Learning to Detect Loop Closure from Range Data

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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?
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Same location? **Yes!**

We need a method that is robust against misclassification and invariant to rotation.
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.
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A machine learning approach for the loop closure detection problem using range sensors.
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Our results: 85% detection rate at 1% false alarm rate.
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Features

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- Circularity
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Invariant to rotation.
Given two scans indexed $m$ and $n$, we take the absolute difference

$$f_i(L^m, L^n) = \|f_i(L^m) - f_i(L^n)\|.$$ 

The set of extracted features $F$ is

$$F(L^m, L^n) = [f_1(L^m, L^n), \ldots, f_{20}(L^m, L^n)].$$

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

The data dimension is reduced from 722 laser points to just 20 features.
We use weak classifiers that are defined as:

\[ c(F(L^m, L^n), \theta) = \begin{cases} 
1 & \text{if } p f_i < p \lambda \\
0 & \text{otherwise} 
\end{cases} \]

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

- \( i \) is index to the particular feature selected.
- \( \lambda \) is a threshold.
- \( p \) is polarity (\( p = \pm 1 \)).
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.
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- **Input:** $N$ pre-labeled range data pairs.
- **Output:** nonlinear strong classifier $c(F(L_m, L_n))$.

We use $c(F(L_m, L_n))$ to detect loop closure in SLAM.

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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.
- Fourth data set used for SLAM experiment. Also from University of Sydney area.
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- 800 range data pairs, 400 matching and 400 non-matching.
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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 Characteristic 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 ⇒ most significant features chosen first.
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- Two most significant features

1. Close Area

2. Area

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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.
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Results

- 1800 robot poses.
- 85759 pairs tested.
- 100% D-rate, 0.05% FA-rate.
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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?