Traditional SLAM(Simultaneous Localization and Mapping) systems paid great attention to geometric information. Based on the solid foundation of Multi-view Geometry, a lot of excellent studies have been carried out. However, problems arise from none geometric modules in SLAM systems. To track the location of cameras, researchers usually perform pixel-level matching operations in tracking threads and optimize poses of a small number of frames as local mapping. No doubt that errors resulted by drift in pose estimation and map evaluation keep accumulating. In the meanwhile, Deep Learning, a data-driven technique, has brought out rapid development in numerous computer vision tasks such as classification and matching. Such achievements reflect that deep learning may be one of the best choices to solve problems related to data association. Therefore, more and more researchers believe that pixel- level or higher level associations between images, the bottleneck of SLAM systems we mentioned above, can also be handled with the help of neural networks. Deep learning has proved its superiority in SLAM systems. Many outstanding studies have employed it to replace some non-geometric modules in traditional SLAM systems [22, 21, 49, 26, 12]. These approaches enhance the overall SLAM system by improving only part of a typical pipeline, such as stereo matching, relocalization and so on. Some re- searchers also attempt to use higher-level features obtained through deep learning models as a supplement to SLAM [37, 35, 1, 6, 15]. These higher-level features are more likely to infer the semantic content-object feature and improve the capability of visual scene understanding. Moreover, end- to-end learning models have also been proposed [51, 16]. These methods outperform traditional SLAM algorithms under specific circumstances and demonstrate the potential of deep learning in SLAM. However, such combination of Deep learning and SLAM have significant shortcomings. Most of Deep Learning methods rely heavily on data used for training, which means that they cannot fit well into unknown environments. For example, we cannot ensure whether the room we want to explore is equipped with chairs and desks and cannot guarantee semantic priority of desks will help in this occasion. What’s more, most Deep-Learning enhanced SLAM systems are designed to reflect advantage of Deep Learning techniques and abandon the strong points of SLAM. As a result, they may sacrifice efficiency, an essential part of SLAM algorithms, for accuracy. Last but not least, some DL-based SLAM techniques take traditional SLAM systems as their underlying framework [49, 26, 12, 9] and make a great many changes to support Deep Learning strategies. Too many replacements may lead to loss of some useful features of the SLAM pipeline and also make it hard for researchers to perform further comparisons with existing studies, let alone migrate these techniques to other SLAM systems. As a result, DL- based SLAM is not mature enough to outperform traditional SLAM systems. Therefore, we make our efforts to put forward a simple, portable and efficient SLAM system. Our basic idea is to improve the robustness of local feature descriptor through deep learning to ensure the accuracy of data association between frames.

LAMP: Large-Scale Autonomous Mapping and Positioning forExploration of Perceptually-Degraded Subterranean Environments

Abstract— Simultaneous Localization and Mapping (SLAM)In large-scale, unknown, and complex subterranean environments is a challenging problem. Sensors must operate in off-nominal conditions; uneven and slippery terrains make wheel odometry inaccurate, while long corridors without salient features make exteroceptive sensing ambiguous and prone to drift; finally, spurious loop closures that are frequent in environments with repetitive appearance, such as tunnels and mines, could result in a significant distortion of the entire map. These challenges are in stark contrast with the need to build highly-accurate 3D maps to support a wide variety of applications, ranging from disaster response to the exploration of underground extraterrestrial worlds. This paper reports on the implementation and testing of a lidar-based multirobot SLAM system developed in the context of the DARPA Subterranean Challenge. We present a system architecture to enhance subterranean operation, including an accurate lidarbased front-end, and a flexible and robust back-end that automatically rejects outlying loop closures. We present an extensive evaluation in large-scale, challenging subterranean environments, including the results obtained in the Tunnel Circuit of the DARPA Subterranean Challenge. Finally, we discuss potential improvements, limitations of the state of the art, and future research directions.

Introduction

Over the past two decades, there has been a growing demand for autonomous unmanned exploration of diverse subterranean environments, from tunnels and urban underground environments to complex cave networks. This surge of interest is motivated by terrestrial applications such as search and rescue, disaster response, and infrastructure monitoring, as well as the unparalleled scientific opportunities offered by exploration of other worlds. Lava tubes, subterranean conduits found on the Moon and Mars, are of particular interest: sheltered from cosmic radiation and temperature fluctuations, they provide ideal conditions for the development for microbial life, as well as potential sites for habitats in future human space missions [1]

Localization and mapping are key capabilities for autonomous underground operation. In typical applications, there is no prior map of the environment, and GPS cannot be relied on to localize the robots. Indeed, the ultimate goal of many autonomous exploration applications is to obtain an accurate 3D map of the environment. Unfortunately, most SLAM systems have inadequate performance when deployed in perceptually-degraded subterranean environments: sensors must operate in off-nominal conditions (poor illumination or lack-thereof, dust, water puddles and non-Lambertian surfaces) which render visual-SLAM approaches unreliable [2]; uneven and slippery terrains make wheel odometry inaccurate, while long, featureless corridors make lidar-based mapping prone to drift; finally, perceptual aliasing, the presence of many similar-looking corridors and intersections, induces spurious loop closures that can degrade the mapping results.

Related work

We review the literature on SLAM systems for subterranean and perceptually degraded environments, and refer the reader to [3] for a broader survey on SLAM. Related work investigates different sensing modalities, including vision [4], visual-inertial [5], [6], and thermalinertial [7]. However, solely relying on vision for underground localization and mapping can be challenging as cameras are directional and sensitive to illumination changes and environmental conditions. Lidar sensors provide a 360◦ horizontal field of view and high sampling rate, and do not rely on external light sources. Therefore, 3D lidar SLAM has been a popular solution to map complex unstructured environments, from early work [8] to more recent systems [9], [10], [11], [12], [13], [20]. Thrun et al. [14] propose an underground mine mapping algorithm that relies on 2D scan matching and a global alignment step. Tardioli et al. [15], [16] propose a system architecture for single and multi-robot exploration in underground tunnels. Zlot etal. [17] present a lidar-based SLAM method for mapping of a 17 km underground copper and gold mine; to detect loop closures, they use a surfel representation and search for matches against previous trajectory segments. Leingartner et al. [18] investigate the performance of off-the-shelf sensors and state-of-the-art mapping algorithms in mapping a 1.5 km long motorway tunnel in an urban search & rescue scenario and conclude that the investigated sensing and mapping techniques are not yet robust enough to deal with these perceptually degraded environments. Jacobson et al. [19] present a semi-supervised method that relies on manual selection of topological landmarks inside a 300 m long tunnel to perform localization using a low cost camera sensor

在大规模，未知和复杂的地下环境中，这是一个具有挑战性的问题。传感器必须在标称条件下工作；不平坦和湿滑的地形使车轮里程计不准确，而没有显着特征的长廊使抽动感知不明确，容易漂移。最后，在具有重复外观的环境（例如隧道和地雷）中经常发生的虚假环路闭合可能会导致整个地图的严重变形。这些挑战与构建高精度3D地图以支持各种应用程序形成了鲜明的对比，这些应用程序涵盖了从灾难响应到探索地下地球世界的各种应用。本文报告了在DARPA地下挑战赛的背景下开发的基于激光雷达的多机器人SLAM系统的实施和测试。我们提出了一种增强地下操作的系统架构，其中包括一个基于激光雷达的精确前端，以及一个可自动拒绝外围回路闭合的灵活而强大的后端。我们在大规模，具有挑战性的地下环境中进行了广泛的评估，包括在DARPA地下挑战赛的隧道赛道中获得的结果。最后，我们讨论了潜在的改进，现有技术的局限性以及未来的研究方向。

介绍

在过去的二十年中，对从隧道和城市地下环境到复杂的洞穴网络的各种地下环境进行自动无人驾驶探索的需求不断增长。兴趣的激增是由诸如搜索和救援，灾难响应和基础架构监视等地面应用以及其他世界的探索所提供的无与伦比的科学机会引起的。熔岩管是在月球和火星上发现的地下管道，特别受关注：不受宇宙辐射和温度波动的影响，它们为微生物生活的发展提供了理想条件，并为未来人类太空飞行任务的栖息地提供了理想的场所[1] ]

定位和制图是自主地下作业的关键功能。在典型应用中，没有先验环境图，并且不能依靠GPS定位机器人。实际上，许多自主勘探应用程序的最终目标是获取环境的准确3D地图。不幸的是，大多数SLAM系统在可感知退化的地下环境中部署时性能不足：传感器必须在非标称条件下（光照不足或缺乏，灰尘，水坑和非朗伯表面）运行，这使视觉SLAM方法变得不可靠[2];不平坦和湿滑的地形使车轮里程计不准确，而漫长而无特色的走廊使基于激光雷达的制图易于漂移；最后，感知混叠，许多外观相似的走廊和交叉点的存在会导致虚假的环路闭合，从而降低贴图效果。

相关工作

我们回顾了有关地下和感知退化环境的SLAM系统的文献，并向读者引荐[3]进行SLAM的更广泛调查。相关工作研究了不同的传感方式，包括视觉[4]，视觉惯性[5]，[6]和热惯性[7]。但是，仅依靠视觉进行地下定位和制图可能会遇到挑战，因为摄像机的方向性很强，并且对照明变化和环境条件敏感。激光雷达传感器可提供360°的水平视野和高采样率，并且不依赖外部光源。因此，从早期的工作[8]到最新的系统[9]，[10]，[11]，[12]，[13]，[20]，3D激光雷达SLAM一直是映射复杂的非结构化环境的流行解决方案。 Thrun等。 [14]提出了一种地下矿山映射算法，该算法依赖于2D扫描匹配和全局对准步骤。 Tardioli等。 [15]，[16]提出了一种用于地下隧道中的单机器人和多机器人勘探的系统架构。 Zlot等。 [17]提出了一种基于激光雷达的SLAM方法，用于绘制一个17公里的地下铜金矿。为了检测循环闭合，他们使用冲浪表示并搜索与先前轨迹段的匹配。 Leingartner等。 [18]研究了在城市搜索与救援场景中绘制1.5公里长的高速公路隧道时，现成的传感器和最新的制图算法的性能，并得出结论：尚未研究调查的传感和制图技术足够强大以应对这些在感知上退化的环境。 Jacobson等。 [19]提出了一种半监督方法，该方法依赖于手动选择300 m长隧道内的拓扑地标以使用低成本相机传感器执行定位。

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Efficient Large-Scale 3D Mobile Mappingand Surface Reconstruction of anUnderground Min

Abstract

Mapping large-scale underground environments, such as mines, tunnels, and caves is typically a time consuming and challenging endeavor. In April 2011, researchers at CSIRO were contracted to map the Northparkes Mine in New South Wales, Australia. The mine operators required a locally accurate 3D surface model in order to determine whether and how some pieces of large equipment could be moved through the decline. Existing techniques utilizing 3D terrestrial scanners mounted on tripods rely on accurate surveyed sensor positions and are relatively expensive, time consuming, and inefficient. Mobile mapping solutions have the potential to map a space more efficiently and completely; however, existing commercial systems are reliant on a GPS signal and navigation- or tactical-grade inertial systems. A 3D SLAM solution developed at CSIRO, consisting of a spinning 2D lidar and industrial-grade MEMS IMU was customized for this particular application. The system was designed to be mounted on a site vehicle which continuously acquires data at typical mine driving speeds without disrupting any mine operations. The deployed system mapped over 17 kilometers of mine tunnel in under two hours, resulting in a dense and accurate georeferenced 3D surface model that was promptly delivered to the mine operators

Introduction

In April 2011, researchers at CSIRO were contracted to map several kilometers of the decline and drive at the Northparkes copper and gold mine in New South Wales, Australia. The mine operators were interested in moving large equipment underground for future operations. In order to do so, a 3D model of the decline and drive was essential to determine the level of disassembly of the equipment required to manage the clearances in the tunnels. The primary requirement was that the model must be locally accurate: drift in the data acquisition trajectory could largely be tolerated, as the most critical aspects were the negotiation of curves and changes in grade. Our research team at CSIRO had an existing relationship with Northparkes Mine based on previous work in automating an underground load-haul-dump vehicle [5]. More recently, our group has been investigating 3D SLAM in challenging environments, and in particular had developed solutions for mobile mapping in GPS-denied areas. Of particular relevance to the proposed mine mapping application, we had been working on a SLAM solution capable of estimating the six degree of freedom pose of a spinning 2D lidar while the platform on which it is mounted is continuously moving [1]. In its simplest form, this solution requires no more than the raw 3D lidar returns as input; however, the use of readings from an inertial measurement unit (IMU) can aid the solution to provide increased robustness and accuracy. Variants of our system had been deployed for mapping suburban streets, industrial environments, forests, caves [8], indoor spaces, and a small section of an underground coal mine. Over the course of these experiments and deployments, our system has been improved considerably in a number of ways, some of which are detailed in this paper. Three-dimensional mapping can play a highly critical role in underground mine development and maintenance, including planning, monitoring, safety, and vehicle localization; however, to date the existing 3D mapping and localization solutions are inefficient, labor intensive, or have not been demonstrated to be reliable, robust, and scalable. The predominant practice for lidar mapping of underground voids (such as mines, tunnels, and caves) is the use of tripod-mounted terrestrial scanners coupled with traditional survey methods to accurately estimate the scanner location [7, 9, 14, 16]. Several solutions using a mobile platform have been proposed in the robotics literature, but thus far these have predominantly been time-consuming “stop-and-scan” solutions where the platform must stop every few meters to acquire a scan（6,10,11,15,17）

抽象

绘制大型地下环境（例如矿山，隧道和洞穴）的地图通常是一项耗时且具有挑战性的工作。 2011年4月，CSIRO的研究人员与澳大利亚新南威尔士州的Northparkes矿签订了合同。矿山运营商需要局部精确的3D表面模型，以便确定是否可以以及如何通过下降移动某些大型设备。利用安装在三脚架上的3D地面扫描仪的现有技术依赖于精确测量的传感器位置，并且相对昂贵，费时且效率低下。移动制图解决方案具有更有效，更完整地绘制空间的潜力；然而，现有的商业系统依赖于GPS信号和导航或战术级惯性系统。由CSIRO开发的3D SLAM解决方案针对此特定应用进行了定制，该解决方案由旋转的2D激光雷达和工业级MEMS IMU组成。该系统被设计为安装在现场车辆上，该车辆以典型的矿山行驶速度连续获取数据，而不会中断任何矿山作业。部署的系统在不到两个小时的时间内绘制了17公里的矿井隧道图，从而生成了密集且准确的地理参考3D表面模型，该模型可立即交付给矿山运营商

介绍

2011年4月，CSIRO的研究人员被合同绘制了下降的几公里，并在澳大利亚新南威尔士州的Northparkes铜和金矿开车。矿山经营者有兴趣将大型设备地下运输，以备将来之用。为此，下降和行驶的3D模型对于确定管理隧道间隙所需的设备拆卸水平至关重要。主要要求是该模型必须局部精确：可以最大程度地容忍数据采集轨迹的漂移，因为最关键的方面是曲线的协商和坡度的变化。我们在CSIRO的研究团队与Northparkes矿场之间已有合作关系，其基础是先前在进行地下载重车自卸车自动化方面的工作[5]。最近，我们的团队一直在研究具有挑战性的环境中的3D SLAM，尤其是已经开发出了GPS受限区域中的移动地图绘制解决方案。与拟议的矿山测绘应用特别相关的是，我们一直在研究SLAM解决方案，该解决方案能够估计旋转的2D激光雷达在其安装平台持续移动时的六个自由度姿态[1]。以最简单的形式，该解决方案只需要原始的3D激光雷达返回作为输入即可。但是，使用惯性测量单元（IMU）的读数可以帮助解决方案提高鲁棒性和准确性。我们已经部署了系统的变体，用于绘制郊区街道，工业环境，森林，洞穴[8]，室内空间以及一小部分地下煤矿的地图。在这些实验和部署过程中，我们的系统已通过多种方式得到了很大的改进，其中一些在本文中进行了详细介绍。三维地图可以在地下矿山的开发和维护中发挥至关重要的作用，包括规划，监控，安全和车辆定位。但是，迄今为止，现有的3D映射和定位解决方案效率低下，劳动强度大，或者尚未证明其可靠，健壮和可扩展。地下空隙（例如矿井，隧道和山洞）的激光雷达测绘的主要做法是使用安装在三脚架上的地面扫描仪，结合传统的测量方法，以准确估算扫描仪的位置[7、9、14、16]。机器人技术文献中已经提出了几种使用移动平台的解决方案，但到目前为止，这些解决方案主要是耗时的“停止并扫描”解决方案，其中平台必须每隔几米就停下来进行一次扫描（6,10,11 ,, 15,17）