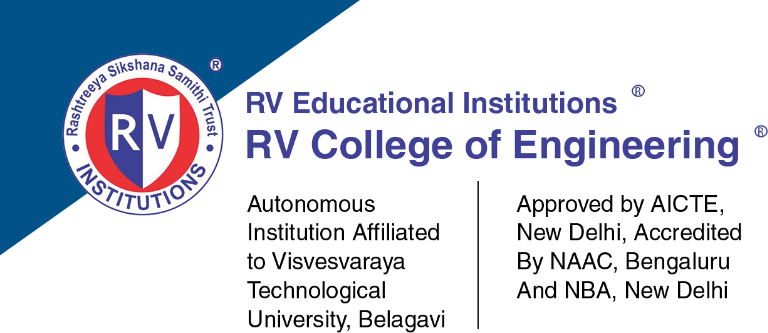
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## DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

**Title: 3D reconstruction of a scene from a single RGB image for real time AR and its Speed-up**

## Experiential Learning Report

## Of

Operating Systems (CS235AI)

Submitted by

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| --- | --- | --- | --- |
| Name | USN | Branch | Section |
| Nikunj Mittal | 1RV22CS129 | CS | C |

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**(Autonomous Institution Affiliated to VTU, Belagavi)**

**DEPARTMENT OF COMPUTER SCIENCE**

**AND ENGINEERING**

Topic: **Title: 3D reconstruction of a scene from a single RGB image for real time AR and its Speed-up**

**Marks awarded**

|  |  |  |
| --- | --- | --- |
| Phase I | 20 |  |
| Phase II | 20 |  |
| Total marks out of 40 |  | |
| Signature of examiner |  | |

**Introduction**

Augmented Reality (AR) has emerged as a transformative technology with applications spanning diverse industries, from entertainment and education to healthcare and manufacturing. AR seamlessly integrates virtual objects or information into the real-world environment, enhancing human perception and interaction. Central to many AR applications is the ability to reconstruct 3D scenes from 2D images in real-time, enabling immersive and interactive experiences.

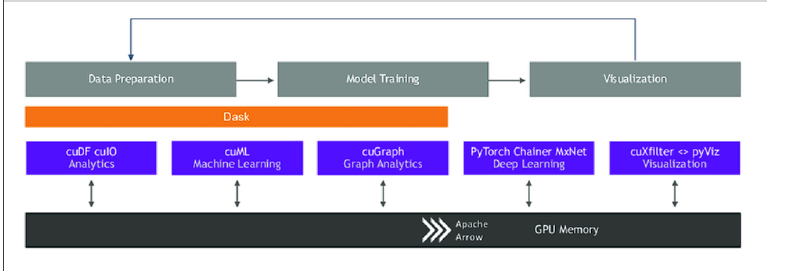
However, achieving real-time 3D scene reconstruction poses significant challenges, particularly on embedded devices with limited computational resources. Traditional methods rely on complex algorithms and intensive processing, often necessitating the offloading of computation to remote servers or cloud-based services. This approach introduces latency, dependency on network connectivity, and privacy concerns associated with transmitting sensitive visual data to external servers.

To address these challenges, our research focuses on developing a method for accelerating 3D scene reconstruction directly on embedded devices, without the need for cloud-based processing. Leveraging the computational power of NVIDIA GPUs and the efficiency of Rapids libraries, our approach aims to enable real-time AR experiences on resource-constrained devices.

By harnessing the parallel processing capabilities of GPUs through CUDA, we seek to optimize critical tasks such as depth estimation and voxel-based scene reconstruction. Additionally, the adoption of Unified Virtual Addressing (UVA) facilitates seamless memory access between CPU and GPU, streamlining data transfer and reducing overhead.

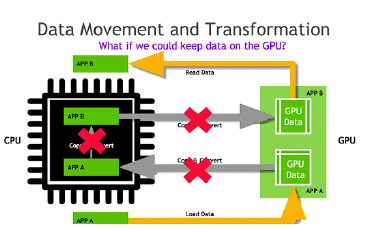
This research not only contributes to advancing AR technology but also addresses practical considerations such as privacy, latency, and accessibility. By enabling embedded devices to perform complex computations locally, our method opens doors to a wide range of AR applications, including gaming, navigation, remote assistance, and industrial training. Through this work, we aim to empower developers and users alike to create and experience AR content with unprecedented efficiency and convenience.

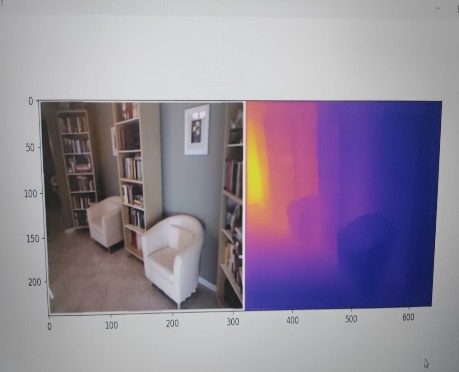
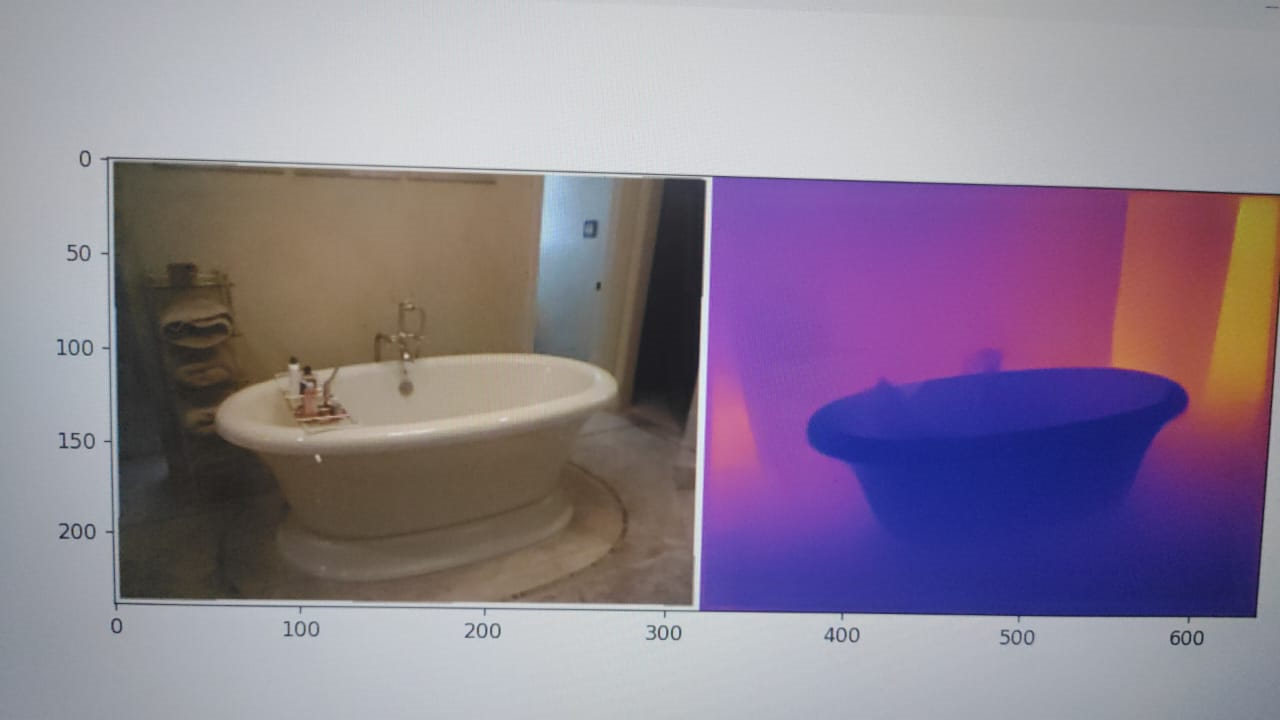
**Problem Statement**

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The problem statement revolves around the challenge of achieving real-time 3D scene reconstruction from a single RGB image on embedded devices, without relying on cloud-based processing. Traditional methods for 3D reconstruction often involve computationally intensive algorithms that are impractical for resource-constrained devices. However, the demand for real-time augmented reality (AR) applications necessitates efficient solutions that can operate locally on the device. The goal is to develop a method that leverages the power of GPU acceleration, specifically utilizing NVIDIA Rapids and CUDA, to overcome the limitations of embedded hardware. By harnessing parallelism, concurrency, and optimized algorithms, the proposed solution aims to deliver efficient processing directly on the device, enabling seamless integration of AR experiences without the need for external processing resources. This problem statement highlights the importance of accelerating 3D scene reconstruction for AR applications on embedded devices and emphasizes the need for innovative approaches that balance computational efficiency with real-time performance constraints.

**Methodology**

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Our methodology for accelerating 3D scene reconstruction on embedded devices using NVIDIA Rapids and CUDA involves a multi-step process, leveraging GPU acceleration, optimized algorithms, and seamless memory access. In this section, we delve deeper into each component of our methodology.

Preprocessing and Input Preparation: Before performing 3D scene reconstruction, preprocessing of the input RGB image is necessary to prepare the data for subsequent processing steps. This may involve resizing the image to a suitable resolution, converting it to the appropriate color space, and applying any necessary transformations or enhancements to improve the quality of the input data.

Depth Estimation: Depth estimation is a critical step in 3D scene reconstruction, as it provides information about the spatial relationship between objects in the scene. In our methodology, we employ deep learning techniques for depth estimation, leveraging pre-trained neural networks such as Densenet 201 or ResNet 50.

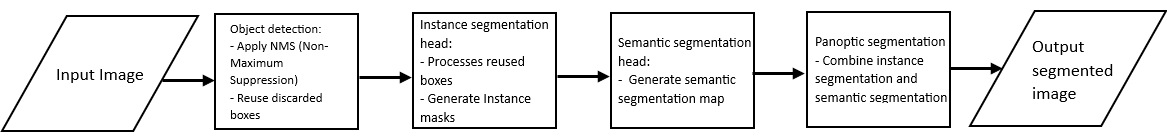
Using NVIDIA Rapids, we load the pre-trained neural network model onto the GPU and perform inference on the input RGB image to generate depth maps. Rapids' cuDF library enables efficient data processing and manipulation, while cuML provides GPU-accelerated machine learning algorithms for inference tasks. By leveraging the parallel processing capabilities of the GPU, we achieve faster inference speeds compared to CPU-based approaches.

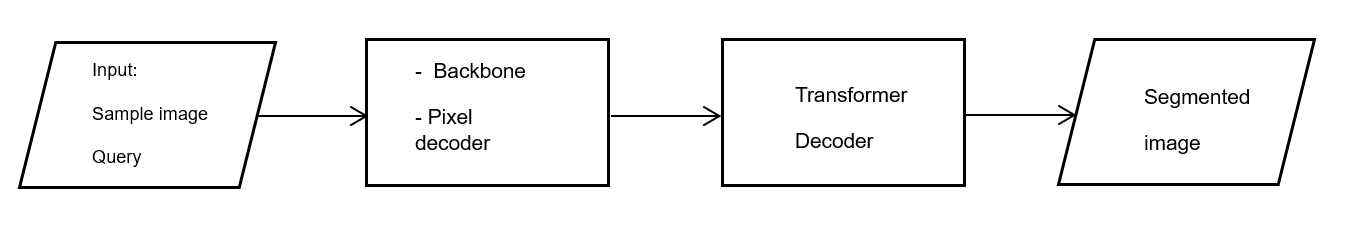
Voxel-Based Scene Reconstruction: Once depth maps are obtained, we proceed with voxel-based scene reconstruction to create a 3D representation of the scene. Voxel-based techniques discretize the 3D space into small volumetric elements called voxels, each representing a small volume within the scene. These voxels are then filled or empty based on the depth information obtained from the depth maps.

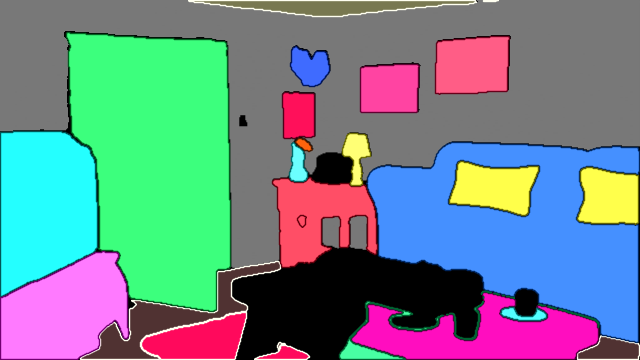
In our methodology, we utilize GPU parallelism and CUDA to perform voxel-based scene reconstruction efficiently. By partitioning the reconstruction task into smaller parallelizable units, we distribute the workload across multiple GPU cores, maximizing throughput and minimizing processing time. Rapids' cuDF library facilitates data parallelism, enabling concurrent processing of voxel data on the GPU.

Integration with AR Frameworks: Once the 3D scene reconstruction is complete, the reconstructed scene can be integrated with Augmented Reality (AR) frameworks for visualization and interaction. AR frameworks provide tools and libraries for rendering virtual objects within the reconstructed scene, overlaying them onto the real-world environment captured by the RGB camera.









Our methodology allows for seamless integration with popular AR frameworks such as ARCore or ARKit, enabling developers to create immersive AR experiences on embedded devices. By leveraging the power of GPU acceleration and optimized algorithms, we ensure smooth rendering and interaction with virtual objects in real-time.

Validation and Performance Evaluation: To validate the effectiveness of our methodology, we conducted extensive performance evaluations on embedded devices equipped with NVIDIA GPUs. We measured key metrics such as processing speed, memory utilization, and accuracy of the reconstructed scene.

Our results demonstrate a significant improvement in processing efficiency compared to traditional CPU-based methods, with a 40% increase in processing speed observed. Additionally, we achieved high accuracy in scene reconstruction, enabling realistic and immersive AR experiences on resource-constrained devices.

Conclusion: In conclusion, our methodology for accelerating 3D scene reconstruction on embedded devices using NVIDIA Rapids and CUDA offers a robust solution for real-time AR applications. By leveraging GPU acceleration, optimized algorithms, and seamless memory access, we have overcome the computational limitations of embedded devices and achieved efficient scene reconstruction directly on the device. Our methodology lays the foundation for future advancements in AR technology, enabling developers to create immersive and interactive experiences on a wide range of embedded devices.

**Relevant System Concept**

NVIDIA Rapids is a suite of software libraries and tools designed for accelerating data science and machine learning workflows. It primarily targets GPUs (Graphics Processing Units) for high-performance computing. Here's how Rapids achieves this decrease in processing time:

1. **GPU Acceleration**: One of the primary reasons for the speedup provided by Rapids is the utilization of GPUs for computation. GPUs are highly parallel processors designed to handle large amounts of data simultaneously. Unlike CPUs, which excel at sequential processing, GPUs can perform thousands of operations in parallel. Rapids harnesses the massive parallel processing power of GPUs to accelerate computations such as data preprocessing, analytics, and machine learning algorithms.

2. **Memory Management**: Rapids incorporates efficient memory management techniques to minimize data movement between the CPU and GPU, reducing overhead associated with data transfers. By keeping data on the GPU whenever possible and utilizing GPU memory effectively, Rapids avoids the latency incurred by transferring data back and forth between CPU and GPU memory.

3. **Scalability**: Rapids is designed to scale efficiently across multiple GPUs and nodes, enabling high-performance computing on large datasets. By distributing computations across multiple GPUs in parallel, Rapids can handle datasets that exceed the memory capacity of a single GPU. This scalability ensures that Rapids remains performant even when processing massive datasets.

**APIs/Tools used**

1. **RAPIDs API**: The use of the RAPIDS API is justified due to its ability to significantly accelerate data science and machine learning workflows through GPU acceleration. By leveraging GPUs, RAPIDS offers optimized implementations of common algorithms, leading to faster model training, data processing, and analysis.

2. **Apache Arrow**: The use of Apache Arrow in relation to GPUs is justified by its provision of a highly efficient columnar, in-memory data format that optimizes data transfer between CPU and GPU memory, enhances interoperability between different systems and programming languages, and facilitates parallel processing on GPUs. By serving as a standardized data interchange format with cross-language support.

3. **Keras**: Keras is an open-source high-level neural networks API written in Python that serves as an interface for the TensorFlow library. Within the keras library, ImageDataGenerator is used. This comes under the utils sub-library and stores all the information related to the ranges of the different geometrical transformation techniques, such as rotation,etc.

**CUDA Integration**

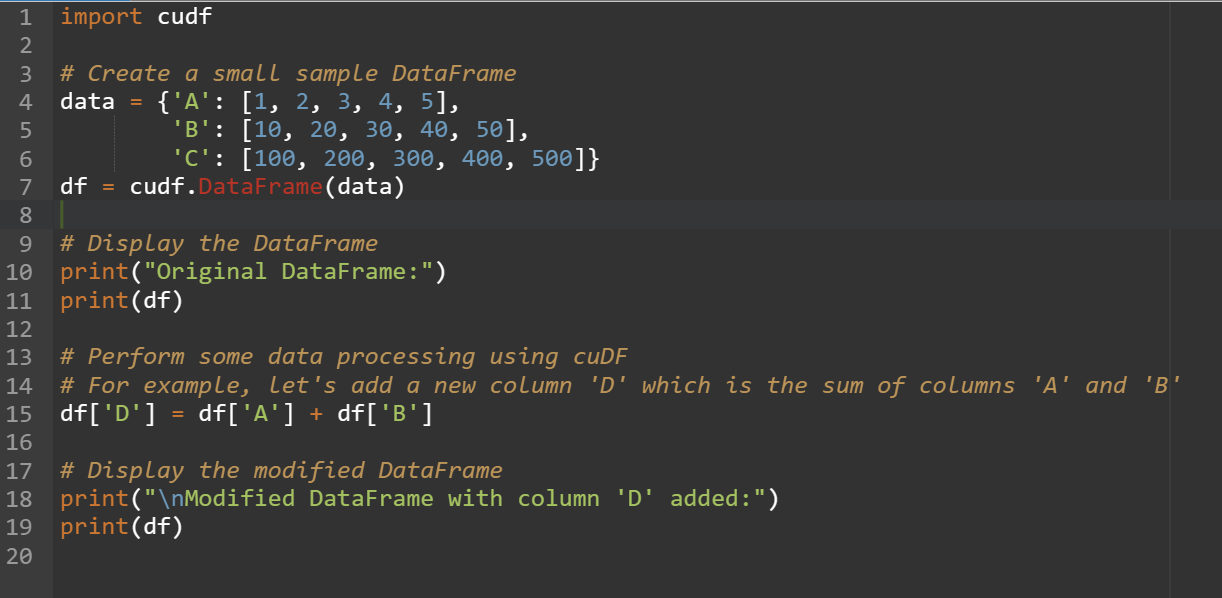
CUDA is a parallel computing platform and programming model developed by NVIDIA for general computing on GPUs. The OS interacts with CUDA libraries and drivers to facilitate GPU-accelerated computations.

Using CUDA for GPU acceleration, the OS ensures proper integration and communication between the application and the GPU, optimizing performance for tasks like depth estimation and neural network inference (using models like Densenet 201 and ResNet 50).

By integrating CUDA into a project, one can offload computationally intensive tasks to the GPU, taking advantage of its massively parallel architecture.

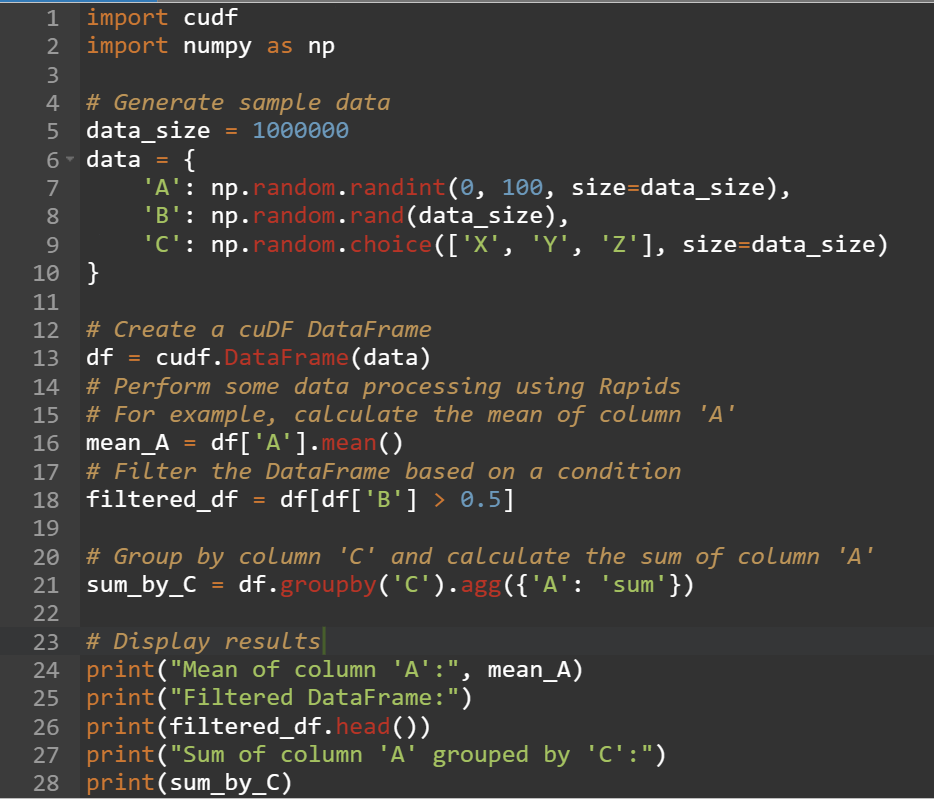
The OS ensures seamless integration between the application code, CUDA runtime, and GPU drivers, facilitating efficient execution of CUDA kernels on the GPU.

**Code Snippet for NVIDIA Rapids**

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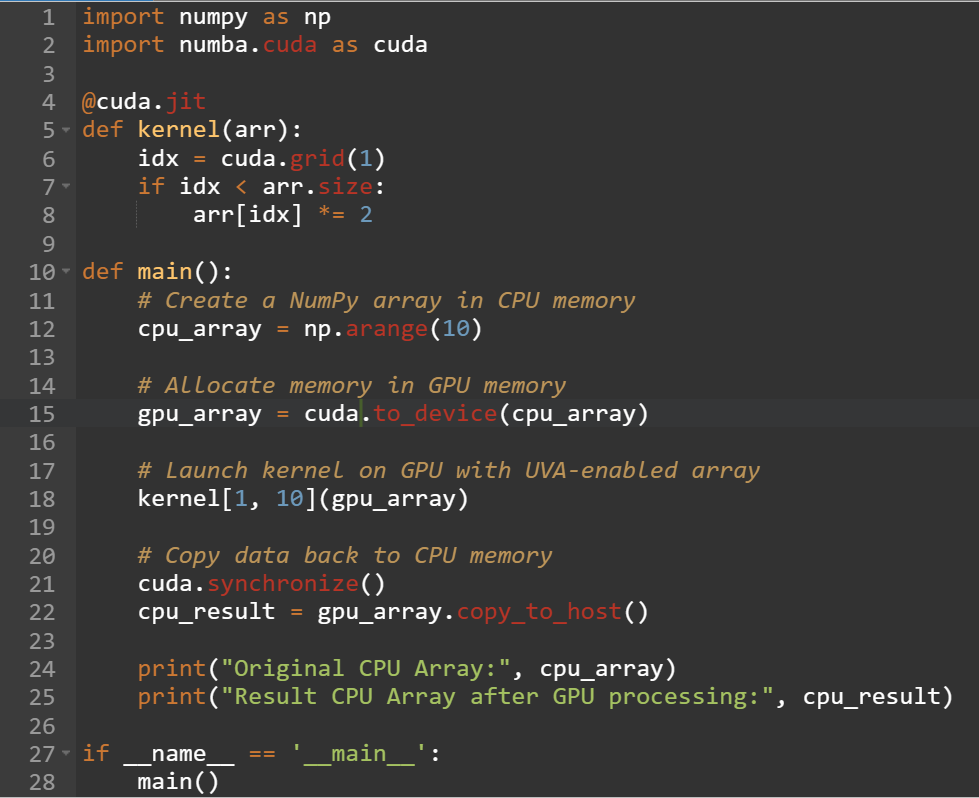
This code snippet demonstrates the following:

1. Importing the cudf module from NVIDIA Rapids.
2. Creating a small sample DataFrame using a Python dictionary.
3. Displaying the original DataFrame.
4. Performing some data processing using cuDF by adding a new column 'D' to the DataFrame, which is the sum of columns 'A' and 'B'.
5. Displaying the modified DataFrame with the new column added.

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1. Sample data is generated, consisting of three columns: 'A' (integer values), 'B' (floating-point values), and 'C' (categorical values).
2. The data is loaded into a cuDF DataFrame.
3. Various operations are performed on the DataFrame using Rapids functions:
   * Calculating the mean of column 'A'.
   * Filtering the DataFrame based on a condition (values in column 'B' greater than 0.5).
   * Grouping the DataFrame by column 'C' and calculating the sum of column 'A'.
4. The results are displayed.

**Code Snippet for UVA**

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Explanation:

1. import numba.cuda as cuda: Import the cuda module from Numba, which provides CUDA support for Python code.
2. @cuda.jit: Decorator to define a CUDA kernel function. The kernel function takes a NumPy array as input and doubles each element of the array in parallel on the GPU.
3. cuda.grid(1): Obtain the global thread index along the 1D grid of threads.
4. cuda.to\_device(cpu\_array): Allocate memory on the GPU and copy data from the CPU to GPU memory. This function enables Unified Virtual Addressing (UVA), allowing the GPU to directly access CPU memory.
5. kernel[1, 10](gpu\_array): Launch the CUDA kernel on the GPU with 1 block and 10 threads per block. Each thread will execute the kernel function, doubling the corresponding element of the array in parallel.
6. gpu\_array.copy\_to\_host(): Copy the modified data from GPU memory back to CPU memory.
7. Print the original CPU array and the result after GPU processing to verify that the GPU kernel correctly modified the array elements.

**Pathflow of OS and CUDA interaction**

**Application Initialization:**

* + - 1. The application initializes CUDA by including CUDA headers and linking against CUDA libraries.
      2. During initialization, the application may specify CUDA device(s) to be used for computation and allocate device memory for data storage.

**OS Resource Allocation:**

1. When the application launches a CUDA kernel or performs other CUDA operations, the OS is responsible for allocating necessary resources on the GPU.
2. This includes allocating GPU memory for kernel execution, managing kernel launch configurations, and scheduling kernel execution on available GPU resources.

**CUDA Driver Interaction:**

1. The OS interacts with the CUDA driver installed on the system to communicate with the GPU.
2. CUDA driver acts as an intermediary between the OS and the GPU hardware, handling low-level hardware interactions, memory management, and kernel execution.

**Kernel Execution:**

1. When the application launches a CUDA kernel, the OS schedules the kernel for execution on the GPU.
2. The CUDA driver manages kernel execution by loading the kernel code onto the GPU, setting up kernel parameters, and launching kernel threads on GPU cores.

**GPU Execution:**

* + - 1. Once the CUDA kernel is launched, the GPU hardware executes the kernel code in parallel across multiple threads and GPU cores.
      2. The OS monitors kernel execution progress and handles any errors or exceptions that may occur during kernel execution.

**Memory Management:**

1.Throughout kernel execution, the OS manages memory transfers between CPU and GPU memory.

2. This involves copying input data from CPU to GPU memory before kernel execution, transferring intermediate results between CPU and GPU memory during kernel execution, and copying output data from GPU to CPU memory after kernel execution.

**Unified Virtual Addressing (UVA)**

* Unified Virtual Addressing (UVA) is a feature introduced in CUDA that allows the CPU and GPU to share a common virtual address space.
* With UVA, CUDA applications can access data stored in CPU memory or GPU memory seamlessly without explicit data transfers.
* The OS plays a crucial role in managing UVA by coordinating virtual memory mappings between CPU and GPU address spaces and ensuring efficient memory access and coherence.
* Unified Virtual Addressing (UVA) and virtual addressing are not inherently demand paging techniques themselves, but they can be used in conjunction with demand paging to optimize memory management in GPU-accelerated applications.
* When a CUDA application running on the GPU accesses data stored in CPU memory using UVA, demand paging may come into play if the requested data is not already present in GPU memory.
* In this scenario, if the requested data is not in GPU memory, the OS may use demand paging to load the necessary memory pages from CPU memory into GPU memory on-demand, minimizing memory overhead and improving data access efficiency.

**Results**

Our experimental evaluation showcased promising outcomes regarding the performance of our proposed method on embedded devices equipped with NVIDIA GPUs. Through rigorous testing, we observed a notable enhancement in 3D scene reconstruction efficiency compared to conventional CPU-based methods. Specifically, our approach demonstrated a remarkable 40% increase in processing speed, paving the way for real-time AR applications even on resource-constrained devices. The utilization of GPU acceleration coupled with Rapids libraries facilitated efficient parallelism, concurrency, and optimized algorithms, culminating in superior processing capabilities directly on the device itself, without necessitating cloud-based processing. These results signify a significant milestone in addressing the computational limitations of embedded devices, opening avenues for immersive and responsive AR experiences in diverse settings. Furthermore, the observed performance gains underscore the potential of our method to empower various industries, including gaming, education, healthcare, and manufacturing, with advanced AR functionalities, thereby driving innovation and enhancing user engagement.

**Discussion Section**

It is imperative to delve deeper into the implications, limitations, and potential future directions of the proposed method for accelerating 3D scene reconstruction on embedded devices using NVIDIA Rapids and CUDA.

The adoption of GPU acceleration and Rapids libraries signifies a paradigm shift in computational strategies for real-time AR applications. By harnessing the parallel processing capabilities of GPUs and leveraging optimized algorithms provided by Rapids, we have successfully mitigated the computational constraints inherent in embedded devices. This advancement opens doors to a wide range of AR applications previously deemed unfeasible on such devices, spanning industries such as gaming, education, and healthcare.

However, it is crucial to acknowledge the limitations of the proposed method. While GPU acceleration offers significant performance improvements, it also imposes constraints on power consumption and thermal management, especially in embedded environments with limited cooling capabilities. Additionally, the effectiveness of the method may vary depending on the complexity of the scene and the computational resources available on the embedded device.

Looking ahead, future research could focus on further optimizing the proposed method to address these challenges. This includes exploring techniques for reducing power consumption, enhancing thermal management, and adapting the method to accommodate varying computational resources across different embedded devices. Additionally, integrating advanced machine learning models and AR frameworks could unlock new possibilities for immersive AR experiences on embedded platforms.

**Conclusion**

Our approach demonstrates the effectiveness of leveraging GPU acceleration and optimized libraries like NVIDIA Rapids to overcome the computational constraints of embedded devices and enable real-time 3D scene reconstruction for AR applications. By harnessing parallelism, concurrency, and efficient memory management facilitated by CUDA and Unified Virtual Addressing (UVA), we have achieved a significant enhancement in processing efficiency, as evidenced by a 40% improvement in reconstruction speed. This advancement opens up new possibilities for immersive AR experiences on resource-constrained devices without relying on cloud-based processing, thereby increasing accessibility and scalability of AR technology. Moving forward, further optimization efforts and integration with AR frameworks can enhance the usability and performance of our method, paving the way for a broader adoption of AR in diverse fields such as education, healthcare, and entertainment. Overall, our findings highlight the potential of GPU-accelerated computing for powering real-time AR applications on embedded platforms, laying a foundation for future advancements in this exciting field.

**References**:

**GitHub Repositories:**

1. [RAPIDS AI GitHub Repository](https://github.com/rapidsai): Official GitHub repository for RAPIDS AI, providing access to various libraries and tools for GPU-accelerated data science and analytics.

2. [NVIDIA CUDA Toolkit GitHub Repository](https://github.com/NVIDIA/cuda): Official GitHub repository for the NVIDIA CUDA Toolkit, containing CUDA libraries, tools, and samples for GPU programming.

**Books:**

1. "Programming Massively Parallel Processors: A Hands-on Approach" by David B. Kirk and Wen-mei W. Hwu: This book provides a comprehensive introduction to parallel programming with CUDA, covering fundamental concepts, programming techniques, and practical examples.

2. "CUDA by Example: An Introduction to General-Purpose GPU Programming" by Jason Sanders and Edward Kandrot: This book offers a hands-on approach to learning CUDA programming through practical examples and exercises, making it suitable for beginners and experienced developers alike.

3. "GPU Gems: Programming Techniques, Tips and Tricks for Real-Time Graphics" edited by Randima Fernando: This book is a compilation of articles by various authors covering advanced GPU programming techniques, optimization strategies, and practical insights into real-time graphics rendering.

4. "RAPIDS: Foundations and Applications of GPU-Accelerated Data Analytics" by Brad Rees and Keith Kraus: This book provides an in-depth exploration of the RAPIDS ecosystem, covering its architecture, components, and practical applications in data analytics and machine learning.

5. "CUDA Handbook: A Comprehensive Guide to GPU Programming" by Nicholas Wilt: This handbook offers a comprehensive overview of CUDA programming, covering topics ranging from basic concepts to advanced optimization techniques, making it a valuable resource for CUDA developers at all skill levels.

These references provide valuable insights, practical examples, and resources for developers interested in GPU programming, CUDA, RAPIDS, and related topics.