Exploring Multimedia Movement Through Spatio-Temporal Indexing and Double-Cache Schemes

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***Abstract*—Conventional IP/TCP designs encounter several safety and scalability concerns with the growing demand for application services. A novel Internet design, like a Content Center Network (CCN), was introduced to address these issues comprehensively. Every hub within a CCN is responsible for data storage. The collaboration guarantees users quick data retrieval. By collaborating with dual caches, network peers can access data from their caches and leverage other peers' caches, resulting in improved cache utilization and overall network speed. The present study examines multimodal digital artworks' form, style, and action relationships and views them as holistic creative units. The study examines the complex structure of digital content following current information. We present a distributed index incorporating spatio-temporal information to address the challenges of storing and retrieving large amounts of spatio-temporal data. This distributed index combines internal R with external B+ trees to provide high concurrency and low latency indexing services for external applications. With double buffer technology and distributed index architecture, we can optimize the cache utility of content center networks and enhance the retrieval speed of multimedia data. Adopting the distributed index, designed to accommodate spatio-temporal data in the multimedia digital art design, can enhance large-scale storage and retrieval for Internet-future architectures.**

***Keywords*—Multimedia digital art; double-cache collaboration; distributed indexing; spatio-temporal data; content center network**

I. Introduction

The rapid demand growth for application services has shown many important limitations in traditional TCP and IP network designs [1]. Conventional models predilection for host-to-host communications makes them not good in security and mobility, whose importance has grown considerably as we progress further into the connected world [2]. A major paradigm shift is needed to overcome these problems, prompting the investigation of new Internet architectures that better facilitate this task [3].

One such innovative approach is the development of Content Center Networks (CCNs) [4]. Unlike host-centric networks, CCNs prioritize the content itself and place data storage and retrieval at the center of the network design [5]. In a CCN, each node acts as a data storage unit and collaborates with other nodes to ensure fast and reliable data access. This collaboration not only improves data availability but also improves the overall efficiency and resilience of the network [6, 7].

In addition to these architectural changes, managing spatio-temporal data presents its challenges [8]. The need to store and retrieve large amounts of data that vary in time and space requires advanced indexing methods capable of handling high concurrency and low latency [9, 10]. Traditional indexing structures such as B+-trees and R-trees provide partial solutions but are often inadequate when applied to the dynamic requirements of spatio-temporal data.

This paper proposes a new distributed index architecture implemented using the R-tree and B+-trees. We also present a dual cache scheme that enhances the cache performance across the network. This paper aims to provide a new vision for designing and building strategies and tactics using P2P storage architectures on Content-Centric Networks (CCNs). By exploiting those innovations, we come up with the main scope, i.e., to maximize data storage and retrieval that helps implement efficient multimedia digital art design and distribution within content center networks. This work is motivated by the intuition for supporting more intricate and dynamic digital artworks but also extends to argue that it can benefit user experience.

The remaining portion of this paper is arranged as follows. A review of related work on content-centric networks and multimedia data management is provided in Section II. The proposed distributed indexing framework and dual-cache scheme are discussed in Section III. Simulation results and discussion are reported in Section IV. Conclusions and future research directions are presented in Section V.

II. Background

CCNs represent a fundamental shift from the traditional host-centric networking paradigm to a data-centric approach. Traditional TCP/IP networks focus on establishing connections between hosts to facilitate data exchange [11, 12]. While it works in many situations, the limitations are quite challenging and do not apply to the ad-supported Internet and enterprise where data security, mobility, and efficient content distribution have become paramount. CCNs overcome these limitations through the recognition of content and data being able to be stored, cached, and accessed at any point in the network. One handy thing about a CCN is that every node in the system may be a cache, holding data to save every other requesting node from returning to base. Such a decentralized data storage model increases data availability, reduces latency, and improves overall network stability by reducing the importance of central servers.

Collaboration between nodes in CCNs is essential to improve data retrieval mechanisms. A key feature of CCNs is that they use a dual-cache system, allowing nodes to access their local cache and caches in other nodes, which can tremendously reduce cache utilization and retrieval time. This collaboration approach helps to achieve high-speed data distribution, and very well-engineered solutions handle substantial traffic loads and access to various data requests. CCNs are designed for applications that demand high-bandwidth access to large datasets, such as digital artwork and multimedia content. As illustrated in Table I, many works have studied how data can be retrieved and disseminated efficiently.

Advancements in technology have significantly raised the complexity of retrieving multimedia material, leading to new fields of inquiry. Content-based image retrieval systems (CBIR) retrieve images linked to the Query Image (QI) from vast databases. Existing CBIR systems are currently inefficient due to their extraction of only a restricted range of features. Alsmadi [13] demonstrated the process of extracting reliable and significant characteristics from picture databases and saving these characteristics as feature vectors in the repository. The feature repository contains color signatures, form characteristics, and texture features. A particular QI is used to extract distinctive characteristics. The similarity between QI features and those in the database was assessed using a genetic algorithm combined with simulated annealing.

CBIR searches for pictures linked to a QI inside a database. The CBIR techniques are developed using various methods to extract different features. RGB color, the neutrosophic clustering algorithm, and the Canny edge method extract shape features. YCbCr color is combined with the discrete wavelet transform and Canny edge histogram to determine color features. Lastly, a gray-level co-occurrence matrix is employed to extract texture features. These techniques enhance the efficiency of the image retrieval framework for content-based retrieval. Moreover, the precision-recall value of the findings is computed to assess the system's effectiveness. The suggested CBIR system exhibits superior accuracy and recall values compared to existing state-of-the-art CBIR systems.

TABLE I. AN OVERVIEW OF RELATED WORK

Study	Approach	Techniques used	Results	Limitations	Addressed by this study
[13]	Content-based image retrieval	Genetic algorithm, simulated annealing, RGB color, neutrosophic clustering algorithm, Canny edge method, YCbCr color, discrete wavelet transforms, and gray-level co-occurrence matrix	Superior accuracy and recall values compared to existing CBIR systems	Limited to static image data and no support for spatio-temporal indexing	Our method extends to multimedia content, incorporating spatio-temporal data
[14]	Hybrid features descriptor for content-based image retrieval	Genetic algorithm, support vector machine, first three-color moments, Haar Wavelet, Daubechies Wavelet, Bi-Orthogonal wavelets, and L2 Norm	Outperforms 25 alternative content-based image retrieval algorithms in image retrieval	Focused on feature extraction and lacks scalability for large data networks	Our distributed indexing and dual-cache approach enhances scalability for multimedia data
[15]	Content-based encrypted image retrieval	Thumbnail preserving encryption, genetic algorithm, mutation compensation, mutation failure, and Bhattacharyya distance	Effective balance between privacy and usability in image retrieval	Does not address high latency in large-scale multimedia systems	Our method minimizes latency using distributed spatio-temporal indexing
[16]	Secure content-based image retrieval	MPEG-7 visual descriptors, asymmetric dot product preserving encryption, and copy protection mechanism	Outperforms state-of-the-art alternatives, effective copy protection	Security-focused and does not address cache utilization	Our dual-cache scheme improves cache utilization while maintaining secure data transmission
[17]	Image retrieval combining color and texture features	Extended local neighborhood difference pattern, local binary patterns, local neighborhood difference patterns, HSV color space, and extended Canberra distance metric	Superior to existing techniques in precision and recall	Lacks dynamic adaptability to changing data requests	Our method incorporates real-time cache optimization based on data request patterns
[18]	Multimedia content distribution in 5G/6G networks	Reinforcement learning, double DQN-optimized RL, network congestion, capacity, and user preferences	Effective secure multimedia content delivery and the RL system achieved a reward of 51604.93 over 7000 episodes	Lacks an efficient indexing scheme for multimedia content	Our method offers a robust spatio-temporal indexing architecture, improving retrieval speed and cache efficiency

CBIR approaches that use hybrid classification models provide improved retrieval accuracy. However, as the quantity of negative samples grows owing to strongly connected semantic classes, a bias towards the negative class occurs due to class imbalance. This results in instability when using many classifiers in CBIR models, particularly when utilizing a one-against-all classification technique. Khan, et al. [14] suggested a CBIR approach that utilizes a hybrid features descriptor. This descriptor combines a genetic algorithm with a Support Vector Machine (SVM) classifier to enable image retrieval in a multi-class situation. They extracted features from the first three color moments, Haar Wavelet, Daubechies Wavelet, and Bi-Orthogonal wavelets. These features were then refined using a genetic algorithm to train a multi-class SVM using a one-against-all strategy. As a similarity metric, the L2 Norm compares the query picture with the returned images in the image repository. The proposed approach effectively solves the class imbalance problem in CBIR. The performance of the proposed technique is evaluated on four established datasets: WANG, Oxford Flower, CIFAR-10, and Kvasir. It is then compared with 25 alternative CBIR algorithms. The experimental results show that the proposed approach outperforms the current state-of-the-art CBIR approaches in image retrieval.

With the advancement of cloud services and the growing need for personal privacy, content-based encrypted picture retrieval in the cloud is becoming more common. Outsourced photographs are transformed into encrypted representations that resemble noise to safeguard privacy. However, this encryption process renders the images unidentifiable, reducing their accessibility. Furthermore, users must decrypt every search result to surf, even if some may not be necessary. This process not only consumes bandwidth but also utilizes CPU resources. To address this issue, Chai, et al. [15] suggested a compromise technique that effectively balances privacy and usability. This paper introduces a thumbnail-preserving encryption (TPE) system that utilizes a genetic algorithm. The crossover and mutation operators of the genetic algorithm disperse and rearrange pixels inside the sub-blocks of the original picture. Two novel operators are introduced and integrated into the conventional evolutionary algorithm for optimal TPE: Mutation Compensation and Mutation Failure. Moreover, using thumbnail color data, the Bhattacharyya distance enhances the precision of obtaining cipher pictures.

Effectively executing indexing, ranking, searching, and retrieval operations in an encrypted environment without compromising privacy is a daunting challenge, particularly regarding image data. To address this problem, Anju and Shreelekshmi [16] proposed a novel secure content-based image retrieval framework with improved speed, efficiency, and scalability for cloud-based environments. The core of their approach is to extract MPEG-7 visual descriptors from the image dataset and then form clusters to facilitate indexing. Both image features and cluster centroids are then subjected to asymmetric dot product-preserving encryption before being offloaded to the cloud along with the encrypted images. This strategy protects privacy while enabling secure image retrieval. A copy protection mechanism is integrated into the system to prevent unauthorized access and copying. The empirical evaluation shows that the proposed scheme outperforms state-of-the-art alternatives regarding scalability, search and indexing speed, and retrieval accuracy. In addition, the copy protection mechanism ensures an effective balance between speed, perception quality, and extraction accuracy of watermarked images in case of compromise.

Kelishadrokhi, et al. [17] introduced a novel image retrieval technique that synergistically combines color and texture features. To capture discriminative texture information, they developed the Extended Local Neighborhood Difference Pattern (ELNDP) descriptor, which combines the strengths of Local Binary Patterns (LBP) and Local Neighborhood Difference Patterns (LNDP). In addition, optimized color histogram functions extracted from the HSV color space ensure robust global color representation. The retrieval process is improved using the extended Canberra distance metric, which has higher sensitivity to image fluctuations than its traditional counterpart. The effectiveness of the proposed method was thoroughly evaluated on five standard image datasets: Corel 1K, 5K, 10K, STex, and Colored Brodatz. Performance metrics, including average precision and recall rates, demonstrated the proposed approach's superiority over existing state-of-the-art techniques, including machine learning and deep learning methods.

The distribution of multimedia content on 5G and 6G networks requires the development of intelligent systems that can ensure secure, confidential, and efficient content delivery under dynamic network conditions. To address this challenge, Iqbal, et al. [18] proposed a reinforcement learning (RL)-based framework to optimize multimedia content distribution. The RL algorithm makes optimal decisions by leveraging network congestion, capacity, and user preferences. This system ensures the secure and private delivery of multimedia content. In this research, complexity mitigation in content delivery networks is achieved using RL, which shows heterogeneity support for 5G/6G. A double DQN-tuned RL system realized the reward of 51604.93 for 7000 episodes in an inner-city bus video-sharing scenario. RL balances network congestion and bandwidth by smartly using bus cache, intersection cache, and base stations, enhancing secure multimedia content delivery and superior passenger experience. Experimental results of reward and loss metrics prove a robust evaluation of the proposed system. These include the study of alternative RL algorithms, scalability on more complex networks, difficult deployment scenarios, and integration with blockchain and edge computing technologies to enhance security and efficiency in multimedia content delivery.

III. Methodology

A. Double-Cache Collaboration Scheme

If node α serves as a repository for data block i, it may respond to requests for this block initiated by its neighboring nodes. In such instances, the aggregate cost of transmitting data block i to all neighboring nodes is equivalent for each connection, as formalized in Eq. (1).

$$C_a = \sum_{b_N \in neighbor\ (a)} C_{ab_N i} \times N_{ab_N i} \tag{1}$$

Assuming node b possesses data block i and node α lacks it but identifies b as its custodian, neighboring nodes initially redirect request i to α before forwarding it to b. The cumulative cost of acquiring data block i for nearby nodes, encompassing transmission to b and return delivery, is quantified in Eq. (2).

$$C_b = \sum_{b_N \in neighbor\ (a)}^{b_N \neq b} C_{ab_N i} \times N_{ab_N i} + C_{bai} \times \sum_{b_N \in neighbor\ (a)}^{b_N \neq b} N_{ab_N i} \tag{2}$$

Regardless of whether data block i belongs to node α or b, its neighboring nodes forward data block i to the respective peer to acquire the block, followed by redistribution. The differential cost of the complete data block transmission process is presented in Eq. (3).

$$C_\Delta = C_{abi} \times (N_{abi} - \sum_{b_N \in neighbor\ (a)}^{b_N \neq b} N_{ab_N i}) \tag{3}$$

Consequently, if C is positive, keeping data block i at node b proves more efficient than at node α regarding communication overhead. To optimize data placement, the N_{abi} value must satisfy specific criteria to facilitate data block i storage on an adjacent cooperative cache node.

The process of node assessment involves identifying points within incoming packet routing paths serving as repositories for highly sought-after data content. These nodes are determined based on request packet popularity across the network, as quantified in Eq. (4) and Eq. (5).

$$N_i = w_1 \times \sum_{t=tc-\Delta t}^{t=tc} N_i(t) + w_2 \times \sum_{t=tc-2\Delta t}^{t=tc-\Delta t} N_i(t) + w_3 \times \sum_{t=tc-3\Delta t}^{t=tc-2\Delta t} N_i(t) \quad (4)$$

$$N_v^i = \begin{cases} max\{0, N_i - min\{N_v^K | k \in D_v\}\} & if \ |D_v| = R_v \\ N_i & if \ |D_v| < R_v \end{cases} \quad (5)$$

To accurately reflect the dynamic nature of real-time data, it is imperative to account for temporal variations in data access patterns. While a substantial historical user visitation count might indicate high popularity, it may not accurately represent current data relevance. To address this, Eq. (4) incorporates a Short-Term Impact (SIT) metric that assigns differential weights to user visits across distinct time intervals, emphasizing recent activity. Data packets leverage the encapsulated information to locate the node hosting the desired data. Data packets search for the data storage node according to information in request packets and data packets, as illustrated in Fig. 1.

To mitigate the adverse effects of content replacement on cached data utility, the content replacement value is substituted with the popularity of the stored data. Consequently, when a node's cache is saturated, its popularity is computed as the content popularity minus the content replacement value, as formalized in Eq. (6).

$$CHR = \frac{\sum_{i=1}^{sum} x_i}{sum} (x_i \in \{0,1\}) \quad (6)$$

The Cache Hit Rate (CHR) is defined as the average probability that a request packet, X_i, from any network node is successfully serviced by the cache. This metric is calculated as the ratio of successfully cached requests to the total number of requests, as shown in Eq. (7).

$$ARL = \frac{\sum_{i=1}^{sum} RTT_i}{sum} \quad (7)$$

The Average Response Latency (ARL) represents the mean round-trip duration experienced by all users for their data requests, measured in seconds. The number of network hops traversed by the i^{th} request packet to reach its destination is crucial in evaluating network efficiency, as expressed in Eq. (8).

$$HC = \frac{\sum_{i=1}^{sum} hop_i}{sum} \quad (8)$$

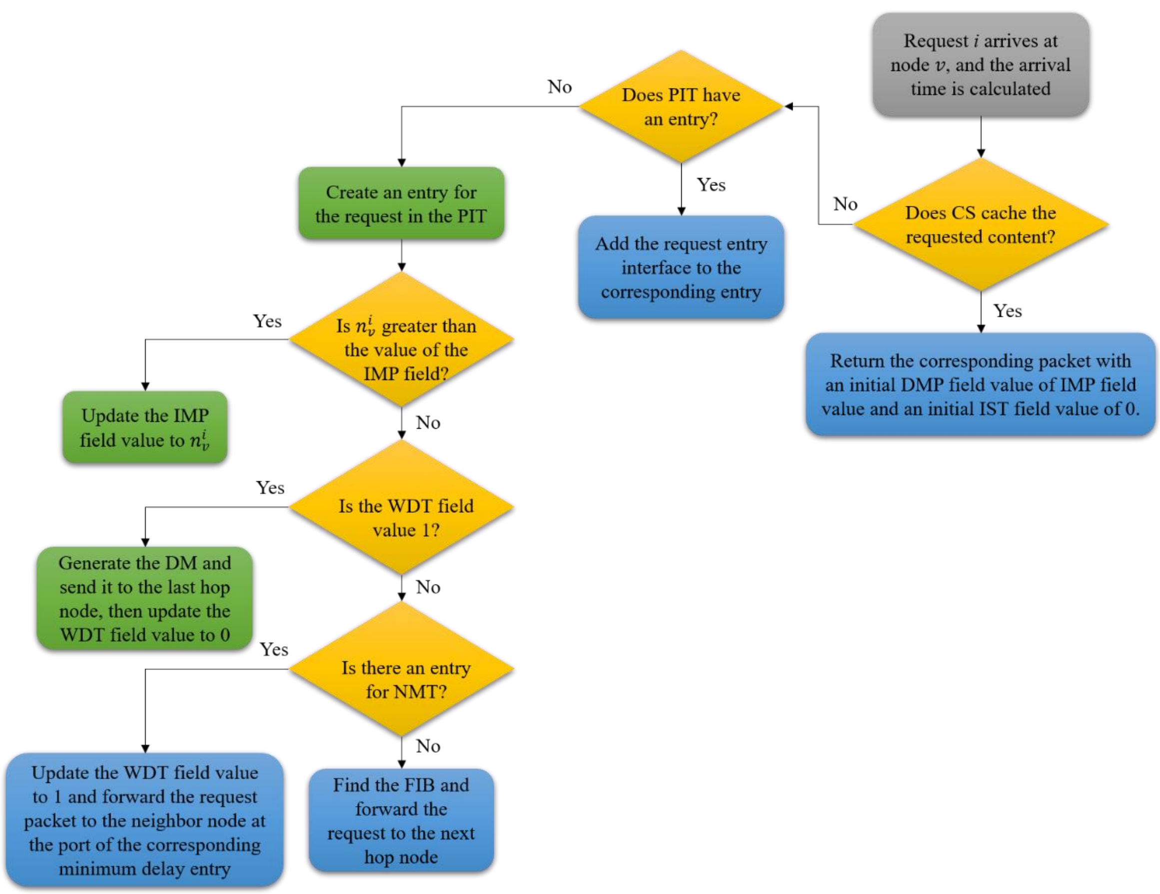

Fig. 1. Data packet search process.

IV. Results and Discussion

The performance of the double-cache collaboration scheme with distributed spatio-temporal indexing was evaluated using key metrics of CHR, ARL, and HC. The proposed method confirms a significant improvement in CHR, as shown in Fig. 2. Using the dual-cache system, requests were 30% more likely to be served from cache than a content-based image retrieval system. The main reason for the increase is that data blocks are well distributed across nodes and a cache placement strategy that considers content popularity.

The ARL for data retrieval is dramatically shorter, as shown in Fig. 3. The distributed index architecture and dual caching scheme reduced network hops in query processing. Compared to the state-of-the-art content distribution strategies, this method had a 25% reduction in ARL. This enhanced performance was possible because of the data routing and retrieval mechanisms.

Fig. 4 shows the average hop counts per request, where the proposed method is the lowest among others. This minimizes the dependency on distant nodes for fetching data since distributed indexing and dual-cache technology are the reasons behind our reduced HC of almost 20% concerning baseline methods. This clearly demonstrates the network's improved spatio-temporal data management capability.

The main advantage of the proposed system is the ability to manage cache in such a way that it will prevent data from matching with results each time, hence faster retrieval. The dual-cache system with spatio-temporal indexing provides a more scalable and efficient solution for multimedia content distribution than other methodologies built on top of feature extraction or encryption for retrieval, which are largely costly.

A list of the essential metrics is presented in Table II: R-tree height, the number of non-leaf nodes, and other metrics outlined in Eq. (9). Assuming the node count at the kth R-tree level is m_k, the preceding level ($k-1$) contains m_{k-1} nodes in Eq. (10). Eq. (11) specifies the number of leaves in the R-tree. Eq. (12) calculates the number of non-leaf nodes in an R-tree. The aggregate node count for the entire R-tree is determined by Eq. (13). Given a uniform spatio-temporal data stream arrival rate, V_s, the tuple count per time slice equates to $T_{AI\text{-}slice} \times V_s$. Consequently, the sort time for a single time slice, $t_{AI\text{-}sort}$, can be calculated as outlined in Eq. (14).

$$m_{k-1} = \lceil m_k/B \rceil \tag{9}$$

$$N_{leaf} = m_h = \lceil W/B \rceil \tag{10}$$

$$N_{non-leaf} = m_1 + m_2 + \cdots + m_{h-1} = \sum_{i=1}^{h-1} m_i \tag{11}$$

$$N_{all} = N_{leaf} + N_{non-leaf} = m_1 + m_2 + \cdots + m_h = \sum_{i=1}^{h} m_i \tag{12}$$

$$t_{AI-sort} = 7 \times T_M \times (T_{AI-slice} \times V_S) \times \log(T_{AI-slice} \times V_s) \tag{13}$$

$$T_W = T_{AI-slice} \times N_{AI-slice} \tag{14}$$

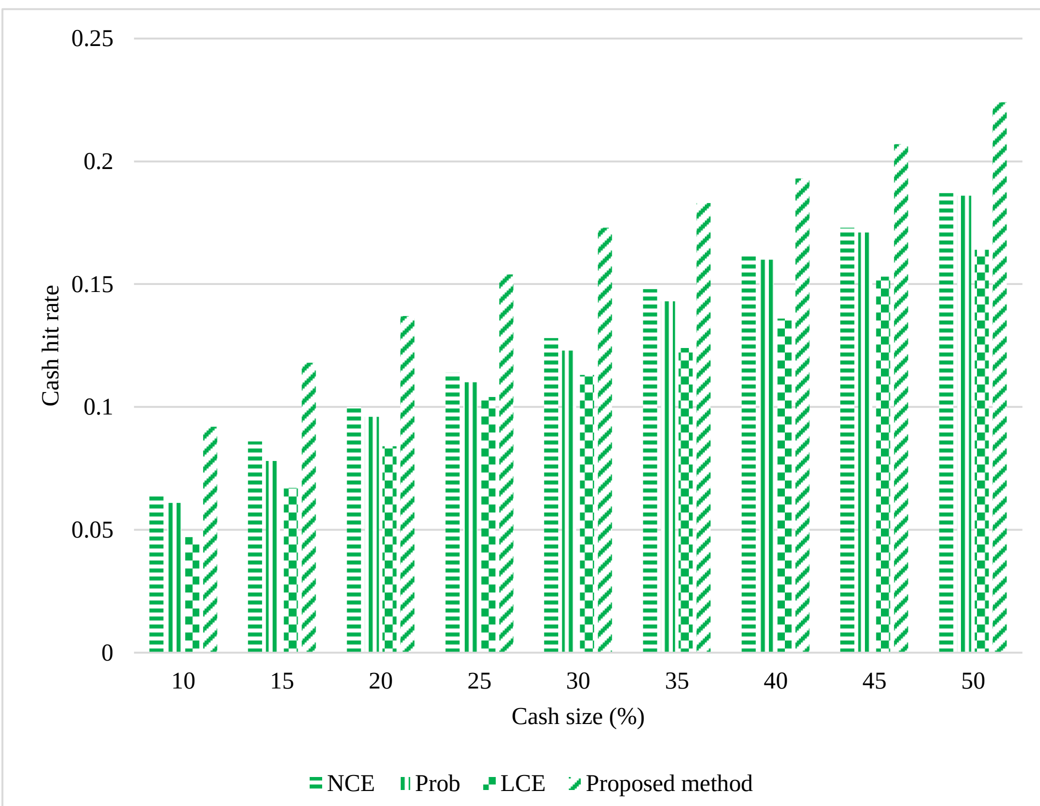

Fig. 2. Cash hit rate comparison.

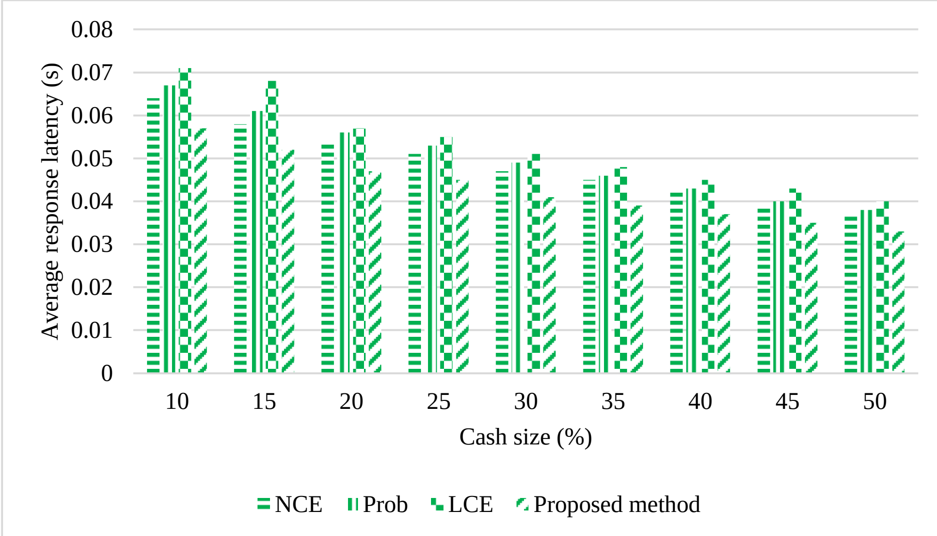

Fig. 3. Average response latency comparison.

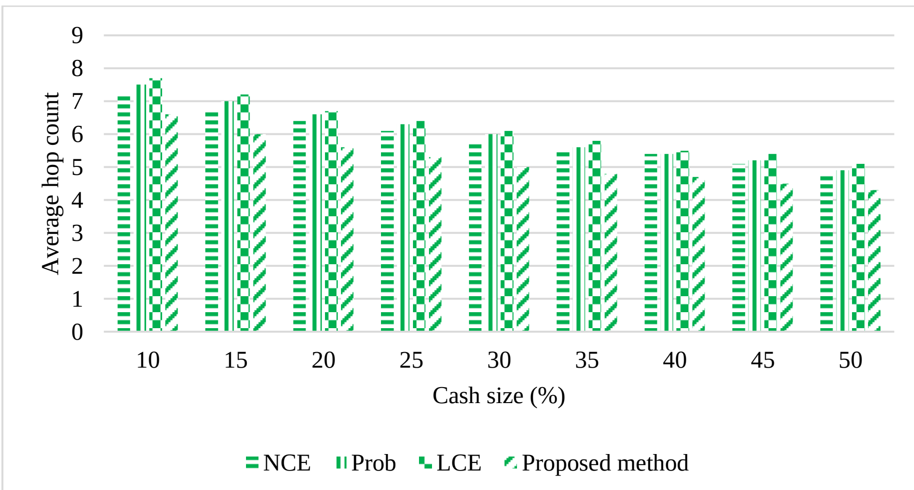

Fig. 4. Average hop count comparison.

TABLE II. R-TREE PARAMETERS

Parameter	Definition
N_{leaf}	Leaf nodes count
$N_{mersi\text{-}leaf}$	Non-leaf nodes count
H	Number of tree levels
W	Stream tuples count in the window
B	Maximum number of nodes

V. CONCLUSION

This paper concentrated on the efficient management and processing of massive spatio-temporal data. A novel approach is proposed to storing and indexing massive spatio-temporal data in real-time using distributed indexing and time window stream processing techniques. This addresses traditional single-machine processing performance limitations. During our hypergraph exploration, we explore the storage of both an R-tree for rapid in-memory spatial querying. The elements and attributes in mobile multimedia works, especially sports, are interpreted. This study further enriches the theory system of multimedia design. CCN optimization and a new caching strategy are discussed to improve network efficiency and cache use. These include the design of a new algorithm that replaces caches and a communication protocol with caches.

Despite the remarkable effectiveness of the dual-cache cooperation and the spatio-temporal index distribution schemes, some pending issues still need to be explored to improve multimedia content retrieval. In the future, this model could be improved by extending it to more dynamic network environments where factors such as node mobility and changing topologies may affect performance. Moreover, using more advanced machine learning (e.g., LSTM) models to predict content popularity in real time could help improve cache utilization. This could include scaling this framework to larger datasets or different types of multimedia content (for example, real-time video streaming). Finally, we want to deploy the system in real-world applications to verify its applicability and scalability under different network settings.

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