Lost! Leveraging the Crowd for Probabilistic Visual Self-Localization

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Introduction

• Localization is a critical part of autonomous systems
• GPS has limited availability can be blocked or degraded
• Plan navigation techniques rely on sensor data (lidar, camera)
• Dead-reckoning can work in low data situations (no lidar, camera)
• Dead-reckoning drifts over time
• Predictions can be calibrated, but what if the model is off
• Can we do this with a crowd system?
• High quality crowdsourced maps are highly valuable [10]
• How can we do this, e.g. to locate a vehicle in a grid
• A major step in an accuracy of 5 m can average

Probabilistic Localization with Visual Odometry

• Arbitrary pose can be estimated from
• Turning, turning and straightening (can limit possible locations in a region)
• Short sequences can be highly ambiguous
• Visual odometry is non-unique and differs from
• Drift over longer sequences
• Approach needed that is able to cope with high
• Degree of uncertainty and ambiguity

Experimental Results

• Gathered separate visual odometry from the KITTI dataset (poses w.r.t. camera)
• Strokes and natural language computed using CLEF2022 (poses w.r.t. camera)
• Prior movement modeling using eigen features
• GPS-based odometry and map projection error computed for comparison

Map-Based Localization Representation

• Binary: 1: rep. street segments, 0: void
• Edges: connecting branches
• Given the street nodes, the vehicle position represented as
• Terms of perturbation and information on the street segments
• ω = distance from the end of the street segment
• P = total branching order to the street segment

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