Visual Assisted EKF SLAM for Planetary Roving Vehicle

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Abstract. Navigation of the planetary rover in the unforeseen planetary environment is an uphill task. In this paper, we presented a visual assisted inertial navigation system. System performance is evaluated by using real world KITTI data set. This work encompasses feature detection, feature matching, outlier rejection and motion estimation of the roving vehicle. This method is effective for the GPS-denied planetary environment. A tightly-coupled sensor blending method, for monocular camera image features and inertial measurement unit is presented for rover’s trajectory estimation. RANSAC is employed, for outlier rejection.

Introduction

Since the start of space exploration in 1950s, robots have played a vital role. Extraterrestrial science counts flybys, orbiters, penetrators, soft landers and rovers. All the space exploration except three manned Moon landings has been conducted by robotic devices. Such robots will play even a more growing role in this extraterrestrial exploration in future. These machines provide scientific knowledge to assist and plan future humanoid missions to broaden human existence in the immense universe [2, 12].

Space exploration is no more a fantasy since men have left the planetary cradle by breaking the chains of gravity and have set their feet on the lunar surface. That one small step became the giant leap for humankind. During last half century, many robotic voyages have proven human ingenuity to access distant places in space. Being our neighbor, the moon has been most visited place so far. After stepping the first stepping stone humans are looking to step onto Martian surface [5, 12].

It is the curiosity that drives humans to seek for habitable environments beyond Earth. Spirit and Opportunity together brought to us what had unseen by human eye before. Now the challenge is to drive autonomously through cluttered and unstructured Martian surface with least human intervention [2].

Since the start of space excursion many state of the art, robots have been seen which have played a vital role in exploring new horizons. Mobile robots are the key component of planetary exploration; this mobility enhances the accessible area on the extraterrestrial surface. Since the beginning, most Rovers are teleoperated by ground-based drivers, sending driving commands to drive up to the area of scientific interest with avoiding the en-route obstacles [2].

Space exploration is entering into a new paradigm with the procedure of autonomous navigation, Auto-Nav for NASA’s Mars science laboratory, Curiosity rover. This technique utilizes onboard cameras for path planning and obstacle avoidance without human intervention. This capability will enhance the pace of scientific discoveries by minimizing the delay due to communication lags [12].

This paper focuses on using the data provided by a single video camera to build a geometric representation of the scene while estimating the motion of the camera as it moves through that scene. This process, called monocular simultaneous localization and mapping (SLAM) [1], has applications for space robotics [2]. A rover attempting to traverse safely in an unforeseen environment must continually determine its position relative to the objects around it [10, 11].
Related Work

Use of vision sensor for autonomous navigation has gained the attention of lots of researchers. Many approaches have been presented with different level of success. The quest is, a robot would see and perceive its environment. There are two lines of research in ego-motion estimation of autonomous vehicles, i.e., visual odometry (VO) and visual SLAM. In visual odometry trajectory is estimated by utilizing the input of single or multiple on-board cameras [3-5, 15].

In 2003, Davison presented the concept of monocular visual simultaneous localization and mapping (SLAM). That algorithm used extended Kalman filter to estimate pose and map. The term visual odometry was first coined by Nister in 2004 [14] in his benchmark paper, another benchmark paper was presented by Klein in 2007, introduced the idea of parallel tracking and mapping (PTAM) to track camera pose and build a map of the environment simultaneously.


In benchmark paper, Two Years of Visual Odometry on the Mars Exploration Rovers [12], Mark Maimone et al. presented their strategies and results of the implementation of visual odometry on unseen Martian surface.

Bench Marking

The method presented in this paper is evaluated by using publically available real-world data set. For standard bench marking, vision community uses watchfully developed datasets and methods as benchmark. These open source robotics datasets provide bench marking datasets with ground truth for comparison. The KITTI dataset includes monocular sequences for a long drive in outdoor environments [6]. These datasets are suitable to benchmark planetary rover motion as they data sets are collected in very large real world environments.

http://www.cvlibs.net/datasets/kitti/raw_data.php

Methodology

For trajectory estimation of rover extended Kalman filter based simultaneous localization and mapping is utilized.

EKF SLAM

Building the map and pose of the robot

Robot control \(u_{t:T} = \{u_1, u_2, \ldots, u_n\}\)

Observations \(z_{t:T} = \{z_1, z_2, \ldots, z_n\}\)

Path of robot \(x_{0:T} = \{x_0, x_1, \ldots, x_T\}\)

State vector \(x_t = (x, y, \Theta, m_{k,x}, m_{k,y}, \ldots, m_{n,x}, m_{n,y})\)

EKF SLAM Prediction

\[
\bar{\mu}_t = \mu_{t-1} + F_s \begin{pmatrix}
-\frac{V}{\omega} \sin \Theta + \frac{V}{\omega} \sin(\Theta + \omega \Delta t) \\
\frac{V}{\omega} \cos \Theta - \frac{V}{\omega} \cos(\Theta + \omega \Delta t) \\
\omega \Delta t
\end{pmatrix}
\]

(1)
\[ \sum_i = G_i \sum_{t-1}^{t} G_i^T + F_x^T R_x F_x \]  

Kalman Gain

\[ K_i = \sum_i H_i^T \left( H_i \sum_i H_i^T + Q \right)^{-1} \]  

Observation function \( H_i^T \)

Range bearing observation

\[ z_i^t = (r_i^t, \phi_i^t)^T \]  

\[ \left( \begin{array}{c} \bar{\mu}_{j,x} \\ \bar{\mu}_{j,y} \end{array} \right) = \left( \begin{array}{c} \mu_{i,x} \\ \mu_{i,y} \end{array} \right) + \left( \begin{array}{c} r_i^t \cos(\phi_i^t + \bar{\mu}_{i,\theta}) \\ r_i^t \sin(\phi_i^t + \bar{\mu}_{i,\theta}) \end{array} \right) \]  

\[ \delta = \left( \begin{array}{c} \delta_x \\ \delta_y \end{array} \right) = \left( \begin{array}{c} \bar{\mu}_{j,x} - \mu_{i,x} \\ \bar{\mu}_{j,y} - \mu_{i,y} \end{array} \right) \]  

\[ q = \delta^T \delta \]  

\[ \tilde{z}_i^t = \left[ \begin{array}{c} \sqrt{q} \\ \alpha \tan(2(\delta_x, \delta_y) - \bar{\mu}_{i,\theta}) \end{array} \right] \]  

\[ \tilde{z}_i^t = h(\bar{\mu}_i) \]  

Compute jacobian \( H_i^j \)

\[ H_i^j = \frac{\partial h(\bar{\mu}_i)}{\partial \mu_i} \]  

\[ H_i^j = H_i^j F_{x,i} \]  

EKF SLAM Correction

\[ Q_i = \begin{pmatrix} \sigma^2_x & 0 \\ 0 & \sigma^2_y \end{pmatrix} \]  

For all observed features \( z_i^t = (r_i^t, \phi_i^t)^T, \ j = C_i \)

If landmark \( j \) never seen before

\[ \left( \begin{array}{c} \bar{\mu}_{j,x} \\ \bar{\mu}_{j,y} \end{array} \right) = \left( \begin{array}{c} \mu_{i,x} \\ \mu_{i,y} \end{array} \right) + \left( \begin{array}{c} r_i^t \cos(\phi_i^t + \bar{\mu}_{i,\theta}) \\ r_i^t \sin(\phi_i^t + \bar{\mu}_{i,\theta}) \end{array} \right) \]  

\[ \delta = \left( \begin{array}{c} \delta_x \\ \delta_y \end{array} \right) = \left( \begin{array}{c} \bar{\mu}_{j,x} - \mu_{i,x} \\ \bar{\mu}_{j,y} - \mu_{i,y} \end{array} \right) \]
\[ q = \delta^T \delta \]  
\[ \tilde{z}_i = \left( \frac{\sqrt{q}}{\tan 2(\delta_y, \delta_x) - \mu_{i,\theta}} \right) \]  
\[ H_i^t = \frac{1}{q} \begin{pmatrix} -\sqrt{q} \delta_x & -\sqrt{q} \delta_y & 0 & \sqrt{q} \delta_x & \sqrt{q} \delta_y \end{pmatrix} F_{i,j} \]  

**Results**

We evaluated our methodology using the benchmark KITTI dataset. We utilize the data of 1392x512 gray scale camera at 10 FPS. The simulation was performed on an Intel Core i7 laptop with 2.3 GHz processor. The picture shows the results of estimated trajectory in comparison with ground truth.

![Estimated trajectory in comparison with ground truth](image)

**Conclusion**

In this paper, we presented camera assisted extended Kalman filter based simultaneous localization and mapping for rover’s trajectory estimation effective for GPS-denied environments. The algorithm presented in this paper has following characteristics:

1. SLAM for GPS-denied environment is presented
2. A tightly-coupled sensor blending method is employed for camera and IMU output
3. Extended Kalman filter is employed for rover’s trajectory estimation
4. Random sample consensuses is employed for outlier rejection
5. Bench mark KITTI dataset is employed for results

**References**


