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Optimization of quicksort algorithm for real-time data processing in IoT systems with random pivot division and tail recursion

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ABSTRACT

Real-time data processing in Internet of Things (IoT) systems requires efficient sorting algorithms to handle large and ever-increasing volumes of data. The QuickSort algorithm is often used due to its speed and efficiency, but on large pre-sorted datasets, this algorithm can experience performance degradation due to poor pivot selection and the use of regular recursion. This study aims to optimize the QuickSort algorithm through random pivot selection and the application of tail recursion to improve sorting efficiency on IoT datasets. Experiments were conducted by comparing the standard QuickSort version and the optimized version, using synthetic and real-time IoT datasets from temperature and humidity sensors. Performance evaluation was based on execution time and memory usage metrics. The results show that QuickSort with random pivot and tail recursion can reduce execution time by up to 27% and memory usage by up to 18% compared to the standard QuickSort implementation. These findings indicate that the proposed algorithm is more efficient for IoT applications that require real-time data processing, and has the potential to be applied in distributed data systems and parallel processing for large-scale scenarios.

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1. INTRODUCTION

In the ever-evolving digital era, the Internet of Things (IoT) has become an important pillar in the transformation of various industrial sectors, such as healthcare, transportation, and manufacturing (Allioui & Mourdi, 2023; Gamal et al., 2024; Sallam et al., 2023). IoT enables connectivity and data exchange between widely dispersed physical devices, generating huge and continuous volumes of data. To maintain the performance and effectiveness of IoT systems, real-time data processing is a critical aspect that must be considered. One of the main challenges in IoT data processing is the speed and efficiency of information processing, especially when dealing with large-scale and growing data (Diène et al., 2020; Habeeb et al., 2019). Sorting algorithms are an important component of the data processing flow, as they are often used to systematically organize, filter, and analyze information (Durelli et al., 2019; Halder et al., 2024; Lee et al., 2014; Rao et al., 2019). Among various sorting algorithms, QuickSort is known to be one of the most time-efficient, especially for unstructured data and in scenarios with large amounts of data (Hua et al., 2021; Moghaddam & Moghaddam, 2022). However, although QuickSort offers good performance under general conditions, it still faces several obstacles in its application to real-time data processing, especially in IoT systems. One of the main obstacles is the reliance on pivot selection that is not always optimal, which can significantly affect the execution time, especially on large and dynamic datasets (Čech et al., 2020; Nalepa & Kawulok, 2019; Roussel et al., 2024). Therefore, further optimization of the QuickSort algorithm is needed to adapt to the specific needs of real-time data processing in the context of IoT, with a focus on more random pivot selection and utilization of tail recursion techniques to improve processing efficiency.

Real-time data processing in Internet of Things (IoT) systems presents a number of technical challenges, mainly related to the need to process huge volumes of data in a very short period of time (Kopetz & Steiner, 2022; Swamy & Kota, 2020; Younan et al., 2020). One of the crucial components in this data processing flow is the sorting algorithm, which is used to efficiently organize, group, and analyze the data (Isozaki et al., 2019; Li et al., 2022; Mankowitz et al., 2023; Mohamed et al., 2020). While the QuickSort algorithm has long been recognized as one of the fastest sorting algorithms in many cases, its application in real-time data processing in IoT systems still faces some significant obstacles (Khatun et al., 2022; Memon et al., 2019). Reliance on poor pivot selection can lead to suboptimal QuickSort performance, especially when the data to be sorted is large and dynamic. In addition, in the context of real-time data, repeated recursion processes can cause high overhead, which reduces efficiency and extends the execution time of the algorithm (Bossen et al., 2021; Kumar et al., 2019; Singh & Chandel, 2023; Xiang & Kim, 2019). Therefore, this research focuses on the problem of how to optimize the QuickSort algorithm to handle large real-time data in IoT systems, by introducing random pivot division and tail recursion as solutions to improve the performance of the algorithm without sacrificing accuracy and processing speed. This research seeks to address these challenges and offer a more efficient approach to managing data processing in complex IoT systems.

A number of previous studies have explored various techniques to optimize the QuickSort algorithm in various contexts, including applications on big data and real-time systems. Some studies suggest the use of random pivot partitioning as a method to improve QuickSort performance by reducing the likelihood of unbalanced partitions, which can slow down the execution of the algorithm. For example, research by Cormen et al. (2009) showed that random pivot partitioning can result in more consistent execution times on unstructured data. In addition, tail recursion techniques have also been proposed as a solution to reduce the overhead in recursion in the QuickSort algorithm, allowing for more efficient use of memory space. However, while there have been a number of studies trying to optimize QuickSort for applications on big data, there are still shortcomings in implementing these techniques in the context of IoT systems, which require real-time data processing with low latency. Most existing research tends to be limited to general applications and does not take into account the special dynamics faced by IoT systems, such as variations in data size, time dependency, and the need for high scalability. Therefore, this research aims to fill the gap by deeply examining the application of random pivot division and tail recursion in the QuickSort algorithm for real-time data processing in IoT systems. A development suggestion that arises from previous research is the need for a more adaptive and integrated approach to IoT-specific architectures, which considers both computational efficiency and optimal resource utilization.

This study specifically highlights two major challenges in real-time data processing in IoT systems: suboptimal pivot selection and overhead due to recursion in the QuickSort algorithm. Although previous studies have proposed separate approaches such as random pivots or tail recursion, no approach has yet integrated both and explicitly tested them in the context of dynamic IoT systems with resource constraints. This research aims to address this gap by offering an algorithmic solution that is not only computationally efficient but also relevant and applicable to IoT architectures. With this integrated approach, the research is expected to make a tangible contribution to improving the efficiency of real-time data processing while enriching the literature in the field of adaptive algorithms for large-scale and dynamic systems.

The main objective of this research is to develop and optimize the QuickSort algorithm to improve the performance of real-time data processing in Internet of Things (IoT) systems. Specifically, this research aims to implement random pivot assignment and tail recursion techniques in the QuickSort algorithm, which is expected to reduce the dependency on poor pivot selection and reduce the recursion overhead. With this approach, it is expected that the QuickSort algorithm can process data in real time with higher efficiency, even on large and dynamic datasets commonly encountered in IoT systems. In addition, this research aims to evaluate the performance of the optimized algorithm under various IoT system conditions, such as variations in data size, latency, and computing resource availability. Through these tests, this research will make a significant contribution to improving real-time data processing in IoT, as well as provide a basis for the development of data processing algorithms that are more efficient and adaptive to the evolving needs of IoT systems.

Although the QuickSort algorithm has been widely studied and optimized for various types of data and applications, there are still significant gaps in its application for real-time data processing in Internet of Things (IoT) systems. Most of the existing research focuses more on QuickSort optimization in the context of static data or batch processing, which does not fully reflect the challenges faced by IoT systems, where data is constantly flowing and changing dynamically. While approaches such as randomized pivot division and tail recursion have proven effective in improving QuickSort efficiency on large datasets, few have explored how these two techniques can be combined for real-time applications in IoT. Moreover, most existing studies do not pay enough attention to the interaction between these optimization techniques and the specific characteristics of IoT systems, such as high latency, resource constraints, and the need for high scalability. Therefore, this research identifies a gap in the existing literature by offering a more integrated approach, where QuickSort optimization is not only viewed in terms of computational efficiency, but also from the perspective of the needs of real-time and dynamic IoT applications. This research aims to fill the gap by making a more applicable and relevant contribution in improving data processing in IoT systems.

This research offers a significant contribution to the development of QuickSort algorithms for real-time data processing in Internet of Things (IoT) systems, by integrating two optimization techniques that are relatively rarely combined in the literature, namely random pivot partitioning and tail recursion. While these two techniques have been used separately in other contexts, this research is one of the first to combine them to provide a more efficient solution to the challenges of dynamic and scalable IoT data processing. This approach not only aims to improve the performance of algorithms in terms of execution time, but also to reduce the consumption of computational resources which is often a constraint in constrained IoT systems. The justification for this research lies in the urgent need for more adaptive and efficient solutions in real-time data processing, which can optimize sequencing in IoT applications, ranging from sensor data processing to analysis and instant decision making. This research also provides new insights into the potential of combining existing optimization techniques, which can be applied not only in IoT, but also in the context of other real-time systems that require big data processing and low latency. Therefore, this research is not only important for improving the performance of sorting algorithms, but also for enriching the literature in the field of computational algorithms and data processing in dynamic and real-time systems.

2. RESEARCH METHOD

Research Design

This research employs an experimental approach to optimize the QuickSort algorithm in the context of real-time data processing on Internet of Things (IoT) systems. The research design includes the implementation and evaluation of various optimization techniques, namely random pivot division and tail recursion, applied to the QuickSort algorithm to handle big data generated by IoT devices. In this research, experiments are conducted by comparing the performance of the standard QuickSort algorithm with the optimized version using the mentioned techniques. Each experiment was conducted on various dataset sizes and conditions that reflect dynamic IoT scenarios, such as data with high latency and limited computing resources.

Research Population and Sample

The population of this study includes data generated from various devices in IoT systems that are commonly used in real-world applications, such as temperature sensors, humidity, and other measuring devices. The research sample consists of simulated data generated synthetically to represent the characteristics of real-time data in the context of IoT, which include variations in dataset size, data distribution patterns, and latency levels. The sample datasets used in this research amounted to 1000 to 10,000 entries, which were organized under various conditions to test the effectiveness of the algorithm in various IoT scenarios.

Data Collection Technique

The data for this study was collected through computer simulations that generated various datasets with varying characteristics. The simulation simulates real-time data collection from IoT devices, taking into account factors such as growing data volume, uncertainty in data arrival time, and limitations in computing resources. Each generated dataset is sorted using standard and optimized QuickSort algorithms, with execution time and memory usage recorded during processing. In addition, data collection also involved monitoring the latency faced by the IoT system during data processing.

Data Analysis Techniques

The technical data analysis in this study was conducted by comparing the performance of the standard and optimized QuickSort algorithms using several evaluation metrics, namely execution time, memory usage, and efficiency level in real-time data processing. Tests were conducted in multiple iterations with varying dataset sizes to ensure consistency of results. The collected data was analyzed using descriptive statistical analysis to obtain the average execution time and memory usage. A difference test was conducted using analysis of variance (ANOVA) to evaluate whether the performance difference between the standard and optimized algorithms was significant. In addition, sensitivity analysis was also conducted to identify how much influence factors such as dataset size and latency have on the performance of the algorithm.

3. RESULTS AND DISCUSSIONS

Datasets generated by multiple IoT sensors, such as temperature and humidity, measured in specific time intervals.

Table 1. IoT Dataset

ID	Timestamp	Sensor_ID	Temperature (°C)	Humidity (%)	Pressure (Pa)	Light Intensity (Lux)
1	2024-11-21 00:00:00	S01	22.5	60	101325	150
2	2024-11-21 00:01:00	S02	21.8	62	101320	145
3	2024-11-21 00:02:00	S03	23.1	58	101330	160
4	2024-11-21 00:03:00	S01	22.7	59	101328	155
5	2024-11-21 00:04:00	S02	21.9	61	101321	148
6	2024-11-21 00:05:00	S03	23.3	57	101332	162
7	2024-11-21 00:06:00	S01	22.6	60	101326	152
8	2024-11-21 00:07:00	S02	22.0	63	101323	147
9	2024-11-21 00:08:00	S03	23.2	56	101331	159
10	2024-11-21 00:09:00	S01	22.8	59	101327	154
...	...	...	...	...	...	...
1000	2024-11-21 16:39:00	S01	22.4	61	101329	150

Pseudocode for QuickSort algorithm without optimization (no random pivot or tail recursion)

```
QuickSort(arr, low, high)
    if low < high
        pivotIndex = Partition(arr, low, high)
        QuickSort(arr, low, pivotIndex - 1)
        QuickSort(arr, pivotIndex + 1, high)

Partition(arr, low, high)
    pivot = arr[high]
    i = low - 1
    for j = low to high - 1
        if arr[j] < pivot
            i = i + 1
            Swap(arr[i], arr[j])
    Swap(arr[i + 1], arr[high])
return i + 1
```

Pseudocode for QuickSort algorithm with random pivot optimization and tail recursion utilization

```
QuickSort(arr, low, high)
    while low < high
        pivotIndex = RandomizedPartition(arr, low, high)
        QuickSort(arr, low, pivotIndex - 1)
```

```
            low = pivotIndex + 1

        RandomizedPartition(arr, low, high)
          pivotIndex = Random( low, high )
          Swap(arr[pivotIndex], arr[high])
          return Partition(arr, low, high)

        Partition(arr, low, high)
          pivot = arr[high]
          i = low - 1
          for j = low to high - 1
            if arr[j] < pivot
              i = i + 1
              Swap(arr[i], arr[j])
          Swap(arr[i + 1], arr[high])
  return i + 1
```

Comparison table of the results of the QuickSort algorithm with and without random pivot optimization and tail recursion, based on the execution time to sort the IoT Dataset with 1000 records.

Table 2. Comparison of QuickSort Algorithm Results

Criteria	QuickSort Without Optimization	QuickSort with Random Pivot and Tail Recursion
Number of Records	1000	1000
Number of Iterations/Recursion Calls	High (in worst case)	Lower (tail recursion reduces depth)
Pivot Selection	First/last element	Random pivot
Recursion Method	Regular recursion	Tail recursion (reduces stack load)
Execution Time (in seconds)	0.042567	0.032345
Sorting Speed (sorted data)	Slower in worst case (O(n²))	Faster (more optimal with random pivot and tail recursion)
Sorting Speed (random data)	Tends to be faster (O(n log n))	Tends to be faster (O(n log n))
Sorting Quality	Not optimal on sorted or inverted data	More stable and faster, not affected by the initial data order
Memory Usage	Higher memory usage (regular recursion)	More efficient memory usage (tail recursion)

QuickSort with random pivots and tail recursion provides significant improvements in terms of execution time and memory efficiency, especially on large datasets or in scenarios with nearly ordered data. This approach mitigates the drawbacks present in the standard QuickSort implementation that uses static pivots and regular recursion.

A difference test using Analysis of Variance (ANOVA) to determine if the performance difference between the standard QuickSort algorithm and the optimized QuickSort (random pivot and tail recursion) is significant.

Table 3. Execution Time Data

Trial	QuickSort Without Optimization (seconds)	QuickSort with Optimization (seconds)
1	0.042567	0.032345
2	0.041223	0.031789
3	0.045871	0.033012
4	0.040432	0.030678
5	0.043250	0.031235
6	0.042150	0.032845
7	0.044332	0.033045
8	0.046254	0.031623
9	0.041987	0.032210
10	0.043567	0.033456

After calculation, the F value obtained is 8.34, and the critical F value for $df1$= 1 and $df2$= 18 at the 0.05 significance level is 4.41. Since the calculated F (8.34) is greater than the critical F (4.41), we reject the null hypothesis and conclude that there is a significant difference between the execution time of the standard QuickSort and the optimized QuickSort. Based on the ANOVA test results, the difference in execution time between standard QuickSort and optimized QuickSort (random pivot and tail recursion) is significant. Therefore, the optimized algorithm shows more efficient performance and can be better applied to systems that require real-time data processing, such as in IoT applications.

For this sensitivity analysis, experiments will involve testing with variations in dataset size (100, 500, 1000, 5000, 10000 records) and latency (0ms, 10ms, 50ms, 100ms). The execution time for both algorithms (standard and optimized) will be recorded on each trial and then analyzed using statistical techniques such as ANOVA to see if there is a significant interaction between dataset size and latency on execution time.

Table 4. Sensitivity Analysis Results

Dataset Size	Latency (ms)	QuickSort Without Optimization (Execution Time - sec)	QuickSort with Optimization (Execution Time - sec)
100	0	0.012	0.010
1000	0	0.042	0.032
1000	10	0.045	0.035
1000	50	0.060	0.045
1000	100	0.070	0.050
5000	0	0.188	0.150
5000	50	0.200	0.160
10000	0	0.420	0.350
10000	100	0.440	0.375

As the dataset size increases, the execution time increases significantly. Optimized QuickSort algorithms tend to be more efficient and have lower execution time compared to the standard QuickSort algorithm, especially on larger datasets. Latency adds to the execution time, especially on larger datasets, but the effect is more pronounced on the less optimized standard QuickSort algorithm. The optimized QuickSort algorithm shows better resilience to latency, thanks to reduced recursion in tail recursion and random pivot selection that reduces recursion depth. This sensitivity analysis shows that QuickSort optimization with random pivots and tail recursion can provide more stable and efficient performance, especially as dataset size and latency increase, which is particularly relevant in IoT applications facing big data and critical response times.

Discussion

The results of the study indicate that the application of QuickSort algorithm optimization through a combination of random pivot selection and the use of tail recursion techniques can significantly improve data processing efficiency in the context of IoT systems. A comparison of execution times between the standard QuickSort algorithm and the optimized version shows that the average execution time of the optimized algorithm is lower, at 0.0323 seconds compared to 0.0425 seconds for the unoptimized algorithm. The ANOVA test conducted yielded an F value of 8.34, exceeding the critical F value at a significance level of 0.05 (4.41), indicating a statistically significant difference. The use of tail recursion specifically reduces stack depth due to recursion, while random pivot selection helps avoid worst-case performance, which typically occurs when the dataset is partially or fully sorted. These results reinforce the argument that an algorithmic approach that is adaptive to data structure and system architecture is essential for real-time data processing in IoT environments.

Further sensitivity analysis shows that the optimized QuickSort algorithm exhibits better resilience to variations in dataset size and system latency. When tested with varying data sizes (100 to 10,000 entries) and latency (0 ms to 100 ms), the optimized algorithm demonstrated more stable and gradual improvements in execution time compared to the standard version. For example, with a dataset size of 10,000 entries and a latency of 100 ms, the standard algorithm recorded a time of 0.440 seconds, while the optimized algorithm only required 0.375 seconds. This indicates that optimization is not only effective under ideal conditions but also in realistic scenarios involving system latency and large data scales, which are characteristic of modern IoT applications. Therefore, this optimized QuickSort implementation is highly relevant for application in distributed systems, edge computing, or sensor-based environments that require high speed and efficiency in real-time data sorting and analysis.

4. CONCLUSION

This study successfully demonstrated that optimizing the QuickSort algorithm through the application of random pivots and tail recursion significantly improves sorting performance, particularly on large datasets commonly found in Internet of Things (IoT) applications. The use of random pivots effectively prevents the worst-case performance often experienced by QuickSort with static pivots, while the implementation of tail recursion reduces recursion depth, optimizes memory usage, and improves execution time efficiency. Test results show that this algorithm is superior in terms of processing time and memory efficiency, making it more suitable for real-time applications requiring fast and effective data processing, such as in IoT systems dealing with large and continuously increasing data volumes. Although the results obtained show significant advantages in sorting efficiency, the generalization of these findings can still be strengthened through further exploration. Further research is recommended to test the algorithm's performance on larger and more diverse datasets, as well as to conduct a comprehensive comparison with other sorting algorithms such as MergeSort and HeapSort, which may have characteristics more suitable for certain types of data. Additionally, integrating this optimized QuickSort algorithm with distributed data management systems and parallel processing could be a promising research direction to enhance performance in more complex and dynamic real-world operational conditions, as commonly encountered in modern IoT architectures.

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