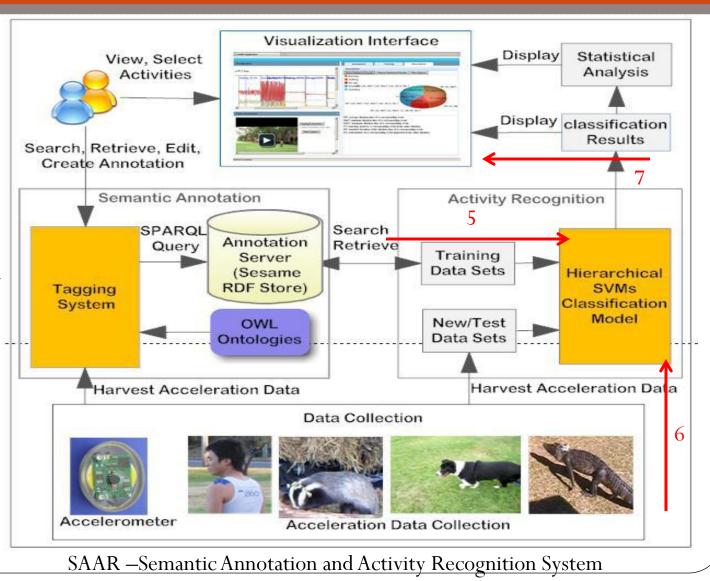
SAAR -Semantic Annotation and Activity Recognition System

Model training and use

Step 5:
search annotations
as training data
set to train SVMs
classification models

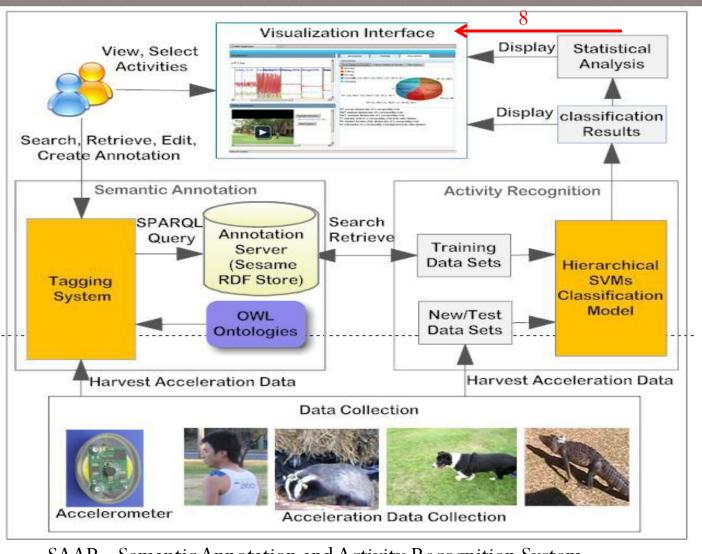
Step 6:
trained classifiers
take new acceleration
data as input to classify
animal activities

Step 7: classification results display in the visualization interface



Statistical summary

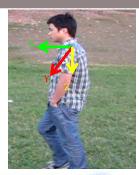
Step 8: statistical analysis takes classification results as input and displays the result in a pie chart



SAAR –Semantic Annotation and Activity Recognition System

Data Collection-Human

- Human data collection
 - Location : University of Queensland
 - 4 males & 4 females
 - Age ranges from 25 to 38
 - For each voluntary
 - 3 minutes walking
 - 3 minutes running
 - 1 minutes sit-ups
 - 3 minutes standing
 - 3 minutes sitting
 - 3 minutes lying
 - Randomly perform these 6 activities over 15 minutes

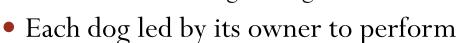






Data Collection-Dog

- Dog data collection
 - Location: Brisbane
 - 6 dogs of different breeds
 - Height and weight
 - 20cm-55cm, 8.9kg-25.8kg



- 2 minutes walking, running, standing,
- 2 minutes Sitting and lying
- Randomly perform these 5 activities for 10 minutes
- One well-trained king charles spaniel
 - 1 minutes foraging/digging
 - 1 minutes climbing







Evaluation-Metrics

- Standard evaluation metrics
 - Accuracy

Precision

Precision = number of true positives number of true positives positives

		Type as determined by a classifier			
		True	False		
Test outc	+ve	True positive	False positive		
ome	-ve	False negative	True negative		

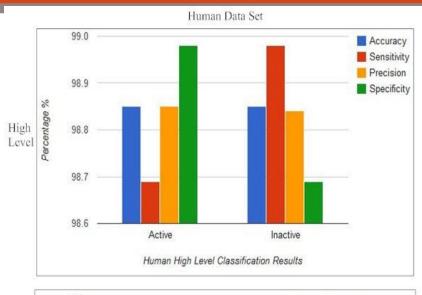
Sensitivity

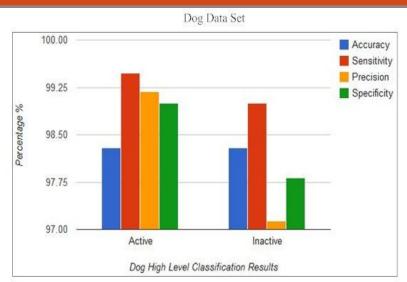
Sensitivity = number of true positives number of false negatives

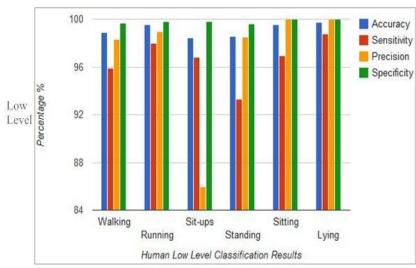
Specificity

Specificity = number of true negatives number of false negatives number of false negatives

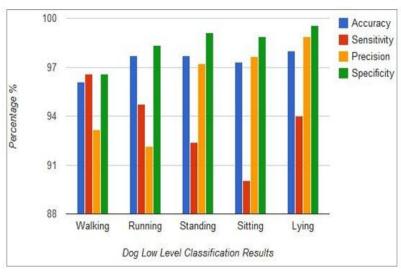
Evaluation-Result-1 Humans and Dogs







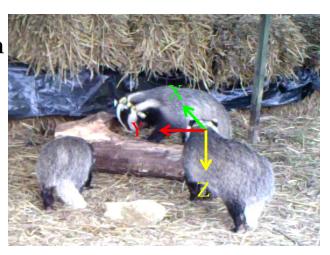
Humans

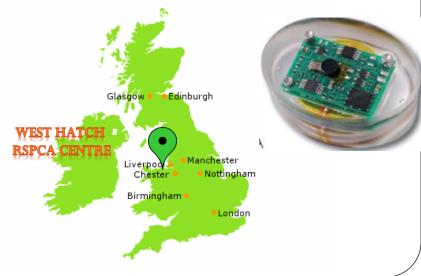


Dogs

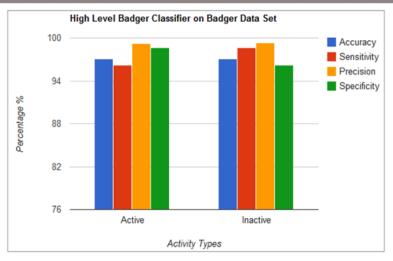
Data Collection-Eurasian Badger

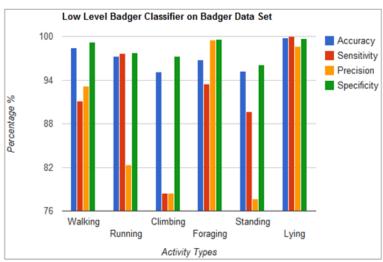
- Eurasian badger collection
 - Location: Somerset, United Kingdom
 - 3 Eurasian badgers
 - Six activities were recorded
 - Walking
 - Running
 - Climbing
 - Foraging
 - Standing
 - Lying



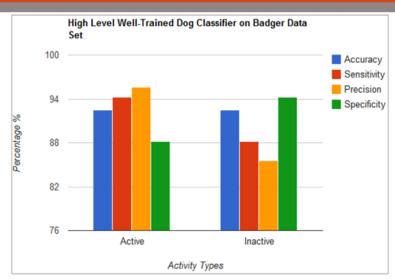


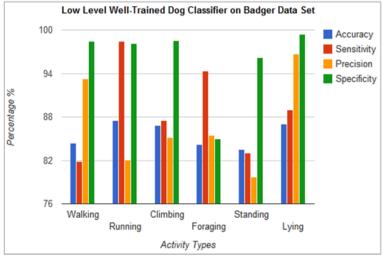
Evaluation-Result 2





Badger(3)





Badger data, dog model

Evaluation - Conclusions

- High level classifiers performs better than low level classifiers
 - High level: accuracy>96%, sensitivity>97%, specificity>96%
 - Low level: accuracy>96%, sensitivity>80%, precision>80%
- Human classifier performs better than dog classifier which performs better than badger classifier
 - More noise the "wilder" the animals
- Species-specific classification models perform better than migrating the classification models across species, but migration still yields reasonable results

Summary

- The Semantic Annotation and Activity Recognitions system delivers
 - An easy-to-use Web-based repository
 - For accelerometer data streams
 - A set of semantic tagging, visualization services
 - For annotation meaning of accelerometer data streams
 - Activity recognition services
 - Accuracy decreases for more "unpredictable" animals
 - Accuracy decreases across species
 - BUT still very useful

Future work

- Future work
 - Integrate GPS data to track animal trajectory + add map visualization
 - Acquire data from wild dingoes, captive tigers, wild birds
 - Apply captive models to wild animals
 - Dogs to foxes, dingoes
 - Birds to bats
 - Horses to camels
 - Evaluate different machine learning methods

Acknowledgement

- Owen R Bidder, from the Swansea Moving Animal Research Team (SMART) at Swansea University College of Science, for providing access to the badger accelerometer data, and for providing comprehensive and useful feed-back
- The China Scholarship Council









Questions?

- Thank you!
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 - ECO-Lab: http://www.uq.edu.au/eco-lab/
 - SAAR: http://seas.metadata.net/saar/

