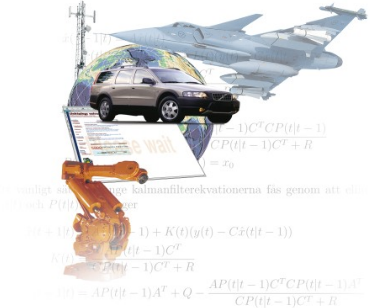
Learning to Detect Loop Closure from Range Data



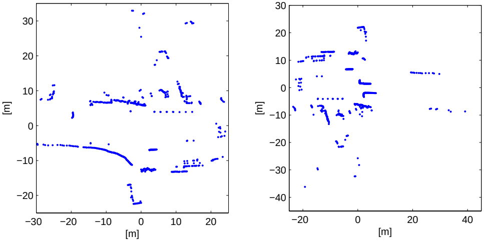
Karl Granström*, Jonas Callmer*, Fabio Ramos†, Juan Nieto†

*Division of Automatic Control
Linköping University, Sweden
†Australian Centre for Field Robotics
University of Sydney, Australia

Motivation

Loop closure detection is an important and difficult problem:

- Loop closure central in SLAM.
- Range sensors are common.
- Difficult in dynamic environments due to occlusion, different view points, etc.

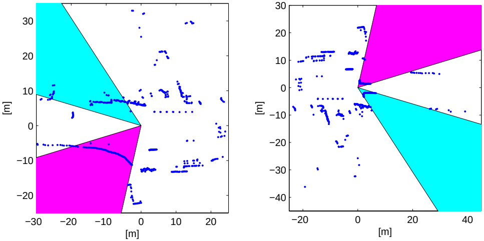


Same location?

Motivation

Loop closure detection is an important and difficult problem:

- Loop closure central in SLAM.
- Range sensors are common.
- Difficult in dynamic environments due to occlusion, different view points, etc.



Same location? **Yes!**

We need a method that is robust against misclassification and invariant to rotation.

- SICK 2D lasers used to collect suburban data.
- Geometric features are extracted from laser range scans.
- Weak classifiers based on absolute difference of features.
- Strong classifier learned from weak classifiers using AdaBoost.

Our Approach

- SICK 2D lasers used to collect suburban data.
- Geometric features are extracted from laser range scans.
- Weak classifiers based on absolute difference of features.
- Strong classifier learned from weak classifiers using AdaBoost.

A machine learning approach for the loop closure detection problem using range sensors.

- Raw laser sensor data instead of classic landmarks. Main advantage is the general representation of the environment.

Relation to Related Work

- Raw laser sensor data instead of classic landmarks. Main advantage is the general representation of the environment.
- Using submaps of consecutive laser scans, loop closure detected **51%** detection rate at **1%** false alarm rate [Bosse, 2008].

englogo

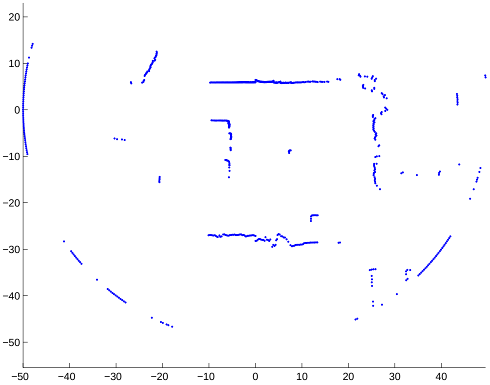
- Raw laser sensor data instead of classic landmarks. Main advantage is the general representation of the environment.
- Using submaps of consecutive laser scans, loop closure detected **51%** detection rate at **1%** false alarm rate [Bosse, 2008].
- Laser features and AdaBoost used to detect humans in office environment. Detection rates of over **90%** [Arras, 2007]. Place recognition performed indoors [Mozos, 2005].

Relation to Related Work

- Raw laser sensor data instead of classic landmarks. Main advantage is the general representation of the environment.
- Using submaps of consecutive laser scans, loop closure detected **51%** detection rate at **1%** false alarm rate [Bosse, 2008].
- Laser features and AdaBoost used to detect humans in office environment. Detection rates of over **90%** [Arras, 2007]. Place recognition performed indoors [Mozos, 2005].

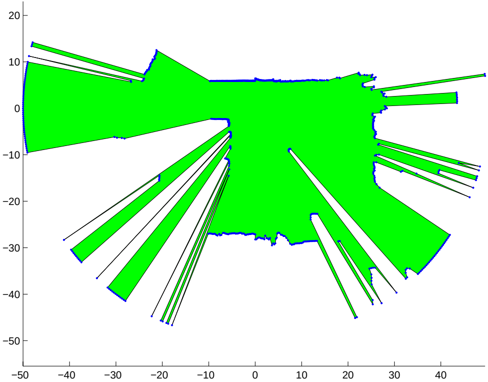
Our results: **85%** detection rate at **1%** false alarm rate.

We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:



We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

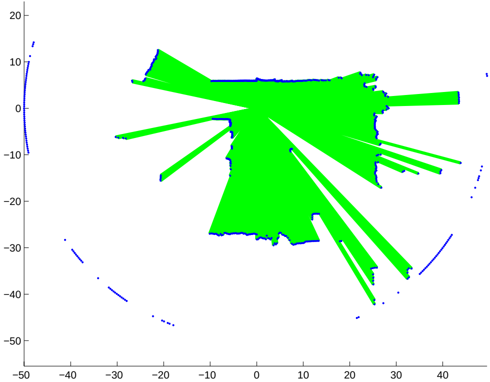
- Area



Features

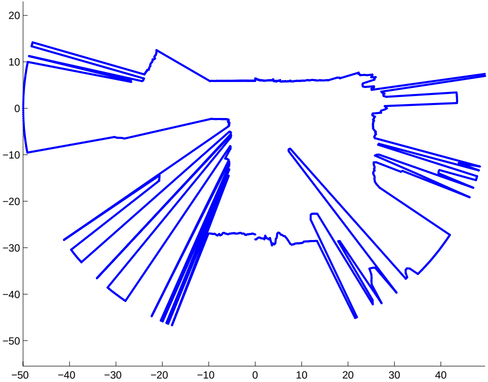
We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

- Area



We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

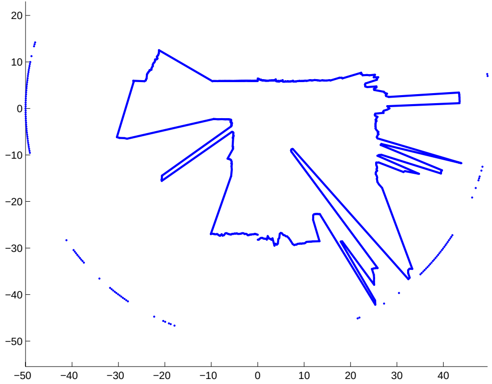
- Area
- Distance



englogo

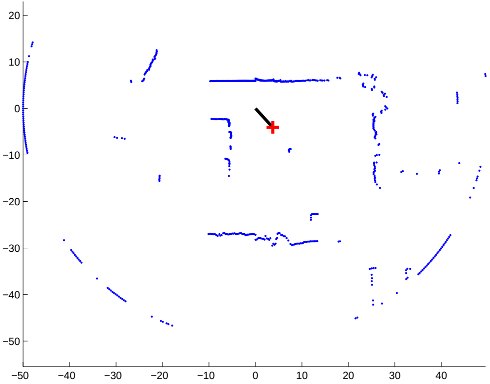
We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

- Area
- Distance



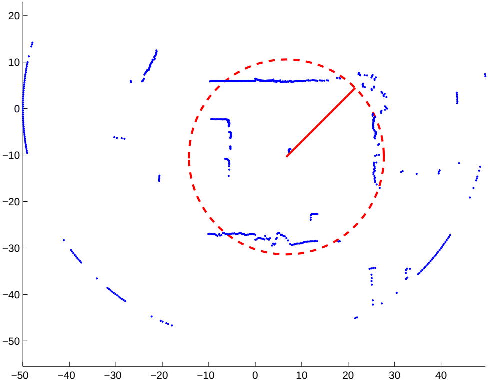
We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

- Area
- Distance
- Centroid



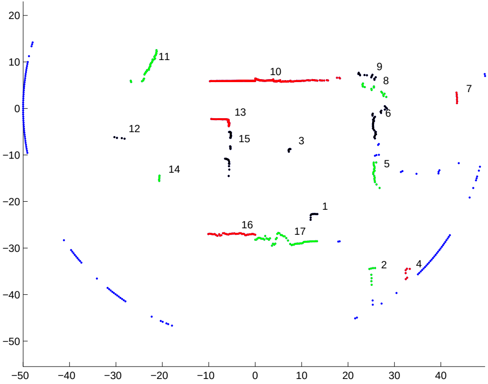
We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

- Area
- Distance
- Centroid
- Circularity



We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

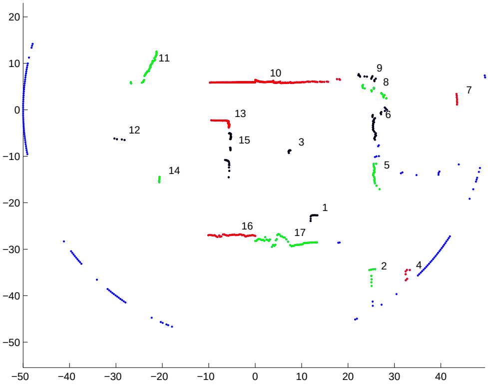
- Area
- Distance
- Centroid
- Circularity
- Group



We use 20 features, $f_1(\mathbf{L}^i), \ldots, f_{20}(\mathbf{L}^i)$, that describe different geometric properties of a range scan $\mathbf{L}^i$, e.g:

- Area
- Distance
- Centroid
- Circularity
- Group

Invariant to rotation.



Given two scans indexed m and n, we take the absolute difference

$$\mathbf{f}_i(\mathbf{L}^m, \mathbf{L}^n) = \|f_i(\mathbf{L}^m) - f_i(\mathbf{L}^n)\| .$$

The set of extracted features $\mathbf{F}$ is

$$\mathbf{F}(\mathbf{L}^m, \mathbf{L}^n) = \left[\mathbf{f}_1(\mathbf{L}^m, \mathbf{L}^n), \ldots, \mathbf{f}_{20}(\mathbf{L}^m, \mathbf{L}^n)\right] .$$

Thus, in the case of using two SICK lasers with 361 returns each:

The data dimension is reduced from 722 laser poins to just 20 features.

We use weak classifiers that are defined as:

$$c(\mathbf{F}(\mathbf{L}^m, \mathbf{L}^n), \theta) = \begin{cases} 1 & \text{if } p\mathbf{f}_i < p\lambda \\ 0 & \text{otherwise} \end{cases}$$

with parameters $\theta = \{i, p, \lambda\}$.

- i is index to the particular feature selected.
- λ is a threshold.
- p is polarity ($p = \pm 1$).

Strong Classifier

AdaBoost used to learn a strong classifier from the weak classifiers.

- Learning phase is an iterative procedure:
  - Train for T iterations.
  - Find weak classifier that best improves performance.
  - Higher weight to misclassified data pairs.
- **+** Low sensitivity to overfitting.
- **–** Sensitive to noisy data and outliers.

Strong Classifier

AdaBoost used to learn a strong classifier from the weak classifiers.

- Learning phase is an iterative procedure:
  - Train for T iterations.
  - Find weak classifier that best improves performance.
  - Higher weight to misclassified data pairs.
- **+** Low sensitivity to overfitting.
- **–** Sensitive to noisy data and outliers.
- **Input:** N pre-labeled range data pairs.
- **Output:** nonlinear strong classifier $\mathbf{c}\left(\mathbf{F}(\mathbf{L}_m, \mathbf{L}_n)\right)$.

We use $\mathbf{c}\left(\mathbf{F}(\mathbf{L}_m, \mathbf{L}_n)\right)$ to detect loop closure in SLAM.

We used data from four outdoor urban/suburban data sets:

- Three data sets were used to find laser range pairs for training.
  - Two from the University of Sydney area.
  - Third from Kenmore, QLD. Publicly available on `radish.sourceforge.net`.

Data used for training and experiments

We used data from four outdoor urban/suburban data sets:

- Three data sets were used to find laser range pairs for training.
  - Two from the University of Sydney area.
  - Third from Kenmore, QLD. Publicly available on `radish.sourceforge.net`.
- 800 range data pairs, 400 matching and 400 non-matching.

Data used for training and experiments

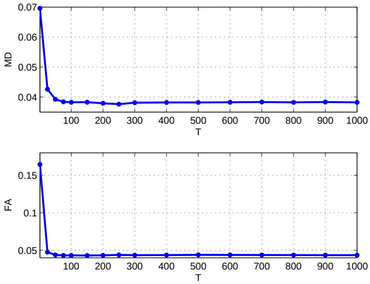
We used data from four outdoor urban/suburban data sets:

- Three data sets were used to find laser range pairs for training.
  - Two from the University of Sydney area.
  - Third from Kenmore, QLD. Publicly available on `radish.sourceforge.net`.
- 800 range data pairs, 400 matching and 400 non-matching.
- Fourth data set used for SLAM experiment. Also from University of Sydney area.

Overfitting Tests

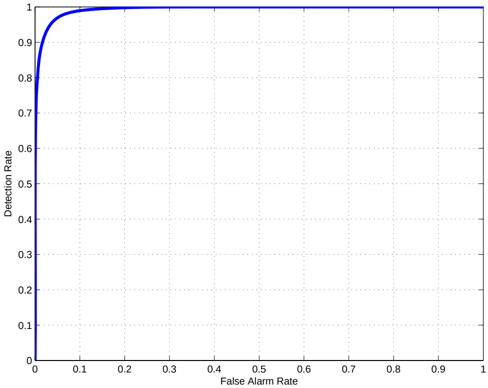
We trained strong classifiers using the 800 range data pairs for different values of T ranging from 1 to 1000.

- Strong classifier evaluated with 10-fold cross validation.
- Error rates approx. constant after 50 rounds, $T = 50$ used experiments.
- Overfitting not a concern.



Using the same 800 data pairs, Receiver Operating Characterisic evaluated with 10-fold cross validation.

- 85% detection rate at 1% false alarm rate.
- Area under curve approximately 0.99.

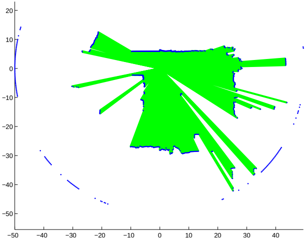


Best features for Loop Closing

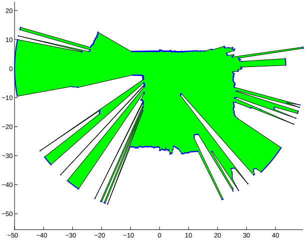
- Best feature selected in each training iteration $\Rightarrow$ most significant features chosen first.
- Strong classifiers trained while removing features one at a time $\Rightarrow$ affects FA and MD rates.

Best features for Loop Closing

- Best feature selected in each training iteration $\Rightarrow$ most significant features chosen first.
- Strong classifiers trained while removing features one at a time $\Rightarrow$ affects FA and MD rates.
- Two most significant features



1. Close Area



2. Area

The strong classifier was tested in an outdoor SLAM experiment.

- SICK laser range sensor.
- GPS

- Exactly Sparse Delayed-state Filter $\Rightarrow$ trajectory based state vector containing a history of robot poses.

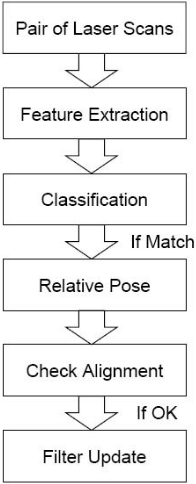
- Exactly Sparse Delayed-state Filter $\Rightarrow$ trajectory based state vector containing a history of robot poses.
- Each pose in the state vector is associated to a laser scan $\Rightarrow$ the map is represented by the state vector and laser scans.

SLAM experiment - estimation

- Exactly Sparse Delayed-state Filter ⇒ trajectory based state vector containing a history of robot poses.
- Each pose in the state vector is associated to a laser scan ⇒ the map is represented by the state vector and laser scans.
- ICP/CRF-match used for estimation of relative pose.

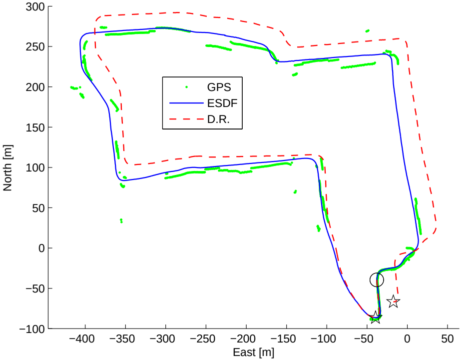
englogo

- Exactly Sparse Delayed-state Filter $\Rightarrow$ trajectory based state vector containing a history of robot poses.
- Each pose in the state vector is associated to a laser scan $\Rightarrow$ the map is represented by the state vector and laser scans.
- ICP/CRF-match used for estimation of relative pose.



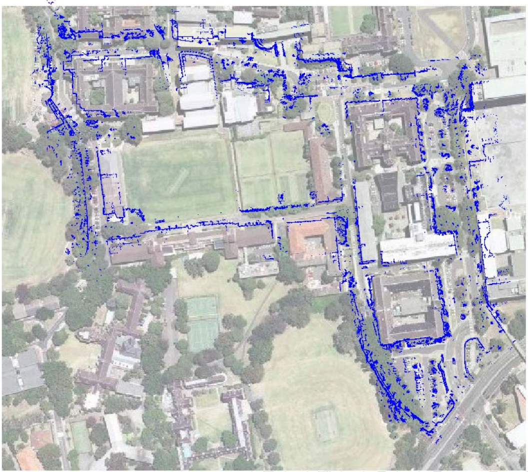
Results

- 1800 robot poses.
- 85759 pairs tested.
- 100% D-rate, 0.05% FA-rate.
- All FA rejected during scan alignment.



Results

- 1800 robot poses.
- 85759 pairs tested.
- 100% D-rate, 0.05% FA-rate.
- All FA rejected during scan alignment.



Conclusions

A machine learning approach for the loop closure detection problem using range sensors.

- 20 rotation invariant features combined with AdaBoost.
- Loop closure can be detected from arbitrary direction.
- High detection 85% for low false alarm 1%.
- SLAM experiment shows the method works in a real problem.

Thank you for listening!

Any questions?