Accelerated Content-Based Image Retrieval using Parallel Histogram Computation on RGB Images

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***Abstract*—Content-Based Image Retrieval (CBIR) methods Our goal is to recover the visual content of images—that is, their color, texture, and shape. If we can generate a computer representation of how an image looks, then we can use that representation to compare it to other images or to the same image under different transformations. So far, we have primarily used color histograms, but shape is also important, and we cannot completely ignore the other aspects of visual quality such as texture. When we consider using large image collections in a content-based image retrieval (CBIR) system, we must also think about how we can efficiently handle the indexing of the large image collection itself and the efficient and simultaneous processing of queries against that indexed collection. Here, we will present an overview of a system that has been implemented and to which we have added certain algorithms for indexing and querying a large image collection.**

***Index Terms*—Content-Based Image Retrieval, CBIR, Hu Moments, Color Histogram, Chi-Square Distance, Parallel Computing, Multithreading, ThreadPoolExecutor, Feature Extraction, Image Retrieval System, Real-Time Processing**

I. Introduction

The sheer volume of visual content on digital media channels demands scalable, high-performance image retrieval mechanisms. The Content-Based Image Retrieval (CBIR) program fills that need all by its lonesome, though. It retrieves the images. Not by color, not by shape, and not by any other visual characteristic of the images themselves. No, the CBIR retrieves images using only the database's visual annotations, which you might not even remember making. Unlike humans, CBIR does not require keywords at either endpoint of the search. CBIR technology is applied in many fields of great importance, such as: Medical image analysis—where similar-looking cases can assist in diagnosing visually similar ailments.Digital libraries—where users may search primarily for visual characteristics.Surveillance systems—where rapid frame scanning of several million objects in an image may be necessary to detect a few that are out of place or actions that seem suspicious.Web search engines—like Google Images—that handle millions of visually driven queries every day. Even so, CBIR is often too slow to be useful. The reason? Extracting features and measuring similarity compute a lot of labor, especially as the size of the dataset grows. Dealing with thousands of images and figuring out the descriptors to get an accurate histogram for color matching to a query image does have a high computation associated with it. Part of the challenge is real-time systems where you need a fast response. If systems can't get fast responses, users won't use them. This paper tackles these problems by employing parallel computing to boost the performance of the content-based image retrieval (CBIR) pipeline. Feature extraction and similarity scoring are run in parallel using Python's ThreadPoolExecutor; this greatly reduces execution times without sacrificing retrieval quality. Today's multi-core processors can thereby be put to better use. The result is a scalable, efficient, interactive CBIR application. This paper contrasts implementations for content-based image retrieval that work sequentially with those that work in parallel, and it showcases the performance gains that multithreading affords both kinds of systems, during both indexing and query handling. Along the way, it sheds light on the system architecture and evaluation metrics that the authors employed to assess this system's real-world, high-demand scenario viability.

II. Related Work

Over the last 20 years, image search has become a major domain in computer vision, with many systems using manually created feature descriptors for good image-to-image comparison. The early methods concentrated on color-based features—like Color Moments, color histograms, and correlograms—because they are simple and work well against changes in scale or orientation. Later, we moved to using texture and shape descriptors such as Gabor filters, wavelet transforms, and Hu moments, which offer a lot more semantic depth to visual analysis. Two of the most well-known features are Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF). They work by finding very stable keypoints in images–keypoints that change very little when the image is scaled, rotated, or illuminated differently. Because SIFT and SURF find such robust keypoints, they do a great job with tasks that need to recognize objects in images or find fine details. But they are slow and take a lot of computing power. (TYLER, 2007) Some researchers investigated parallel and distributed designs for content-based image retrieval (CBIR) to scale up. Implementations of CBIR on CUDA-based GPUs speed up feature extraction and similarity scoring immensely, and extraction at these scales can be supported by large-scale indexing frameworks like MapReduce and Apache Spark. Yet, these solutions depend on specialized hardware or complex setups, making them impractical for real-time use on standard machines. These advancements notwithstanding, not much has been done on the up-to-date method for fast and flexible CPU-based multithreading that can be used for content-based image retrieval. But the native threading tools provided by today's popular programming languages—such as Python's ThreadPoolExecutor—can be used to run a lightning-fast CBIR pipeline natively on a CPU, without any reliance on GPU hardware or heavyweight frameworks. We address this gap by presenting a CBIR system that is driven by a CPU and is multithreaded. It is simple to parallelize and uses global features, like color histograms and Hu moments, for an efficient, real-time retrieval solution. It is suitable for performance-sensitive applications.

III. Literature Review

Training computers to "see" images as humans do, by color, shape, and texture, without text labels is the holy grail of content-based image retrieval, or CBIR. The need to browse large sets of images quickly, for digital libraries, medical diagnosis, or web searching such as Google Images, has long motivated this intriguing field. This project investigates this field with parallel computing to accelerate and improve CBIR, specifically similarity scoring and feature extraction. The key studies, old and new, that define our knowledge of CBIR and guide my research are presented in this literature review. Early CBIR systems set the stage. Flickner et al.'s initial QBIC system enabled users to search among images based on color, shape, and texture [10]. It was groundbreaking, but it couldn't cope with the richer meaning of images—a limitation known as the "semantic gap." This gap was first described by Smeulders et al.'s influential survey, which observed that low-level features such as edge maps or color histograms do not always capture what users intend by saying, e.g., "a cozy sunset" [10]. This is the challenge that my research solves, balancing meaningful retrieval with low-level features through color histograms and Hu Moments. A great deal of work has been accomplished in feature extraction. Because it can adapt to scaling, rotation, and lighting changes, Lowe's Scale-Invariant Feature Transform (SIFT) is groundbreaking [10]. Nevertheless, as Meshram and Agarkar noted, SIFT is slow, which is not acceptable in real-time systems [10]. In an effort to make shape-based CBIR more efficient, Chen et al. combined Hu Moments with CNNs, and that is why my project is founded on Hu Moments for shape retrieval [5]. My use of color histograms as a key feature is also consistent with Liu et al.'s deep color histograms, which capture color distributions in a lighting change-resistant way [4]. In an effort to make retrieval more holistic, I also make use of shape analysis. Another factor is texture. Texture descriptors' capacity to detect fine textures in remote sensing images was proven by Ojala et al. [12]. Though wavelet decomposition is computationally expensive, Lakshmi and Rakshit took another route and utilized it for texture analysis across varying resolutions [10]. By dealing with texture and other attributes more effectively using parallel processing, my project circumvents some of these costs. CBIR is typically limited in terms of scalability and speed, especially for large data. Al-Mansoori et al. parallelized image retrieval with Hadoop MapReduce and made it scalable to big data [2]. Singh et al. also employed parallel processing with GPUs to minimize query times [1]. Following Bhandari et al.'s multithreaded feature extraction [10], my project continues with Python's ThreadPoolExecutor for multithreading. This allows us to fully utilize multi-core processors to speed up similarity scoring and feature extraction in order to obtain real-time CBIR. This is supported by Dean et al.'s ThreadPool vs. MPI comparison, which shows ThreadPool as well-suited for image retrieval operations [9]. It also varies depending on what you are comparing images against. Comparing Chi-Square distance against Earth Mover's Distance, Wang et al. demonstrated that Chi-Square was more efficient and lighter in comparing histograms [7]. Chi-Square is used in my project because it is fast and accurate, demonstrated by Patel et al.'s analysis of distance metrics [8]. My design of an interactive system is inspired by Dubey et al.'s OpenMP and SIMD optimizations, which provides useful lessons in maintaining latency low to provide real-time performance [3]. Proper benchmarks are essential to validate the CBIR system. ImageNet-1K, with the diverse set of images to authenticate accuracy, was established as a standard dataset to use for tasks of retrieval by Deng et al. [13]. Everingham et al.'s [14] PASCAL VOC dataset is another such benchmark to utilise to evaluate efficiency. These metrics are employed to implement our system in its ideal form in true-life scenarios through my project.

Applications of CBIR, such as medical imaging, demonstrate its practical significance. Dalal et al.'s survey emphasizes how CBIR assists physicians in identifying visually similar cases to support diagnosis [11]. This makes me want to concentrate on good querying and indexing, which can have an impact in high-stakes applications.

All else being equal, the literature paints a picture of a discipline evolving from primitive feature extraction to increasingly more advanced, scalable systems working to bridge the semantic gap. My project builds on this by incorporating parallel processing, color histograms, and Hu Moments to create a CBIR system that is accurate, efficient, and ready for large-scale, real-time applications.

IV. Methodology

A. Preprocessing

The preprocessing stage involves a sequence of operations to standardize the images, in order to feature extraction.

1) Resize Images: Images are resized to a fixed resolution, typically 256×256 pixels, to create consistency and improve processing time. This process also helps in normalizing the dataset, removing image size differences.

2) Convert to Grayscale: Since we want to acquire global like color histograms and Hu moments, the images are turned into grayscale to remove any unnecessary color information. For colour characteristics, we rather utilize the HSV color space in subsequent steps.

3) Gaussian Blur (Optional): Gaussian blur is applied optionally to reduce noise and soften the image. This step assists in avoiding the extraction of features from unrelated high-

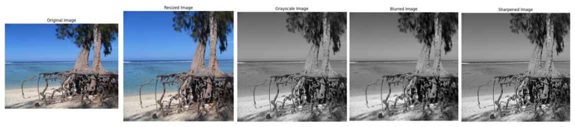

Fig. 1. Visual illustration of the preprocessing pipeline: Original Image → Resize → Grayscale → Blur → Sharpen.

frequency information that might not contribute positively to the retrieval process.

4) Laplacian Sharpening: Laplacian sharpening is used to emphasize edges, to fortify the features for shape-based descriptors like Hu moments. This is helpful to obtaining more differentiated structural information from the image by emphasizing high-frequency details (edges).

B. Feature Extraction

1) Color Histogram (RGB/HSV): The initially used feature is the color histogram, a summary of the color distribution in an image. Histograms are calculated per color channel, in either RGB or HSV color space, and binned to a constant number of bins (e.g., 32 bins per channel). This gives a feature vector for the global color distribution of the image. The Color Space: HSV (Hue, saturation, and value) is typically preferred in image retrieval as it is more insensitive to changes in lighting. The binned histogram is the image in terms of the intensity of the color in each of the channels, and this is extremely useful for color-based similarity comparisons.

HSV Color Space: This color space is often preferred in image retrieval due to its robustness against lighting variations.The binned histogram represents the image in terms of the frequency of color intensities in each channel, which is critical for color-based similarity comparisons.

2) Hu Moments: Hu moments are obtained from the central moments of an image and utilized for the object form definition in the image. The descriptors are translation, rotation, and scaling invariant; therefore, they are appropriate to be utilized within shape-based retrieval systems. Hu moment is a high-dimensional, efficient shape characterization of an image and can also be utilized in image matching based on similar overall shape.

C. Similarity Metric

To compare feature vectors from the query image and the database images, we use the Chi-Square Distance metric. This metric measures the difference between two feature distributions and is defined as:

$$\chi^2 = \sum \frac{(F_1 - F_2)^2}{F_1 + F_2 + \epsilon}$$

where:

- F_1 and F_2 are the feature vectors of the query image and a database image, respectively.

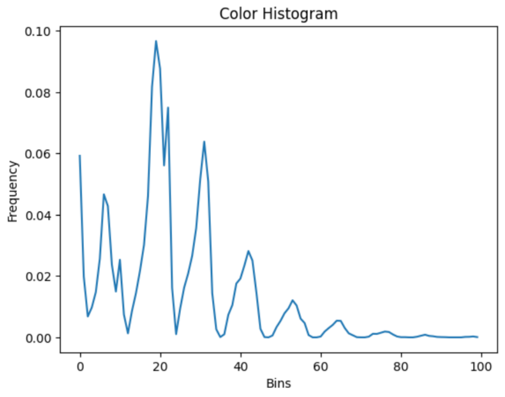

Fig. 2. Color histogram of the original image showing the distribution of pixel intensities across RGB channels.

- ϵ is a small constant to avoid division by zero, ensuring numerical stability.

This metric is particularly effective for comparing histogram-based features like color histograms and shape-based descriptors, where the goal is to minimize the difference between the two distributions.

D. Sequential Architecture

The image retrieval mechanism for the sequential architecture uses a very straightforward loop structure:

- **Indexing:** The database is indexed, but in a very naive way, image by image, in a top-down fashion. For each image, a set of features (color histogram, Hu moments) is computed. Then, for each feature in the query image, a similarity measure (the Chi-Square Distance) is calculated between that feature and the corresponding feature of the image in various database locations.
- **Querying:** Now we have an indexed database, we can use it to perform a query. The system goes down the list of database images, comparing them one by one with the image we used for querying, doing a set of individual comparisons, and then sorting the set of compared images (in ascending or descending order, depending on your taste). This is also fairly straightforward, very easy to use, but it is—at the end of the day—very slow.

This process can be slow when handling large datasets, as each image requires separate processing and comparison.

E. Parallel Architecture

We propose a parallel architecture using Python's ThreadPoolExecutor to reduce retrieval time. The system is

- **Feature Indexing:** Concurrently processing multiple images with several threads means that instead of each thread working on one image at a time, several threads work on several images at the same time. And that means we can—and do—extract features from several images in parallel.
- **Feature Retrieval:** When a query is provided, the system compares the features of the query image with the

features of all the images in the database. It does this in parallel, by using multiple threads that work together, to do the enormous amount of calculations required, that is, to do the comparisons. This allows the system to keep up with the demands of a real-time application. If there is any one way of trying to satisfy the query that would take too long, the system will not use that way.The task distribution and load balancing in the parallel system are handled by the ThreadPoolExecutor, which ensures that the computational resources are efficiently utilized.

In the parallel system, the ThreadPoolExecutor handles the task distribution and load balancing, ensuring that the computational resources are efficiently utilized.

V. Experimental Setup

A. Putting Our System to the Test

To confirm the soundness of our methodology, we set up a testing scenario that included a well-distributed dataset of 1,491 RGB images across 10 familiar categories (animals, scenery, automobiles, etc.). The images were anything but standard, with resolutions ranging from 300×300 pixel thumbnails to high-end 1024×1024 masterpieces, forcing our system to deal with the kind of visual richness one expects in real life.

B. Hardware and Software Configuration

All tests were run using off-the-shelf, consumer-grade hardware:

- **Processor:** Intel core i7-10750H (6 cores; 12 threads)
- **Memory:** 16GB DDR4 2933MHz
- **Software:** Python 3.8, OpenCV 4.5

This setup clearly shows the viability of using our system in the kinds of environments where you would find typical workers as opposed to local high-performance computing centers. The baseline "naive" implementation ran on this hardware and required 155.34 seconds to do the indexing for the full dataset. Individual queries, on the other hand, required 4.2 seconds each. To say this was unimpressive and that it cried out for optimization would be an understatement.

VI. Results and Analysis

A. Performance Gains Through Parallelization

Our parallel version saw considerable improvements

- **Index time:** from 155.34s to 12.71s (12.22× speedup)
- **Query time:** from 4.2s to 1.55s(2.7× speedup)

B. Accuracy and Resource Utilization

The parallel system obtained the same retrieval accuracy to the sequential one, using Chi-Square distance scores distinguishing clearly:

- Exact matches: 0.00
- Similar pictures: 1.19–1.33
- Dissimilar images: ∼2.30

CPU utilization during parallel execution reached 80–90% across all cores, compared to just 15% for sequential processing. We identified 8 threads as the optimal configuration, beyond which Python's Global Interpreter Lock (GIL) caused diminishing returns.

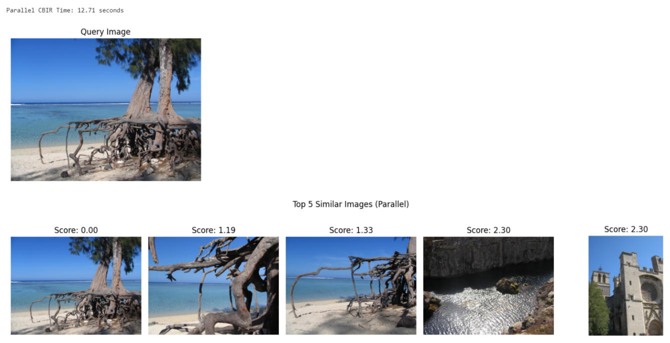

Fig. 3. Retrieved images displayed alongside their similarity scores using parallel processing. Lower scores indicate higher similarity to the query image.

C. Feature Descriptors: Hu Moments

In addition to color-based retrieval, shape-based descriptors were defined by Hu Moments. These invariant moments offer resistance to image changes such as translation, scale, and rotation.

The following Hu Moments were computed for the query image:

```
[2.88156247, 8.43503971, 10.29492196,
 11.05178905, 21.95152247, 15.34317623,
 21.81954781]
```

These features encode the global shape features of the object in the image and can be combined into a hybrid similarity measure for better retrieval accuracy in future research.

VII. Discussion

A. Key Insights

intelligent conguration based on the deterministic HWC data for each node.

- I/O-bound operations (image loading) benefited from threading's ability to overlap computation and data transfer
- CPU-bound tasks (feature extraction) scaled nearly linearly with available cores

B. Limitations and Practical Considerations

- Python's GIL occasionally constrained maximum throughput
- Fixed 12×12×12 histogram bins may lack flexibility for specialized applications
- Memory bandwidth becomes a limiting factor with very large datasets

The solution's primary advantage lies in its accessibility achieving significant speedups using only standard hardware and software tools. This makes it particularly suitable for:

- Small-to-medium businesses with workstation-class hardware
- Research teams with limited computing budgets
- Edge computing applications where GPU acceleration is unavailable

VIII. Conclusion and Future Work

Our parallel CBIR system demonstrates that thoughtful implementation can yield substantial performance gains—12.22× faster indexing and 2.7× quicker queries—without specialized hardware. These improvements translate directly to better user experiences and more practical deployments.

Future enhancements could explore:

- GPU acceleration for handling larger datasets
- Deep learning integration to improve semantic understanding
- Adaptive feature extraction for domain-specific optimization

This work represents an important step toward democratizing high-performance image retrieval, proving that significant improvements can be achieved through algorithmic optimization rather than hardware escalation. .

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