New Conditional Sampling Strategies for Speeded-Up RANSAC
Tom Botterill, Steven Mills, Richard Green

RANSAC—popular algorithm for fitting a model to outlier-contaminated data points
Hypothesise: Randomly choose a small set of data points and fit a model to them
Test: Count data points compatible with this model
Repeat until a large set of compatible data points are found. If the model is correct these are inliers

Problem
Doesn't work with high outlier rates—finding an inlier set is too unlikely

Solutions

1: Use information from previous hypothesis sets failing
(they were probably contaminated by outliers)

2: Estimate inlier probabilities
RANSAC sampling assumes all data points equally likely to be inliers, however in many situations the prior probability of a data point being an inlier can be estimated. This can then be used to guide hypothesis set selection.

Existing Solutions
Guided-MLESAC sampling (Tordoff and Murray, 2005) chooses data points with relative likelihood proportional to their prior inlier probability.
✔ Always better than RANSAC
✗ Works poorly with large numbers of unlikely data points

PROSAC sampling (Chum and Matas, 2005) sorts data points by prior probability, then chooses hypothesis sets in approximate order of prior likelihood
✔ Works very well when a small number of data points have high inlier probability
✗ Works poorly in many circumstances (equally likely data points or when few data points have high inlier probability), because independence assumed

Proposed solution: At each time choose most likely hypothesis set based on prior probabilities, conditional on the history of failed hypothesis sets.

...but closed-form solution intractable. 2 approaches to approximate solution:

1: SimSAC
Estimate most likely hypothesis set by simulation. Full simulation computationally intractable so make independence assumption between posterior inlier probabilities.
✔ Outperforms other methods at choosing hypothesis sets
✗ Too costly in many circumstances

2: BaySAC
Assume all inlier probabilities independent and use Naive Bayes update.
✔ Negligible cost and works surprisingly well despite assumptions.

Results: SimSAC and BaySAC outperform previous sampling strategies, performs well even with unreliable prior probability estimates.

BaySAC → Robust Single Camera SLAM

BaySAC + Essential matrix estimation
Unreliable Bag-of-Words matches
Fast wide-baseline feature matching for single camera SLAM

+ easily modified to work with N—M correspondences