Data Fusion for Inertial-Centric Indoor Localisation

Michal Kozlowski[1]; Dallan Byrne[1]; Raul Santos-Rodriguez[2]; Robert Piechocki[1]

[1]Department of Electrical and Electronic Engineering, University of Bristol
[2]Department of Engineering Mathematics, University of Bristol

University of BRISTOL

MOTIVATION

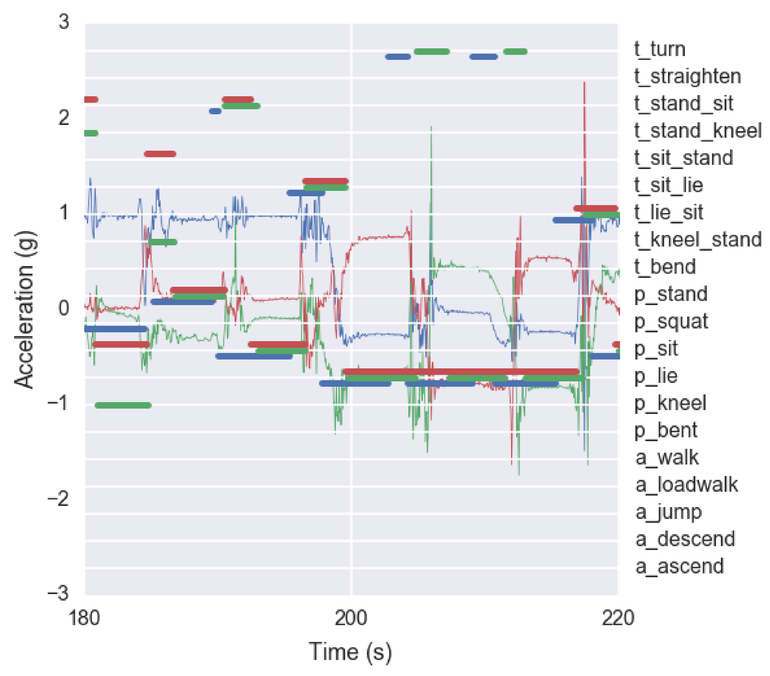
- The amalgamation of different passive sensors can be utilised in order to provide an accurate location[1]. However, it is only the basic human instincts, such as periodicity and routine, that make this possible. The fact that behaviours and tasks recur naturally is an important assumption.
- In order to localise an individual in a residential house with sparse sensor output, a method is devised, whereby the semantic information from an additional source is learned.
- Sparse sensor output in this context means that the relative ratio of the available sensors in a house, as well as cleanliness of the data they provide to the geographical complexity of the house is low.
- A number of graphical models are tested to see which performs best when classifying ambulation information, which can then be fed into a Bayesian Network for location inference.

DATA PROCESSING

The method in this paper is based on SPHERE challenge dataset[2]. The test-bed house was filled with Access Points (APs) which provide the RSS information. The users were asked to wear a SPHERE wrist wearable, which served as a RSS anchor as well as accelerometer sensor.

1. **Data Imputation** - The data was initially noisy and required a number of pre-processing algorithms to replace the missing data points. These were based on Gaussian Processes.

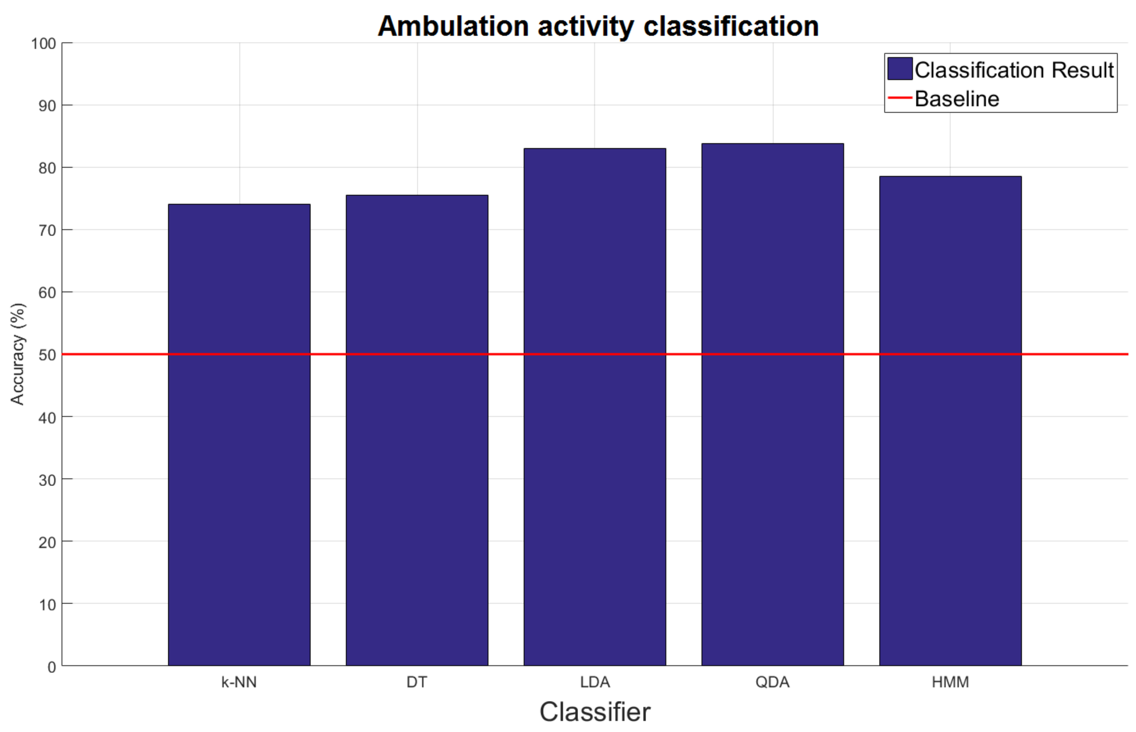
2. **Temporal Aggregation** - Then, the dataset was aggregated into time bins of different lengths to aid with feature extraction. Length of **6.4** seconds[3] was chosen, among others.



FEATURE EXTRACTION

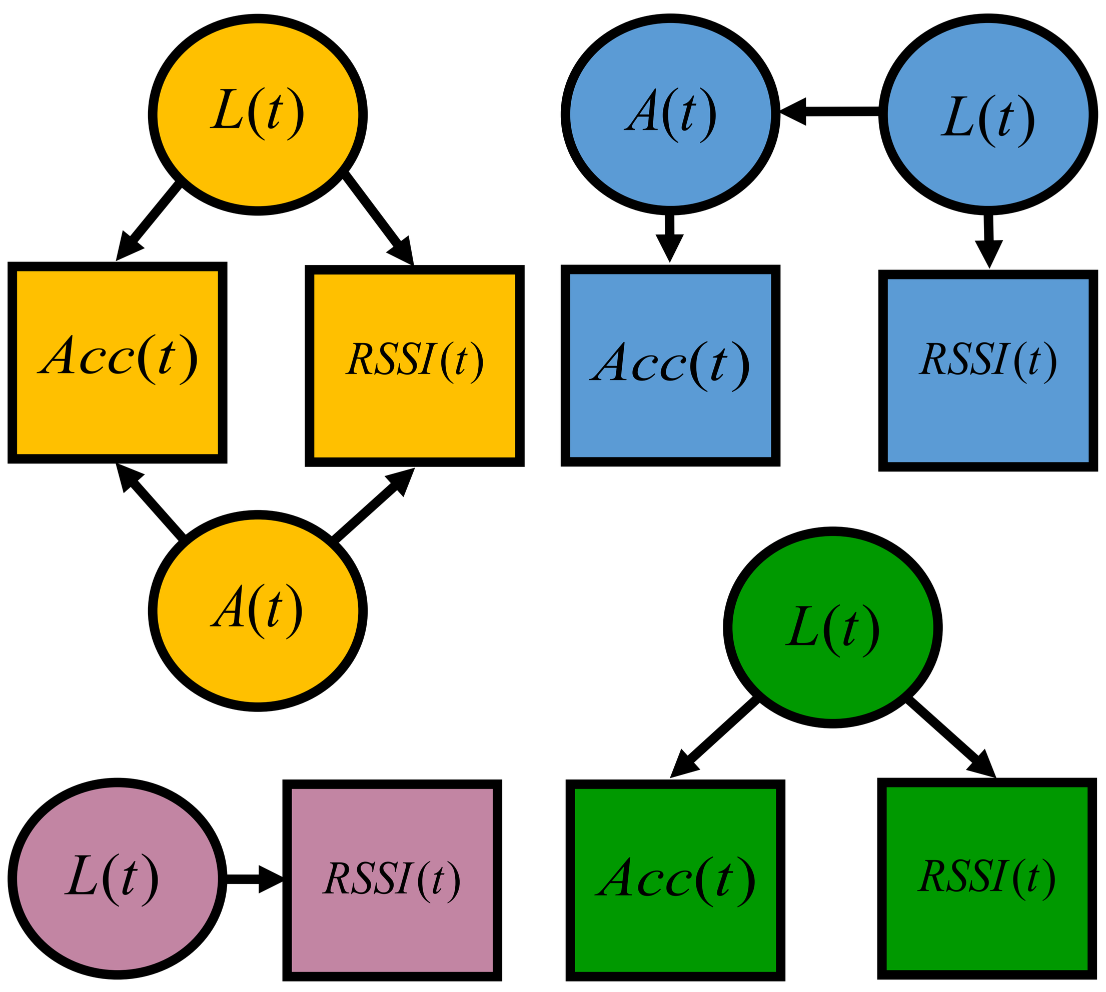
Feature sets optimised to recognising the ambulation were then extracted. This involved extracting numerous accelerometer features and establishing the best set based on ambulation recognition from multiple classifiers using mRMR. The optimal-features and the result from the classification are shown below:

Feature
1. Variance
2. Mean/Median/Mode
3. Sum
4. RMS
5. Standard Deviation
6. Range
7. Kurtosis
8. Skewness
9. Max/Min
10. Area
11. 25% Percentile



MODELS & METHODS

- A method based on Bayesian Networks was devised to test the assumptions.
- A number of different graphical models were tested to see which can outperform a baseline (shown here in purple)
- This is to establish which relationship between the accelerometer values, the activity, the location and the RSSI values is optimal.



RESULTS

- The best feature extraction period found was an 6.4s second non-overlapping rolling window, as per literature. The most dominant features were also the simplest - Variance, Mean/Median/Mode and Sum scoring the best.
- The models shown that the accuracy can be improved given an inertial sensor. The models were tested on two metrics, temporal accuracy and distance between classified locations. The different models, and their performance can be seen below:

	Model 1	Model 2	Model 3	Model 4
Accuracy (%)	78.4%	78.54%	60.88%	62.18%
Distance error (m)	0.8m	0.96m	1.64m	1.61m

CONCLUSION

- The study proved that by the use of semantic information, inferring the location of an individual in their own home could be improved. An accelerometer output was associated with an activity and a location, subject to a variety
- There still are a number of avenues to pursue in this area. In the future, the work will include expanding this algorithm to associate other sensors present in the node network in the house, and perhaps even including the geographical topology of the house to aid the accuracy of the localisation.

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