Adapting Polynomial Mahalanobis Distance for Self-supervised Learning in an Outdoor Environment

Miloslav Richter, Petr Petyovsky and Ondrej Miksik

Laboratory of Telepresence and Robotics & Computer Vision Group, Faculty of Electrical Engineering and Communication, Brno University of Technology, Brno, Czech Republic

Introduction

- Autonomous robot navigation is one of the most extensively studied problem in the field of mobile robotics
  - The goal is to detect the drivable surface ahead of the robot
  - Common sensors provide information about obstacles in a near field, however long-range sensing is needed for high speed vehicles
  - A combination of short range sensors with a camera is commonly used to overcome such limitations
- Generally, state-of-the-art approaches use color based segmentation of road/non-road regions in particular
  - The question is, how the belonging to a model is measured
  - Many algorithms employ Mahalanobis distance, however it is assumed, that the data points have a normal distribution.
- Recently proposed Polynomial Mahalanobis Distance (Grudic & Mulligen, RSS 2006) represents more discriminative metric

Polynomial Mahalanobis Distance

- Grudic and Mulligen proposed framework for efficient computation of a PMD by iterative forward mapping from lower to higher order polynomial terms:
  \[ d_{PM}(z_i, z_j) = d_{M_1}(z_i, z_j) + \sum_{l=1}^{L} d_{M_l}(g_l, g'_l). \] (1)
  where \( L > 1 \) defines \( q = 2^l \)-order PMD and \( g_l, g'_l \) are projected polynomial terms into level \( l \)
- Neither Euclidean, nor standard Mahalanobis distance respect highly non-linear character of sample points. The superior results are obtained with PMD, because it maps its feature points into higher order polynomial terms
- The problem is, that PMD expects, that the sample points could be approximated by a higher order polynomial term – even with only a small number of similar points, PMD degenerates and does not follow the sample points precisely

Three Stage Algorithm

- Continues re-learning of models stored in the pool
  - Each model is represented by a codebook, which consists from parts:
    1. The first one represents "strong model" (memory) – cf Fig. 6, blue part
    2. "Temporary model", cache, is used for weak hypothesis (orange part)
  - Both parts consist of codewords represented by their mean value, min/max brightness, mass and time of last update
    1. Preprocessing (k-means clustering)
      - To split the training samples into different parts to create multiple models in the pool
      - Reduces computational complexity and deals with outliers
    2. Update
      - Iteratively updates all road models (codebooks) in the pool, which overlap clusters from the preprocessing stage, otherwise the new codebook is created
    3. Measurement
      - Scores the pixels outside of the training area if they belong to the road/non-road region

Results

- TSA successfully deals with picking of suitable training samples and provides self-supervised learning algorithm for long-term road representation
- TSA is not sensitive to a regularization constant \( \sigma^2 \) and a level \( L \) of the PMD
  - “Strong” and “Weak” parts of models represent “road history” and sudden changes of road appearance
  - Proposed algorithm is robust to outliers

Conclusions

Figure 1: Output of our system

Figure 2: Synthetic sample points distribution (the brighter the background is, the closer to the reference point denoted by the blue rectangle). Distance metrics from left: Euclidean, Mahalanobis, Second, Fourth and Eighth Order PMD

Figure 3: Various sizes of a training area - stability strongly decreases with larger training area (images from left, to right: purple, blue, green, red)

Figure 4: Various orders of PMD with \( L \in \{4, 8\} \), \( \sigma^2 = 10^{-5} \)

Figure 5: Influence of various \( \sigma^2 \); \( L = 4 \), \( \sigma^2 = \{10^{-4}, 10^{-5}, 10^{-6}\} \)

Figure 6: A Three Stage Algorithm overview.

Figure 7: Proposed algorithm – various road surfaces and light conditions.

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ondra.miksik@gmail.com http://www.miksik.co.uk