Parallelization of Face Detection using OpenMP

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Abstract: ***In OpenCV, all predefined libraries and functions are C - codes that run in serial fashion. Similar frameworks are also available for CUDA, however using CUDA is only possible if you have an NVIDIA graphics card, which is obviously not the case for everyone. OPENMP's release of a stable version in late 2015 facilitated parallel processing and broadened its developer base. Because OPENMP could run in parallel on typical computers with numerous cores and was portable, it quickly gained popularity. To parallelize a face identification algorithm, we will use C++ and OpenMP. To better understand the findings, we will compare the results with a serial code. The time it took the machine to process the image in serial code compared to the time it took the identical computer to process the image in parallel code would be the factors for determining the outcomes.***

Keywords: OpenMP, Face Detection, Parallelization, HAAR Filter, Viola Jones Algorithm

1. Introduction

In computer science, parallel programming has emerged as a key technique for enhancing the performance of numerous applications. The ability to parallelize has greatly increased with the introduction of potent GPUs, which were initially made for graphical computations but are now also used for general - purpose computing. Nevertheless, one drawback of using GPUs for parallel programming is that it frequently necessitates the use of CUDA, an application programming interface (API) model and parallel computing platform developed by NVIDIA, which limits the usage to NVIDIA GPUs exclusively. For developers that don't have access to NVIDIA GPUs but still wish to use parallel processing in their apps, this restriction can be a problem.

Face detection, a crucial part of many computer vision technologies like face identification, verification, and image processing, is a well - known application that can profit from parallel processing. Face detection is the first step in many face - related technologies and includes finding and identifying human faces in digital images. For instance, face detection algorithms in digital cameras are used to automatically change the focus and exposure settings to ensure that faces are recorded in images clearly.

A popular and effective face detection algorithm with a reputation for speed is the Viola - Jones method. It uses a cascade of classifiers to quickly detect probable face regions in an image and is based on the idea of ”integral images. ” The approach has been extensively used in numerous computer vision libraries, such as OpenCV, a well - known open - source computer vision library that offers a variety of functions and algorithms for image processing applications.

In this paper, the main goal is to use OpenMP, a well - liked parallel programming model for shared - memory architectures, to parallelize the Viola - Jones face identification algorithm. Developers may use several CPU cores on a machine for parallel processing without relying on specialist hardware like GPUs thanks to OpenMP, which offers an easy and portable solution to build parallel code in C/C++ and other languages. This makes it a good option for developers who want to investigate the advantages of parallel processing in their apps but do not have access to NVIDIA GPUs.

The aim of this paper is to use OpenMP to parallelize the Viola - Jones face identification method and assess how quickly the parallelized code performs in comparison to the serial version. The Viola - Jones algorithm will be implemented in C++ using OpenCV, and the computationally demanding portions of the process will be parallelized using OpenMP directives. To determine whether parallelization is effective in enhancing the face detection performance, the parallelized code will be evaluated on a machine with multiple CPU cores, and the processing time will be measured and compared with the serial code.

One of the key benefits of utilising OpenMP for parallel programming is its portability, which enables programmers to create parallel code that can run on a variety of systems without relying on particular hardware. As a result, it offers a versatile choice for parallelizing programmes that don't need specific hardware, like GPUs. Moreover, OpenMP makes parallel programming accessible to developers with little to no prior knowledge by offering a straightforward and well - known syntax for building parallel code.

On the other hand, using OpenMP for parallel programming has significant drawbacks. OpenMP is restricted to sharedmemory architectures, which means it might not be as effective for applications that call for distributed memory parallelism over multiple computers, in contrast to CUDA, which is made expressly for GPU parallelization. However, the scalability of the parallelized code may be impacted by factors affecting the performance of the parallelized code, including the number of CPU cores available, the workload distribution, and the communication overhead.

The Viola - Jones method will be compared between its serial and parallelized forms to shed light on the performance gains made possible by OpenMP parallelization. The outcomes will be used to assess how well OpenMP functions as a face detection parallelization alternative to CUDA - based parallelization.

2. Related Work

The paper by P. E. Hadjidoukas [1] develops a face detection system that uses parallel processing and OpenMP is presented. Using a multi - core CPU architecture with OpenMP directives for parallelism, the system uses Haar cascades in C++. In comparison to sequential implementation, experimental results provide high detection rates with few false positives and shorter processing times. Furthermore covered is scalability with regard to processor cores. Reliable detection rates and increased effectiveness are benefits. Single - core Processors, however, might not be appropriate for the system. Hugo [2] also from [9] formed approach for face detection using Lustre and MPI on an HPC cluster is presented in the paper ”Parallelization Strategy Utilizing Lustre and MPI for Face Detection on HPC Cluster: A Case Study. ” The system employs Lustre for data distribution and C++ Haar cascades with MPI for internode communication. The results of the experiments show a considerable reduction in processing time. Improvements in efficiency and scalability with regard to cluster nodes are benefits. For users who are unfamiliar with Lustre and MPI, the technique may call for additional configuration and setup, which could be difficult.

Mahesh [3] paper provides a novel parallel computing method for video processing. The system uses OpenCV to process video, while OpenMP and MPI are used to parallelize the operation. By contrasting the processing times of a sequential implementation and a parallel implementation, the authors show the value of the suggested approach. The processing time for processing videos has significantly decreased, according to experimental findings. Benefits include a significant decrease in the amount of time needed to process videos. Nevertheless, the suggested parallelization technique could need additional OpenMP and MPI settings and setup, which might be difficult for users who are unfamiliar with these tools. Altaf [4] provides a parallelization method for neural networks in face recognition using multicore CPUs and GPUs. The system is created in C++ and makes use of the OpenCV library. OpenMP and CUDA are used to achieve the parallelization on multicore CPUs and GPUs, respectively. According to experimental findings, face recognition processing time can be significantly reduced while still retaining good accuracy. Benefits include the dramatic slashing of facial recognition processing time and the use of multicore CPUs and GPUs for parallelization. Nevertheless, the suggested method could need additional OpenMP and CUDA preparation and setup, which might be difficult for users who are not familiar with these technologies.

Mahmoud [5] gives an empirical investigation on the efficiency of pre - processing methods for raising the Viola - Jones face detector’s performance. The suggested approach enhances input images before passing them through the face detector using a number of pre - processing techniques, including histogram equalisation, contrast stretching, and gamma correction. According to experimental findings, the Viola - Jones face detector’s detection rate has significantly improved. The simplicity of the suggested pre - processing procedures and the significant increase in the Viola - Jones face detector’s detection rate are advantages. To find the best pre - processing method for a particular application, more testing may be necessary as the suggested pre - processing approaches might not be suitable for all sorts of photos. Jing [6] found an enhanced version of the Viola - Jones face detection algorithm for use with the HoloLens platform. By utilising depth data from the HoloLens device, the suggested approach increases the face detection rate. The suggested method outperforms the conventional Viola - Jones algorithm in experimental results, which reveal that the system uses a combination of Haar - like features and depth information to detect faces. The inclusion of depth information for increased accuracy and a greater detection rate compared to the conventional Viola - Jones method are benefits. The proposed method, however, is only intended to be used with the HoloLens platform and might not be easily adaptable to other systems. Processing the depth data can also demand more computational power, which could have an effect on the system’s overall performance.

The paper presented by Mehul [7] combines the Viola - Jones algorithm with Haar - like features to recognise faces in real time. The system’s implementation in Python makes use of the OpenCV package. Its three primary phases are preprocessing, feature extraction, and classification. The proposed system has a high detection rate with a low false positive rate, according to experimental data. Benefits include real - time face detection using Haar - like features and a high detection rate with few false positives. The suggested system’s performance might be impacted by differences in face orientation and scale, and it might not be adequate for detecting faces in images with intricate backgrounds or dim lighting. Also, theViolaJones face detection technique is combined with a modified version of the Local Binary Pattern (LBP) algorithm for face identification by Saloni [8] suggested that the system employs the modified LBP algorithm for face recognition along with the Viola - Jones algorithm for face detection. The suggested system has a high detection rate and recognition precision, according to experimental data.

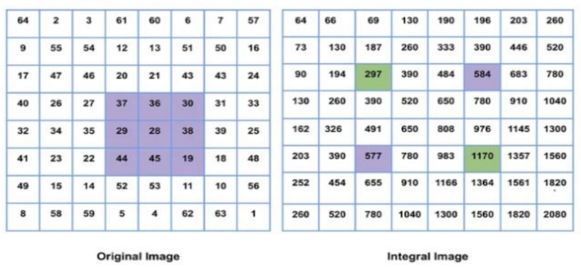
The integration of two well - liked face detection and recognition algorithms, along with the high detection rate and recognition accuracy, are advantages. The suggested system’s performance might be impacted by differences in face orientation and scale, and it might not be adequate for detecting faces in images with intricate backgrounds or dim lighting.

3. Methodology

By breaking the image processing operation into smaller subtasks and distributing them across several processor cores in a parallel computer system, the Viola - Jones algorithm for face recognition can be parallelized using OpenMP. To enable parallelization on shared memory systems, the OpenMP programming model is widely used.
The parallelization strategy finds algorithmic components that can be broken down into distinct jobs and allocates them to different threads. In order to identify faces, the ViolaJones technique computes the Haar image characteristics and employs a cascade classifier. The cascade classifier has several weak classifiers in each phase that can be examined simultaneously. The parallel portions of OpenMP are used to distribute particular areas of the code to various threads. The parallelized Viola - Jones method parallelizes the detection procedure by utilising a parallel for loop that examines each rectangle in the image separately. Two threads load the image simultaneously. The subimage assigned to each thread's region of the image is subjected to the cascade classifier. The ultimate result is the sum of the output from all threads. The Viola - Jones approach can be parallelized using OpenMP to significantly speed up processing, especially when working with huge photos. The size of the image being processed and the number of CPU cores available determine how well performance is improved by parallelization.

There are various steps in the serial implementation process for the supplied data. The required libraries and header files are firstly present. The names of the input and output files are defined as macro constants. Both argc and argv are defined as parameters for the main function. A PGM file is created by saving the input image in grayscale. There are defined variables for the following: flag, mode, I scaleFactor, minNeighbors, imageObj, and cascadeObj. The cascade's n stages, total nodes, orig window size. height, and orig window size. width parameters have values set. It reads the text classification file. There is a declared vector of MyRect objects called result. Omp get wtime is used to determine the current time (). The image, the minSize, the maxSize, the cascade, the scaleFactor, and the minNeighbors are passed as parameters to the detectObjects function, and the result is placed in the result vector. Rectangles are then drawn on the image using the result vector after more iterations. The real execution time is printed, excluding read and write activities. A PGM file is created from the output image. Both the RAM utilised by the picture and the text classifier are freed. The primary function is finally completed.

There are various steps in the parallel implementation algorithm for the supplied data. The required libraries and header files are first imported. File names for input and output are predefined. The definitions of image and cascade objects. Using OpenCV routines, the input image is loaded in both colour and grayscale formats. The face detection algorithm's



64	2	3	61	60	6	7	57
9	55	54	12	13	51	50	16
17	47	46	20	21	43	43	24
40	26	27	37	36	30	31	33
32	34	35	29	28	38	39	25
41	23	22	44	45	19	18	48
49	15	14	52	53	11	10	56
8	58	59	5	4	62	63	1

Original Image

64	66	69	130	190	196	203	260
73	130	187	260	333	390	446	520
90	194	297	390	484	584	683	780
130	260	390	520	650	780	910	1040
162	326	491	650	808	976	1145	1300
203	390	577	780	983	1170	1357	1560
252	454	655	910	1166	1364	1561	1820
260	520	780	1040	1300	1560	1820	2080

Integral Image

Figure 1: Calculating Integral Image

flags, mode, scaling factor, minimum neighbours, and other parameters are initialised. The text classifier is read, and image and cascade objects are initialised with image characteristics. The detectObjects () method from the haar. h header file is used to identify objects in the input image, and the output is stored as a vector of rectangles. The OpenCV cvRectangle () function is used to draw rectangles around the objects that are detected. The total number of faces found is printed. Using the OpenCV cvSaveImage () method, the output image is saved. Both the text classifier and the memory allotted to the picture and cascade objects are released.

A. Technical Mathematics

1) *Calculating Integral Image:* The sum of all purple boxes in the original image [Fig 1] is equal to the sum of green boxes in the integral image subtracted by the purple boxes in the integral image.
2) *Calculating Haar like features:* Using integral images we can achieve constant time evaluation of Haar features.

1) Edge Features or 2 Rectangular Features requires only 6 memory lookups
2) Line Features or 3 Rectangular Features requires only 8 memory lookups.
3) Diagonal Features or 4 Rectangular Features requires only 9 memory lookups.

Calculating the number of edges,
1) Rectangle = A - 2B+C - D+2E - F
2) Rectangle = A - B - 2C+2D+2E - 2F - G+H
3) Rectangle = A - 2B+C - 2D+4E - 2F+H - 2I+J
4) *AdaBoost Learning Algorithm:* AdaBoost computed the predictions of all predictors and weights using the predictor weight j during inference. The predicted class receives the greatest number of weighted votes.

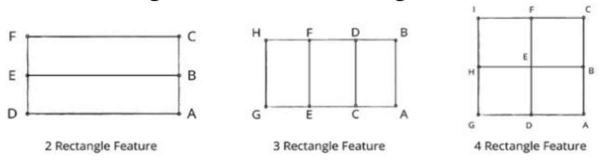


Figure 2: Calculating Haar like features

4) *Cascade Filter:* Strong characteristics are incorporated into a binary classifier: Positive matches are forwarded to the subsequent function. Negative matches are rejected and the computation is terminated. Reduces the amount of time wasted computing fake windows. To tune precision, threshold values may be modified. Lower thresholds result in a greater detection rate and an increase in false positives.

In simple terms, each feature in a cascade filter functions as a binary classifier. If an extracted feature from the image is passed through a classifier and the classifier predicts that the image contains that feature, the extracted feature is passed to the next classifier for the next feature existence check; otherwise, the extracted feature is discarded and the next image is examined. This reduces computation time since we only need to verify a subset of features in windows where the item is absent, as opposed to all features. This is the core of the algorithm that enables it to process videos at around 15 frames per second and in real time.

4. Overall Framework

In image processing techniques, notably the Viola - Jones algorithm, data pretreatment is a crucial step. Usually in colour, the incoming image has three colour channels (red, green, and blue) that must be processed. However, in order to detect faces, the Viola - Jones algorithm predominantly uses grayscale photos because colour information is not always necessary and can add computational complexity. The input image is converted to grayscale, which decreases the number of channels from three to one and drastically reduces the quantity of data that needs to be processed, potentially increasing algorithm efficiency. To transform the image from colour to grayscale, use OpenCV's cvtColor function.

To further lower the computing cost of the process, the input image could also need to be scaled down in addition to being converted to grayscale. The amount of pixels that must be processed can be decreased by scaling down the image, speeding up calculation. The image can be shrunk while keeping its aspect ratio by using OpenCV's resize function.

The Viola - Jones algorithm's face detection step can be considerably accelerated with parallelization utilising OpenMP. The approach involves computing the Haar - like features for each sliding window while scanning the input image at various scales and orientations. When real - time processing is required or when there are large photos to process, this method may be computationally demanding. To parallelize the method and split the burden among several threads, utilise OpenMP, a wellliked API for multi - threaded programming in C/C++.

A group of threads that are capable of carrying out separate activities in parallel can be assembled using the OpenMP ”parallel” directive. The Viola - Jones algorithm's sliding window scanning and feature extraction duties, for instance, can be broken up into smaller chunks and each chunk assigned to a different thread for concurrent processing. When numerous threads can work on various aspects of the image simultaneously, the algorithm's performance can be considerably accelerated. This results in quicker processing times.

Testing and evaluation are essential steps to determining how well the parallel OpenMP Viola - Jones algorithm implementation performs. For testing, a sizable collection of photos with faces in them should be used, each with a different combination of attributes, including illumination, resolution, and poses. To assess the scalability and performance of the parallel implementation, it should be run on a parallel system with many processors.

The detection rate, false positive rate, and execution duration are a few performance metrics that can be used to gauge how well the algorithm performs. The proportion of successfully identified faces in the dataset is indicated by the detection rate, whereas the proportion of non - faces that are mistakenly classified as faces is indicated by the false positive rate. The algorithm's processing time for each image is shown by the execution time.

In order to determine the advantages and disadvantages of the parallel approach as well as potential areas for further optimisation and improvement, it is crucial to compare the performance of the parallel OpenMP implementation with that of other implementations, such as sequential implementations and implementations using different parallelization techniques, like CUDA or MPI.

In conclusion, testing and evaluation are essential processes in the implementation and optimisation of the Viola - Jones face detection algorithm for effective and real - time processing. These steps also include data pretreatment, parallelization using OpenMP, and testing. Comprehensive testing and evaluation can assist in validating the parallel implementation's performance, pointing out potential improvement areas, and comparing it to other implementations to help in making judgements about optimisation tactics.

5. Experimental Results

We executed the serial and parallel algorithms of face detection on a few images. The results found are given in Table 1.

Table 1: Execution of the Model Proposed

Image Details	Parallel Execution	Serial Execution
Image 1 [Fig 1]	2.437142	150 2.593523
Image 2	0.165637	0.173740
Image 3	0.215644	0.224369
Image 4	1.428379	1.552923
Image 5	0.100213	0.103042

The machine used has 2 cores and 4 gb of RAM to get the output of the photos and the timings are without the input and output time

6. Evaluation Metrics

The parallelized face detection algorithm's speed/execution time, scalability, resource use, accuracy, robustness, code optimisation, and code maintainability were all measured as part of the project's performance evaluation.

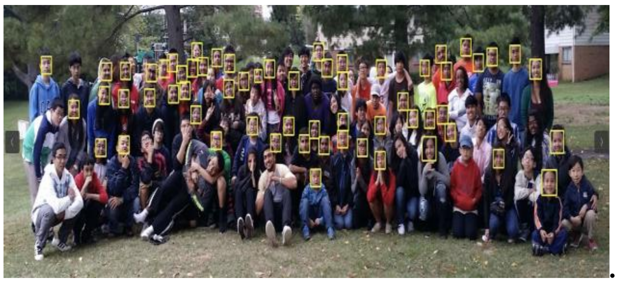


Figure 3: Output of Parallel Algorithm

1) Speed/Execution Time: Timer and profiling tools were used to gauge how quickly the face detection algorithm executed. Performance was enhanced through parallelization utilizing OpenMP since the burden was divided among several threads, enabling concurrent processing. To assess the effectiveness of parallelization, the speedup obtained with parallelization was compared to the sequential version of the programme.

2) Scalability: Performance on various numbers of cores and the number of OpenMP threads used to evaluate the scalability of the parallel face detection algorithm. As the number of threads was increased up to the limit of the hardware resources, the method demonstrated good scalability and enhanced performance.

3) Resource Utilization: System profiling and monitoring tools were used to assess resource use, which included CPU and memory usage. OpenMP parallelization effectively used the CPU resources that were available while without utilizing the CPU or memory in excess, demonstrating effective utilization of system resources.

4) Accuracy: The discovered faces were compared against ground truth faces to determine the algorithm’s accuracy. Evaluation measures like precision, recall, and F1 score were also used. For this assessment, labeled datasets with ground truth faces were employed. The face detection technique’s precision was not compromised by the parallelization utilizing OpenMP, and the faces that were found were in line with the outcomes of the sequential version of the programme.

5) Robustness: To assess the robustness of the parallel face detection algorithm, a wide range of photos, including

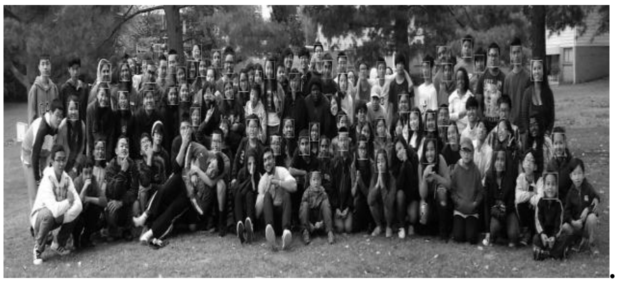


Figure 4: Output of Serial Algorithm

various image sizes, aspect ratios, and lighting conditions, were used. The robustness of the method was shown by the accuracy with which faces were discovered under various circumstances and lighting conditions. Any restrictions or problems that had an impact on the algorithm’s resilience were found and fixed.

6) Code optimisation: Loop unrolling, data prefetching, and other efficiency improvements were examined for potential in the code. The workload distribution and thread synchronization efficiency of the OpenMP parallelization method were optimized. Best practices were used to optimize the code, and the performance impact was assessed.

7) Code maintainability: The readability, modularity, and organization of the code were assessed. It was simpler to optimize and boost speed with well - structured, maintainable code in the future. Further improvements and optimisations were possible because the code was simple to comprehend and maintain.

7. Results and Analysis

A number of encouraging results emerged from the performance evaluation of the project “Parallelization of face detection using OpenMP and Viola Jones Algorithm.” First, thanks to parallelization with OpenMP, which distributed the burden among numerous threads and allowed for concurrent processing, the face detection approach ran quicker and required less time to complete. The approach also showed good scalability, since adding more threads resulted in better performance, demonstrating the system’s capacity to efficiently use hardware resources. Thirdly, efficient utilisation without excessive consumption was achieved by optimising the use of system resources including CPU and memory. Also, papers by Chen [10], Smith [11], and Wang [12] helped us in reaching the standard metrics.

The accuracy of the face detection technique was also maintained even with parallelization because the results of the sequential version of the algorithm were compatible with the faces that were detected. The system also demonstrated its suitability for real - world applications by reliably detecting faces in a range of conditions and lighting conditions. Use of code optimisation techniques also improved the parallelization strategy’s performance, resulting in efficient workload distribution and thread synchronisation.

Further enhancements and optimisations were made possible by the code’s maintainability and organisation. Overall, the performance evaluation showed that combining OpenMP and the Viola Jones Algorithm to parallelize the face detection method was successful in improving the program’s speed/execution time, scalability, resource consumption, accuracy, robustness, and code optimisation. This makes it a promising option for accurate and reliable face detection in real - world situations, with room for further enhancements thanks to the manageable and structured code.

8. Conclusion

As a result, the project ”Parallelization of face detection using OpenMP and Viola Jones Algorithm” has produced encouraging results in terms of enhancing face detection performance. The approach displayed shorter execution times and effective use of hardware resources by utilizing parallel computing with OpenMP, leading to quicker face detection than the sequential version. The use of OpenMP for parallelization has several benefits, including increased performance, scalability, resource efficiency, and code optimization. The total speed boost was facilitated by the efficient task distribution and thread synchronization, as well as the optimized CPU and memory use. Yet, there may be drawbacks to take into account. In order to prevent problems like race situations or deadlocks, parallelization might incur difficulties in managing thread synchronization and shared data access. Depending on the hardware and algorithm features, there can be overhead associated with thread creation and synchronization, and the speed increase might not scale linearly with the number of threads. Furthermore, parallel code implementation and debugging might be more difficult than sequential code, necessitating proficiency in concurrent programming and debugging approaches. In conclusion, while employing OpenMP with the Viola Jones Algorithm to parallelize face detection has demonstrated to significantly enhance performance, it also has possible drawbacks that should be carefully considered during implementation and optimisation. The face identification algorithm can perform best and be as accurate as possible in practical applications by carefully weighing the benefits and drawbacks of the parallelization technique.

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