汕頭大學
SHANTOU UNIVERSITY

基于云的视觉SLAM回环检测

Cloud Based Visual Inertial SLAM System

指导教师：范衡

答辩人：邓富荣

电子信息工程

汕頭大學
SHANTOU UNIVERSITY

目录

项 目 内 容

PROJECT

本项目研究目的：

针对SLAM目前的研究瓶颈，本文致力于提出一个在大噪声环境下，依然能保持较高精确度，并且适用于算力配置较低的嵌入式设备的视觉SLAM系统。

本项目研究内容主要有以下三点：

- 在VINS_Mono的基础上提出基于云的视觉SLAM系统。
- 提出视觉噪声点检测方法。
- 提出权值优化机制。

基于云的视觉SLAM系统

- 受益于云端的储存能力和计算能力，回环检测的词袋模型可以拓展的更加庞大，这有助于提升回环检测的准确性。
- 基于中央式处理的架构有利于词袋模型的复用。
- 释放机器人端全局优化和回环检测的高运算量成本，为嵌入式设备视线实时运行提供可能。

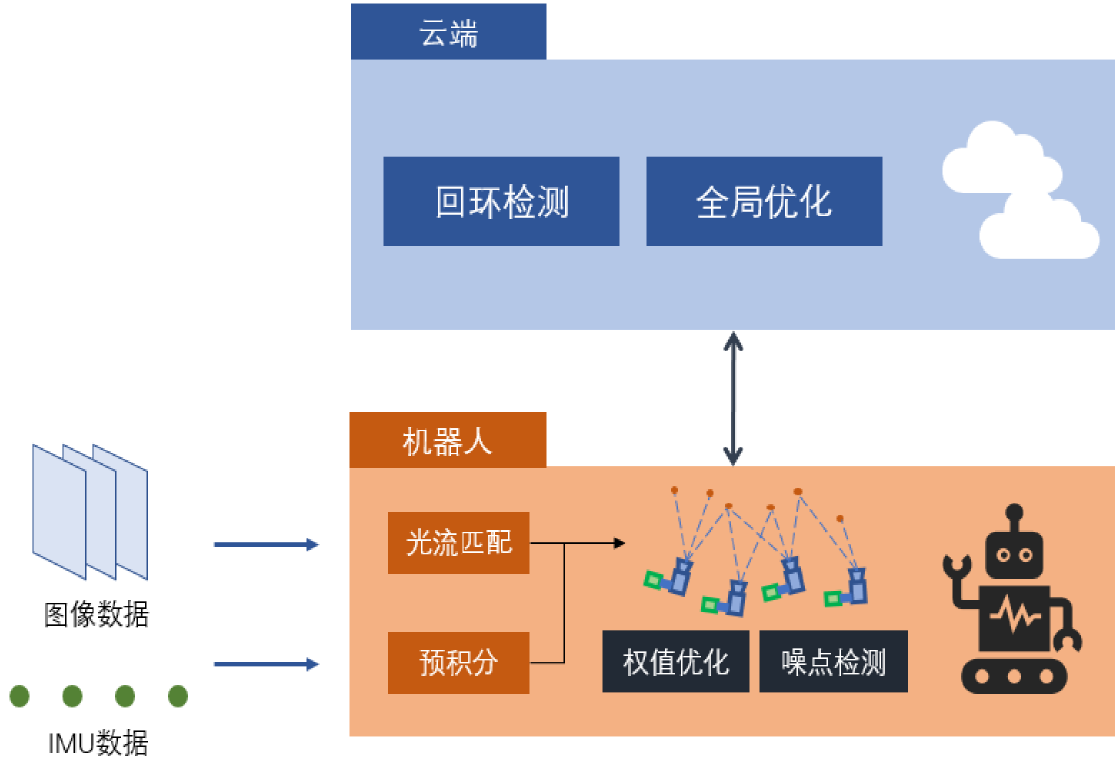


Fig.1 系统架构

视觉噪声点检测

动态物体等噪声点的存在会破坏SLAM**对极几何约束**，导致定位误差增大。因此本文使用IMU测量值获得先验位姿，并预测下一时刻特征点在图像的位置。若实际观测值与预测位置有较大误差，我们则认为该点是大噪声点并进行剔除。

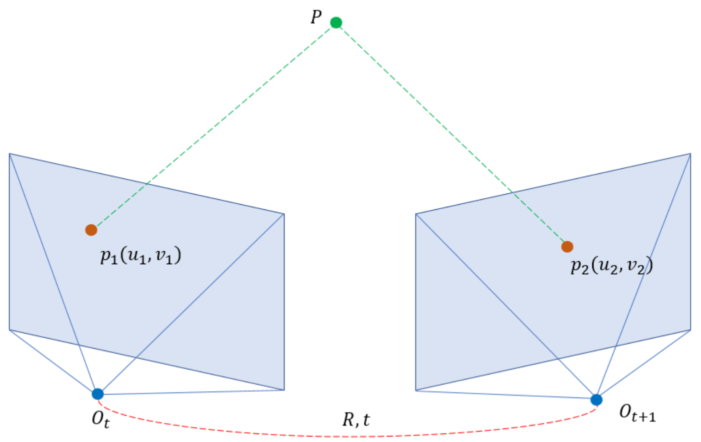


Fig.1 对极几何

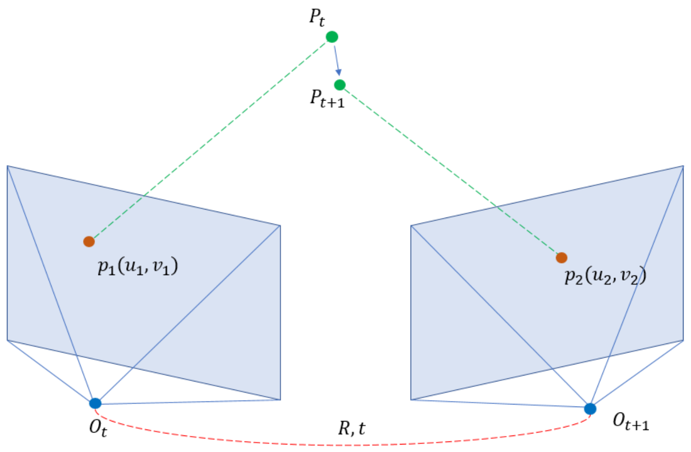


Fig.2 动态物体破坏对极几何

静态物体	$P_t = P_{t+1}$ $K^{-1}p_1 = R^{-1}(K^{-1}p_2 - \mathrm{t})$
噪声点	$P_t \neq P_{t+1}$ $K^{-1}p_1 \neq R^{-1}(K^{-1}p_2 - \mathrm{t})$

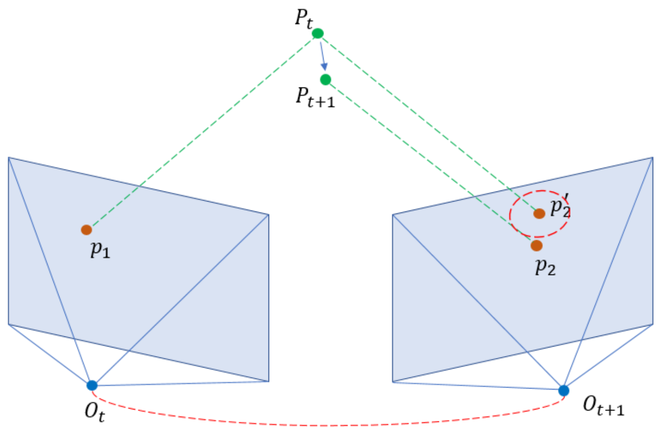


Fig.3 噪声点检测

权值优化机制

通过代入场景直观地分析，我们发现人在估计自身运动的过程中，不会在盲目而随机地选取参照物，反而是优先选择更有参照价值的物体。换言之，在人的视野中各个参照物存在一个置信度，它衡量的是根据该参照物所评估的运动是否可信。正是利用这种性质，本文提出权值优化的概念：给各个特征点分配一个权值，在优化过程中优先调整权值大的特征点参数，以提升系统的精确度。

权值分配：

$$\rho_i = \frac{N}{n} * \exp(-\|\delta p_i\|^2)$$

目标函数：

$$\min_X \left\{ \sum_{i=0}^{N} \rho_i * r_c(z_i^c, X) + \sum_{j=0}^{M} r_b\left(z_j^{IMU}, X\right) \right\}$$

注：ρ_i为某点权值，δp_i为观测值和估计值的误差，N为最大特征点数量，n为实际特征点的数量，X为状态向量，z_i^c为相机观测值，z_j^{IMU}为IMU观测值，$r_c(z_i^c, X)$为重投影误差，$r_b\left(z_j^{IMU}, X\right)$为IMU误差。

实 验 方 案

EXPERIMENT

为了验证该思想的可行性，本项目使用Euroc惯性视觉SLAM数据集[22]进行测试，并与近几年优秀的算法VINS_Mono[1]和ICE_BA[23]进行对比。本文通过模拟下雨场景，在不同噪声程度下设计了以下四个实验：

实验一：噪声与信号比为0

实验二：噪声与信号比为0.001

实验三：噪声与信号比为0.003

实验四：噪声与信号比为0.005

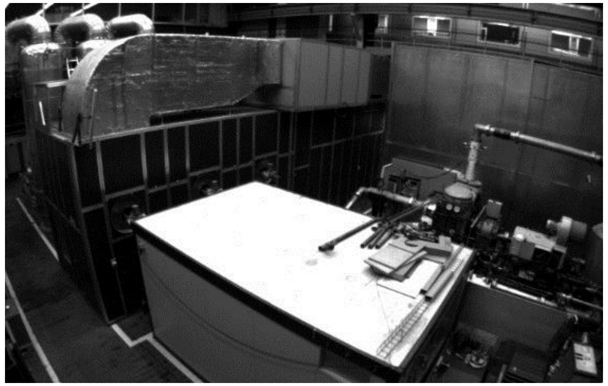


Fig.1 实验一

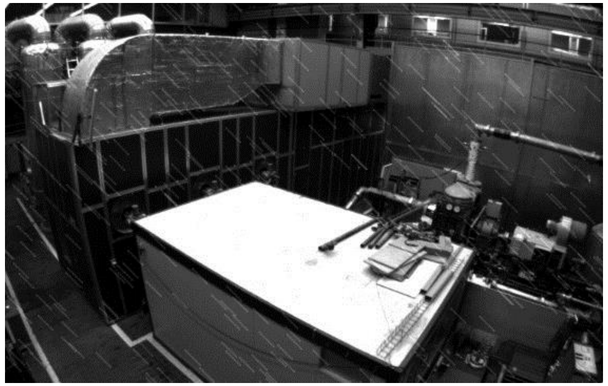


Fig.2 实验二

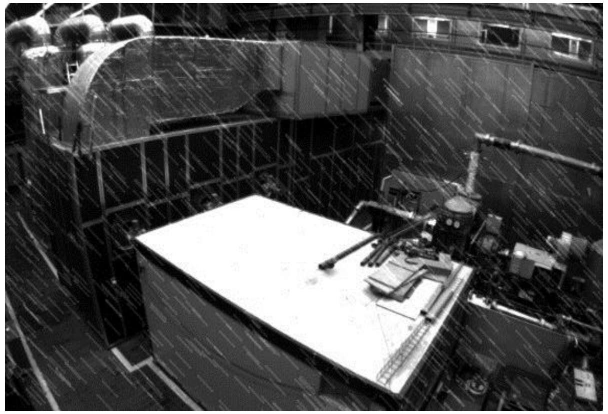


Fig.3 实验三

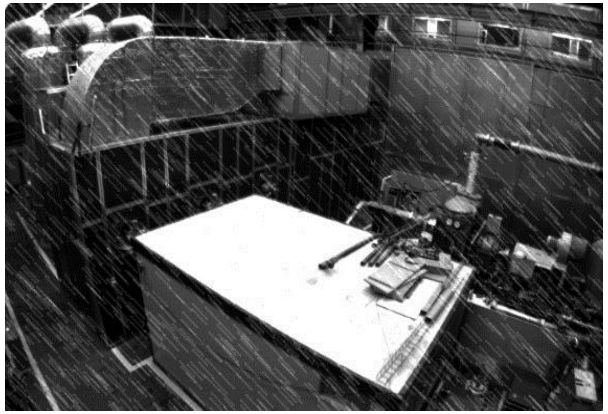
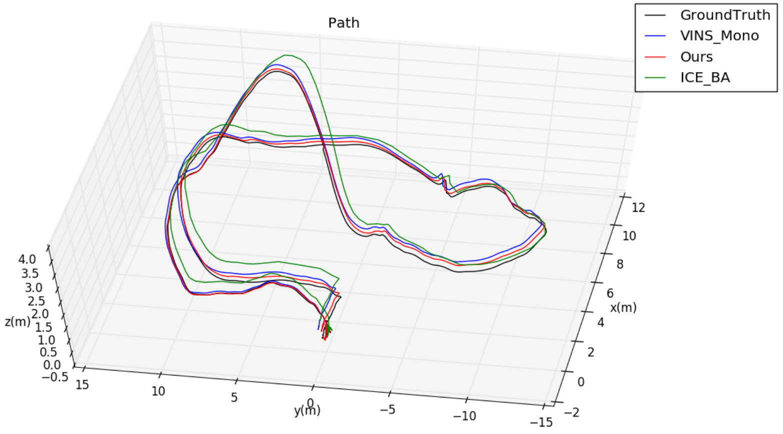


Fig.4 实验四

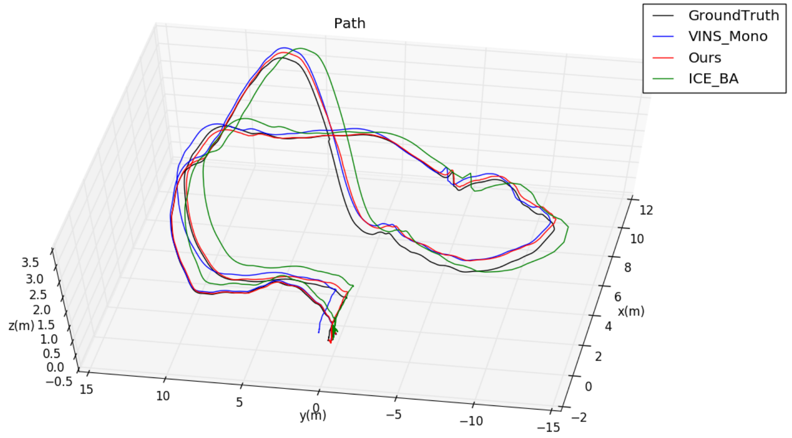
实 验 结 果

RESULT

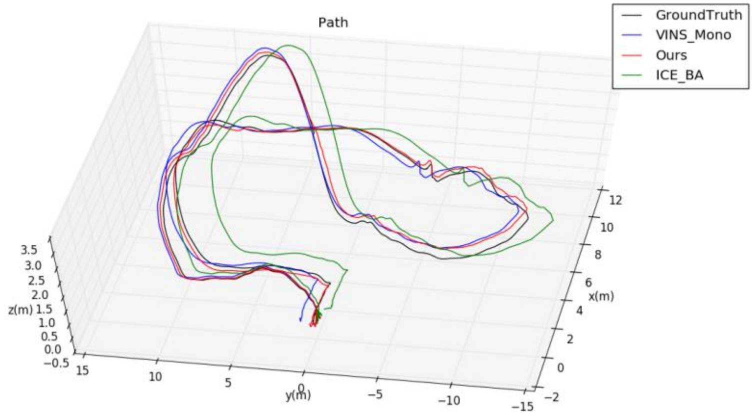
四个实验下各个算法的路径结果对比：



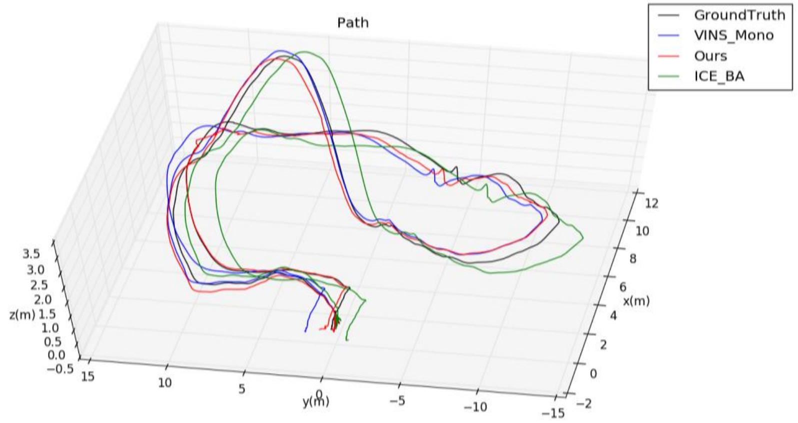
实验一



实验二

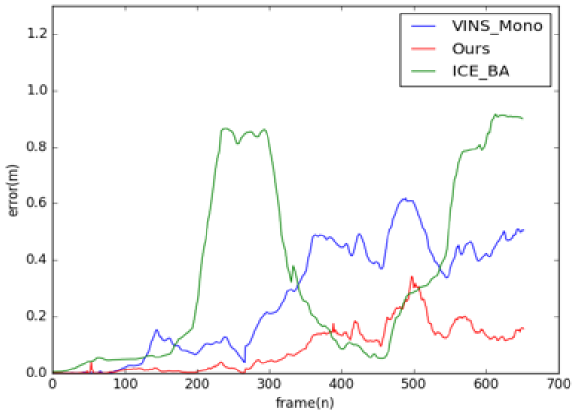


实验三

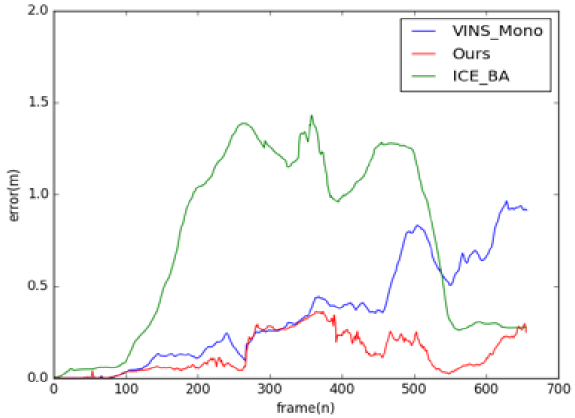


实验四

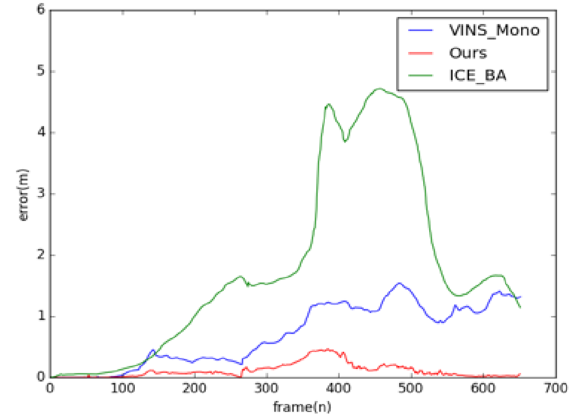
四个实验下各个算法的位置误差随时间的变化曲线：



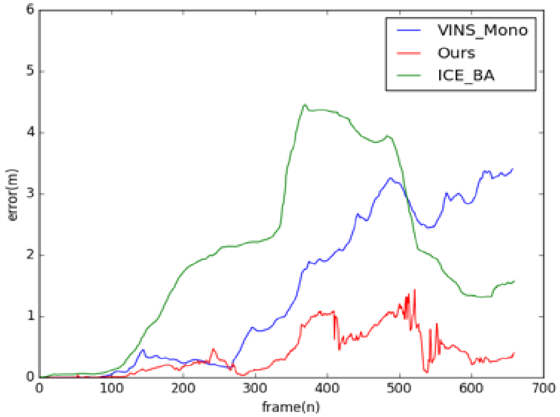
实验一



实验二



实验三



实验四

	0.000	0.001	0.003	0.005
ICE_BA	0.356	0.744	1.799	1.994
VINS_Mono	0.265	0.346	0.698	1.389
Ours	0.085	0.134	0.111	0.373

表 4-1 各算法的平均误差（m）

通过横向纵向比较，可以得出结论：本系统与其他两个算法相比，其定位精度更加精准，在大噪声环境下的鲁棒性更高。

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