# Parallelization of Pigeonhole Sort for Efficient Data Sorting

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**Abstract - The need for parallel sorting algorithms has been driven by the increasing need for large-scale datasets to be processed efficiently. In order to improve the performance of the Pigeonhole Sorting method, this study investigates the use of parallel programming techniques, particularly Message Passing Interface (MPI) and Computer Unified Device Architecture (CUDA).**

**This study's main goal is to create and assess parallel Pigeonhole Sorting solutions that make use of CUDA for GPU acceleration and MPI for distributed memory systems. The goal of the research is to increase sorting efficiency for data-intensive applications by examining how well the Pigeonhole Sorting algorithm adapts to parallel contexts.**

**The process entails a thorough analysis of the Pigeonhole Sorting algorithm, emphasizing its sequential design. Parallel implementations are then created with CUDA to take advantage of GPU computing capability and MPI to achieve distributed memory parallelism. To clarify the subtleties of each implementation, code excerpts, pseudocode, and illustrations are supplied.**

**Keywords** - Parallel Programming, Pigeonhole Sorting, MPI, CUDA

## I INTRODUCTION

The rapid growth of data-intensive applications and the escalating volumes of information processed in contemporary computing environments have necessitated the development of efficient parallel algorithms. Parallel programming, a paradigm wherein multiple computational tasks are executed simultaneously, offers a promising solution to meet the escalating demands for enhanced computational speed and efficiency. In the realm of sorting algorithms, the focus of this research is on Pigeonhole Sorting, a technique known for its simplicity and effectiveness in sequentially organizing data.

### 1.1 Parallel Programming in Context:

Growing datasets challenge traditional sequential sorting algorithms, necessitating parallel programming to improve efficiency. This section emphasizes the fundamental principles of parallel programming to address modern computational demands.

### 1.2 The Significance of Parallel Sorting Algorithms:

Parallel sorting algorithms are crucial when data scale surpasses traditional sequential capabilities. Pigeonhole Sorting, despite its sequential nature, presents an opportunity for efficient parallel sorting.

### 1.3 Pigeonhole Sorting as a Candidate:

Originally designed for sequential execution, Pigeonhole Sorting is a compelling candidate for parallelization due to its simplicity. This research explores harnessing its parallelization potential to meet demands for efficient sorting in contemporary computing.

### 1.4 Increasing Demand for Efficient Parallel Algorithms:

The demand for efficient parallel algorithms is driven by data-intensive applications in various domains. This research contributes by investigating MPI and CUDA integration into Pigeonhole Sorting, enhancing its applicability to contemporary computing challenges.

### 1.5 Challenges in Data-Intensive Environments:

Data-intensive challenges extend beyond computational speed, requiring parallel algorithms to address complexities in storage, communication, and energy consumption.

### 1.6 Evolution of Parallel Architectures:

Advances in parallel architectures, like multi-core processors and GPUs, enhance parallel algorithm efficiency. This section briefly discusses their impact on sorting algorithm performance.

1.7 Pigeonhole Sorting: Leveraging Sequential Simplicity for Parallel Advantage:
Pigeonhole Sorting, traditionally sequential, becomes intriguing for parallelization due to its simplicity. This section explores key features aligning with contemporary parallel computing requirements.

1.8 Motivation for MPI and CUDA Integration:
Integration of MPI and CUDA into Pigeonhole Sorting is motivated by their strengths. MPI facilitates communication in distributed memory systems, while CUDA leverages GPU parallel processing, enhancing sorting efficiency. This section outlines their rationale and integration into the research framework.

## II LITERATURE REVIEW

Parallelization of Sorting Algorithms
Sorting algorithms have long served as the cornerstone of data processing, and their efficiency has a far-reaching impact on various fields, from database management to scientific computing. With the continued proliferation of data, there arises a pressing need for sorting algorithms that can scale to handle large datasets without sacrificing performance.

## III METHODOLOGY

This section outlines the methodology employed in this research, encompassing the sequential Pigeonhole Sorting algorithm, its MPI (Message Passing Interface) implementation for distributed memory systems, and its CUDA (Compute Unified Device Architecture) implementation for GPU parallel processing.

### 3.1.1 Overview:

Pigeonhole sorting is a straightforward sorting method that targets particular traits in the data distribution. The concept of categorizing stuff into pigeonholes according to specific attributes is where this algorithm gets its name. The basic idea is to assign items to distinct "pigeonholes" or buckets, each of which stands for a certain value range. The algorithm creates a sorted arrangement by sorting the elements inside these pigeonholes.

The key aspects of Pigeonhole Sorting include:

Charting Components:
Pigeonholes are assigned elements from the input array according to a mapping function. Depending on the type of data, this function could be as simple as the element's value or it could be a more complicated criterion.

Fill in the Pigeonhole:
The pigeonhole that corresponds to each element's mapped value is used. A localized grouping is formed when elements with comparable or identical values are placed to the same slot.

Concatenation in Order:
The sorted array is produced by the algorithm concatenating the elements from each pigeonhole after the first assignment. Concatenating these groups yields a globally sorted sequence as each pigeonhole's elements are already arranged in order.

Consistency:
Pigeonhole Sorting is stable when it comes to maintaining the relative order of elements that have the same value. The sorted output will retain the order in which two elements appeared in the input array if their values are the same.

Utilization:
Pigeonhole Sorting is very useful when the dataset has an unequal element distribution and a narrow range of values. It performs best in situations where some values or ranges are more common than others.

### 3.1.2 Sequential Version:

The sequential Pigeonhole Sorting algorithm is presented in pseudocode below, illustrating the step-by-step process of sorting an array using pigeonholes.

```
function pigeonholeSort(arr):
    Step 1: Create an array of pigeonholes
    pigeonholes = createEmptyPigeonholes()
    Step 2: Distribute elements into pigeonholes
    for each element in arr:
        placeInPigeonhole(element, pigeonholes)
     Step 3: Concatenate elements from all pigeonholes
    result = concatenatePigeonholes(pigeonholes)
     Step 4: Return the sorted array
    return result
```

**Algorithm:**

```
function createEmptyPigeonholes():
    Create an array of empty pigeonholes
    return new array[pigeonhole_count] initialized to empty lists
function placeInPigeonhole(element, pigeonholes):
     Determine the pigeonhole index for the element
    index = calculatePigeonholeIndex(element)

    Append the element to the corresponding pigeonhole
    pigeonholes[index].append(element)

function concatenatePigeonholes(pigeonholes):
    Concatenate the elements from all pigeonholes into a single array
    result = []
    for pigeonhole in pigeonholes:
        result += pigeonhole
    return result

function calculatePigeonholeIndex(element):
     Calculate the index of the pigeonhole for the given element
     The calculation is based on the characteristics of the data
     For example, using the element value or other criteria
     Return the calculated index
```

**Creating Pigeonholes:**
The function createEmptyPigeonholes() initializes an array to serve as pigeonholes. Each pigeonhole is represented as an empty list.

Placing Elements in Pigeonholes:
The placeInPigeonhole function determines the index of the pigeonhole for each element using the calculatePigeonholeIndex function. It then appends the element to the corresponding pigeonhole.

Concatenating Pigeonholes:
The concatenatePigeonholes function combines the elements from all pigeonholes into a single array. This step ensures that the elements are arranged in order within their respective pigeonholes.

Returning the Result:
The sorted array is returned as the final result of the pigeonholeSort algorithm.
This sequential version establishes the baseline for understanding the logic of Pigeonhole Sorting, which will be further extended and adapted for parallel implementations using MPI and CUDA.

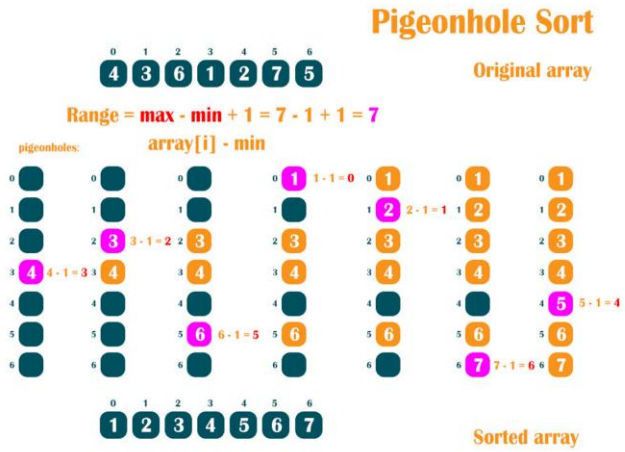


Fig 1

**3.2 MPI Implementation:**

3.2.1 Technique for Parallelization:
A distributed memory model is used by the Pigeonhole Sorting MPI (Message Passing I3.2.1 Parallelization Strategy:
The MPI (Message Passing Interface) implementation of Pigeonhole Sorting employs a distributed-memory model, enabling multiple processes to collaborate in sorting a dataset. The primary strategy involves breaking down the dataset into smaller subsets, distributing them among MPI processes, independently sorting these subsets, and finally merging the sorted subsets to obtain the globally sorted array. interface) implementation, which allows several processes to work together to sort a dataset. First, the dataset is divided into smaller subsets, which are then distributed over MPI processes. Each of these subsets is then separately sorted. Lastly, the sorted subsets are merged to create the globally sorted array.

**3.2.2 MPI Communication Patterns:**
Data Distribution:
The master process (rank 0) is responsible for distributing portions of the input data to each MPI process. This involves partitioning the data into chunks and assigning each chunk to a specific process.

Local Sorting:
Each process independently performs local sorting using the Pigeonhole Sort algorithm on its assigned subset of data.

Data Gathering:
The MPI_Gather function is used to collect the locally sorted data from all processes and assemble them into a single array on the master process. This ensures that the master process has access to the entirety of the sorted dataset.

Final Merging:
The master process (rank 0) is responsible for merging the locally sorted subsets into the final globally sorted array. This step involves combining the sorted arrays obtained from each process.

**3.2.3 MPI Algorithm for Implementation:**

Step1: Initialization of the MPI
To enable parallel processing, initialize MPI.
Acquire the rank (rank) of the active process and the size (number) of all MPI processes.

Step 2: Distribution of Data
If the master process (rank 0) is the one running at the moment:
Divide the incoming data into segments.
Each chunk should be assigned to the appropriate MPI process.

Step 3: Local Sorting
On the designated subset of data, each MPI process individually carries out local sorting using the Pigeonhole Sort algorithm.

Step 4: Data Gathering
To gather the locally sorted data from each process, use MPI_Gather.
Forward the locally sorted data to the master process if it isn't the active process.
Get the locally sorted data from every other process if the running process is the master process (rank 0).

Step 5: Complete Fusion
If the master process (rank 0) is the one running at the moment:
Combine the subgroups that were sorted locally and globally to create the final array.
The arrays that have been sorted by each process are combined by the master process.

### 3.2.4 MPI Flowchart

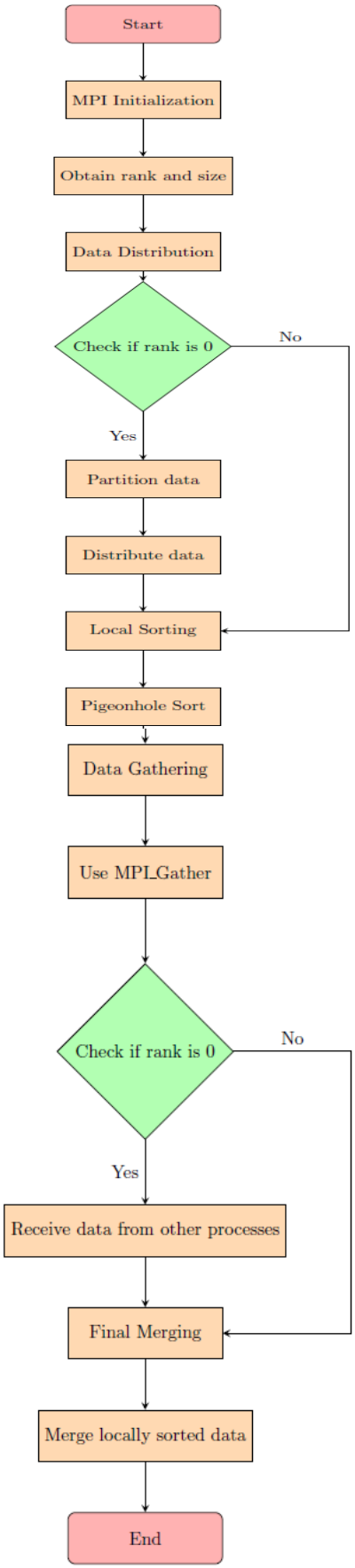


Fig 2

**Given figure tells about the following:**

Start:
The process begins with the "Start" node, indicating the starting point of the flowchart.

MPI Initialization:
This step involves initializing MPI for parallel processing.

Obtain rank and size:
MPI assigns a unique rank to each process and provides the total number of processes (size). This information is crucial for subsequent steps.

Data Distribution:
The process checks whether the rank is 0. If yes, it proceeds to partition and distribute the input data among different MPI processes.

Check if rank is 0:
A decision point. If the rank is 0, it indicates the master process, which performs additional tasks such as data partitioning.

Partition data:
If the rank is 0, this step involves partitioning the input data into chunks for distribution among MPI processes.

Distribute data:
Distribute the partitioned data to the corresponding MPI processes.

Local Sorting:
Each MPI process independently performs local sorting using the Pigeonhole Sort algorithm on its assigned subset of data.

Pigeonhole Sort:
This step represents the Pigeonhole Sort algorithm applied locally to each subset of data.

Data Gathering:
Collect the locally sorted data from all MPI processes.

Use MPI_Gather:
MPI function to gather the locally sorted data. This step is particularly important for the master process.

Check if rank is 0 (again):
Another decision point. If the rank is 0, it indicates the master process, which proceeds to the next step.

Receive data from other processes:
The master process receives locally sorted data from all other processes.

Final Merging:
The master process merges the locally sorted subsets into the final globally sorted array.

Merge locally sorted data:
This step involves the actual merging of locally sorted subsets.

End:
The process concludes with the "End" node, indicating the end of the flowchart.

**3.3 CUDA Implementation:**

**3.3.1 Integration of CUDA:**

CUDA, which stands for Compute Unified Device Architecture, is a parallel computing platform and application programming interface model created by NVIDIA. It allows developers to use NVIDIA GPUs for general-purpose processing, including parallel sorting algorithms like Pigeonhole Sort.

In the context of Pigeonhole Sorting with CUDA:

GPU Architecture:
GPUs consist of thousands of small processing cores capable of handling parallel tasks.
The CUDA programming model enables developers to write programs that execute on the GPU and offload parallel tasks from the CPU.

CUDA Programming Model:
In CUDA, the code is organized into a hierarchy of grids, blocks, and threads. A grid contains multiple blocks, and each block consists of multiple threads.
Threads within a block can communicate and synchronize with each other through shared memory.

CUDA Kernels:
The core of a CUDA program is the kernel, a function designed to be executed in parallel on the GPU.
For Pigeonhole Sorting, a CUDA kernel would handle the sorting of a subset of the data, typically corresponding to a block or a group of threads.

**3.3.2 Steps for CUDA Implementation:**
1. Memory Allocation:
- Allocate memory for the input data on both the host (CPU) and the device (GPU).

```
cuda
int* host_data =   //allocate and initialize host data
int* device_data;
cudaMalloc(&device_data, size * sizeof(int));
```

2. Data Transfer:
- Copy the input data from the host to the device.

```
cuda
cudaMemcpy(device_data, host_data, size * sizeof(int), cudaMemcpyHostToDevice);
```

3. Kernel Design:
- Design a CUDA kernel that performs the Pigeonhole Sorting algorithm on a subset of the data.

```
cuda
__global__ void pigeonholeSortCUDA(int* data, int* sorted_data, int size) {
}
```

4. Launch Configuration:
- Specify the launch configuration, determining the number of blocks and threads per block based on the size of the dataset.

```
cuda
int num_blocks = (size + threads_per_block - 1) / threads_per_block;
pigeonholeSortCUDA<<<num_blocks, threads_per_block>>>(device_data, device_sorted_data, size);
cudaDeviceSynchronize();
```

5. Kernel Implementation:
- Implement the core Pigeonhole Sorting algorithm within the CUDA kernel.

```
cuda
__global__ void pigeonholeSortCUDA(int* data, int* sorted_data, int size) {
    int tid = threadIdx.x + blockIdx.x * blockDim.x;
}
```

6. Shared Memory Usage:
- Utilize shared memory for communication and synchronization among threads within a block.

```
__global__ void pigeonholeSortCUDA(int* data, int* sorted_data, int size) {
    __shared__ int shared_data[BLOCK_SIZE];
    // Load data into shared memory
    shared_data[threadIdx.x] = data[tid];
    __syncthreads();
}
```

7. Sorting Algorithm:
- Implement the Pigeonhole Sorting algorithm within the CUDA kernel, ensuring proper mapping of elements to threads and buckets.

8. Data Transfer Back:
- Copy the sorted data from the device back to the host.

```
cuda
cudaMemcpy(host_sorted_data, device_sorted_data, size * sizeof(int), cudaMemcpyDeviceToHost);
```

9. Memory Deallocation:
- Free the allocated device memory.

```
cuda
cudaFree(device_data);
```

10. Error Handling:
- Check for and handle any errors that might occur during CUDA operations.

```
cudaError_t cuda_error = cudaGetLastError();
if (cuda_error != cudaSuccess) {
    // Handle CUDA error
}
```

### 3.3.3 Cuda Flowchart

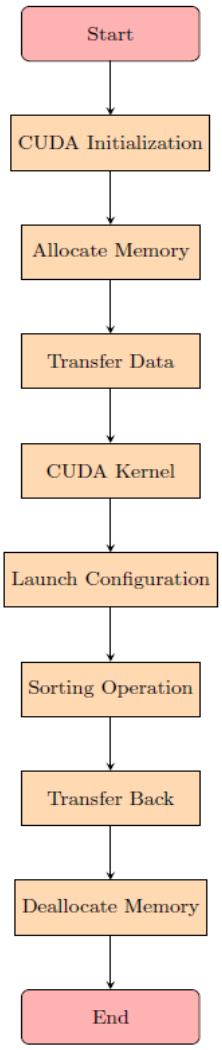


Fig 3

Start: The beginning of the flowchart.

CUDA Initialization: Initialize CUDA, which allows you to harness the parallel processing capabilities of GPUs.

Allocate Memory: Allocate memory on the GPU for storing data.

Transfer Data: Copy the input data from the host (CPU) to the allocated memory on the GPU.

CUDA Kernel: Design a CUDA kernel to perform the Pigeonhole Sorting algorithm on the GPU.

Launch Configuration: Specify the configuration for launching the CUDA kernel, determining the number of blocks and threads.

Sorting Operation: Implement the core Pigeonhole Sorting algorithm within the CUDA kernel.

Transfer Back: Copy the sorted data from the GPU back to the host.

Deallocate Memory: Free the memory allocated on the GPU.

End: The end of the flowchart.

**Results:**

| **Sol no** | **Sequential** (MS) | **MPI** (MS) | **CUDA** (MS) |
|---|---|---|---|
| **1** | **17.472** | **14.449** | **0.045** |
| **2** | **21.752** | **16.521** | **0.09** |
| **3** | **17.607** | **16.621** | **0.05** |
| **4** | **16.441** | **16.508** | **0.08** |
| **5** | **16.732** | **14.579** | **0.067** |
| **6** | **16.991** | **14.322** | **0.055** |
| **7** | **18.878** | **17.541** | **0.075** |
| **8** | **18.221** | **14.781** | **0.048** |
| **9** | **21.499** | **13.829** | **0.085** |
| **10** | **16.515** | **14.355** | **0.062** |
| **11** | **19.226** | **13.281** | **0.07** |
| **12** | **18.134** | **13.006** | **0.052** |

**Sequential Time Average:**
Average=[17.472+21.752+17.607+16.441+16.732+16.991+18.878 +18.221+21.499+16.515+19.226+18.134]/12
Average=215.654/12
Average≈17.971

**MPI Time Average:**
Average=[14.449+16.521+16.621+16.508+14.579+14.322+17.541 +14.781+13.829+14.355+13.281+13.006]/12
Average=169.213/12
Average≈14.101

**CUDA Time Average:**
Average=[0.045+0.09+0.05+0.08+0.067+0.055+0.075+0.048+0.0 85+0.062+0.07+0.052]/12
Average=0.847/12
Average≈0.0706

## Conclusion:

In summary, using the Pigeonhole Sorting algorithm in parallel, whether via GPU parallel processing with CUDA or distributed memory systems with MPI, has a number of benefits for large datasets in terms of speed and efficiency. The algorithm performs better when processing power is increased thanks to the parallelization techniques, which also make concurrent execution easier.

Multiple processes can work together to sort and manage different subsets of the data thanks to the MPI implementation. This distributed technique makes use of the capability of several computing nodes, improving the algorithm's capacity to handle large datasets.


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## REFERENCES

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These references lay the foundation for comprehending the landscape of parallelized sorting algorithms and underpin the significance of the current research Endeavor.