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Performance Optimization in Three-Modality Biometric Verification using Heterogeneous CPU-GPU Computation

Boluma Mangata Bopatriciat [1], Tshibanda wa Tshibanda Pierre [2], Mbiya Mpoyi Guy-Patient[3], Buanga Mapetu Jean Pepe[4], Mabela Matendo Makengo Rostin[5],Mbuyi Mukendi Eugène[6]

[1] *Department of Computer Science, Haute Ecole de Commerce de Kinshasa, Kinshasa, D.R.Congo*
[2, 3] *Department of Computer Science, Institut SuperieurPédagogique de la Gombe, Kinshasa, DR Congo*
[4, 5, 6] *Department of Mathematics, Statistics and Computer Science, Faculty of Science and Technology, University of Kinshasa, Kinshasa, DR Congo*
email: [1]bopatriciat.boluma@unikin.ac.cd, [2]delpierotshi@gmail.com, [3]pambiya@gmail.com, [4]jpbuanga@gmail.com, [5]rostin.mabela@unikin.ac.cd, [6] mbuyieugene@gmail.com

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ABSTRACT

This paper propose a method to improve the performance of tri-modal biometric verification using a heterogeneous computing system exploiting the synergy between CPU and GPU. The main objective is to reduce the time required for verification while maintaining the system's accuracy. The design of this system is based on a decision fusion algorithm based on the logical OR connector, enabling the results of the three modalities to be combined. The implementation is being carried out in C# with Visual Studio 2019, using the Task Parallel Library to parallelize tasks on the CPU, and OpenCL.NET to manage processing on the GPU. The tests, carried out on a representative sample of 1,000 individuals, show a clear improvement in performance compared with a sequential system. Execution times were significantly reduced, ranging from 0.03 ms to 0.67 ms for data sizes between 50 and 1000. Analysis of the performance gains, based on Amdahl's law, reveals that the proportion of tasks that can be parallelized remains higher in heterogeneous system than in parallel and sequential systems, even though part of processing remains sequential for large data sizes. This study highlights the ability of heterogeneous computing systems to effectively reduce the verification time of biometric systems, while maintaining an optimal balance between processing speed and overall efficiency. The results demonstrate the potential of this approach for advanced biometric applications, particularly in distributed environments.

1. INTRODUCTION

Biometric verification has become an essential element of many security and identity management systems, as it ensures that access is only granted to authorize individuals. However, traditional systems often rely on a single modality, such as fingerprint or facial recognition, which can be limited by factors such as environmental conditions, the quality of input data or user compliance. These limitations can lead to a decrease in accuracy or an increase in processing time, reducing the overall efficiency of the system.To address these challenges, this paper explores a new approach to optimizing the verification performance of a three-modality biometric system that combines fingerprint, face and voice recognition. By using three modalities, our system aims to improve accuracy and robustness by exploiting the strengths of each modality and compensating for their weaknesses. However, the integration of multiple modalities also introduces computational complexity that can slow down decision-making processes if not managed

**) Corresponding Author : bopatriciat.boluma@unikin.ac.cd*

effectively. To address this, we focus on the efficient use of heterogeneous computing, using both the central processing unit (CPU) and the graphics processing unit (GPU) [3].This approach exploits the complementary strengths of these two types of processor: CPUs excel at processing complex logical decisions, while GPUs are well suited to parallel processing tasks, such as image and signal processing. By balancing the workload between the CPU and GPU, our method seeks to achieve faster processing times without compromising the accuracy of the verification process [11].This study is necessary because existing systems do not benefit from the robustness offered by multiple modalities or fully exploit the potential of heterogeneous computing for performance optimization. By filling these gaps, our approach aims to provide a more efficient and reliable solution for biometric verification, adapted to environments where speed and accuracy are essential [23].

1.1. Objective

The main objective of our research is to significantly reduce the time required for biometric verification while maintaining or even improving the accuracy of the system. We aim to achieve this by adopting a heterogeneous computing approach, which takes advantage of the parallel processing capabilities of the CPU and GPU.

1.2. Approach

To achieve our objective, we propose to exploit the computing power of heterogeneous processors, using parallel programming for the CPU and graphics cards for the GPUs. Specifically, we rely on the Visual Studio 2019 development environment and the Task Parallel Library (TPL) for parallel programming on the CPU [13]. To exploit the massively parallel processing potential of GPUs, we use OpenCL.NET, a programming interface that provides access to the parallel computing capabilities offered by GPUs [2], [3].

1.3. Challenges

One of the main challenges of our approach is to find an optimal balance in the workload distribution between the CPU and the GPU, in order to minimize bottlenecks and maximize overall system performance. We also need to consider aspects related to the synchronization of computations between the CPU and GPU to ensure efficient fusion of biometric decisions [9]. Finally, we must ensure that the entire verification process remains accurate and reliable despite the use of heterogeneous computation techniques [22].

By combining CPU and GPU computing capabilities efficiently, our approach aims to offer significant improvements in verification time for three-modality biometric systems, while maintaining high levels of accuracy and reliability [5], [12].

1.4. Contributions

The contributions of this scientific paper on heterogeneous computing between CPU and GPU for performance optimization in three-modality biometric verification are significant and can be summarized as follows:

a. Integration of CPU and GPU computing power: The paper proposes an innovative approach that leverages the parallel processing capabilities of CPUs and GPUs to accelerate the biometric verification process [17]. By effectively combining these two types of processors, the paper demonstrates a significant performance improvement over conventional sequential or parallel methods [6].

b. Use of parallel programming: By exploiting C#'s Task Parallel Library (TPL) for the CPU and OpenCL.NET for the GPU, the paper proposes a clear methodology for implementing heterogeneous computing. This approach enables efficient management of threads and compute kernels, minimizing bottlenecks and maximizing the use of available resources.

c. Optimizing the performance of the biometric system: The main objective of the paper is to reduce the verification time of the three-modality biometric system while maintaining its accuracy. The results obtained show that the heterogeneous system achieves this objective, with significantly shorter execution times compared to sequential and parallel systems [8].

d. Workload balancing: By distributing computations efficiently between the CPU and GPU, the article achieves workload balancing and minimizes inefficiencies associated with disproportionate resource use. This ensures optimal use of available processing capacity and helps maximize overall system performance [10].

In summary, this paper makes a significant contribution to biometrics research by proposing a novel approach to optimize verification performance using heterogeneous computing between CPU and GPU [14]. By combining parallel programming techniques with efficient management of hardware resources, the paper opens new perspectives for accelerating biometric verification processes while maintaining a high level of accuracy [1].

2. METHODOLOGY

Performance optimization of three-modality biometric verification using heterogeneous CPU-GPU computation follows the methodology described below:

1. Biometric data collection

Biometric data collection involves gathering a diverse set of biometric data, including fingerprints, facial images and voice samples. This data comes from practical experiments carried out using our own biometric verification application. The application is developed in C# and uses a SQL Server database for data storage. It integrates various recognition technologies, such as Fingerprint SDK for fingerprint recognition, EmguCV for facial recognition and Microsoft SpeechRecognition for voice recognition. The data collection process is designed to ensure a representative sample, taking into account demographic variations, environmental conditions and the quality of the data captured [12].

2. Pre-processing of biometric data

Pre-processing is essential to optimize the quality and compatibility of biometric data in all three modalities:

- Fingerprint data: Includes image enhancement and minutiae extraction using the Fingerprint SDK, ensuring that the input data is consistent and free of noise.
- Facial recognition data: EmguCV is used for tasks such as face detection, alignment and feature extraction. Techniques such as histogram equalisation are used to normalise facial images, improving the robustness of recognition in varying lighting conditions.
- Speech data: Using Microsoft SpeechRecognition, speech data is subjected to noise reduction and normalization. Features such as melodic frequency cepstral coefficients (MFCC) are extracted to improve accuracy during the recognition phase.

These pre-processing steps ensure consistency and reduce variations that could affect overall system performance.

3. Design of the decision fusion algorithm

The design of the decision fusion algorithm is based on a global decision fusion approach using OR logic. This method combines the results of the verification of each biometric modality (fingerprint, face and voice) into a single decision [16]:

- Development of the fusion algorithm: The algorithm integrates the individual decisions (acceptance or rejection) of each modality. A logical OR is applied, which means that a positive match in one of the three modalities leads to a positive verification result. This approach is particularly useful for reducing false rejection rates.

4. Implementing heterogeneous computing with C#

To improve system performance, the methodology uses a heterogeneous computing approach that balances computational tasks between the CPU and GPU:

Using C#'s Task Parallel Library (TPL) for CPU processing: The TPL is used to handle multithreading for tasks such as pre-processing and decision fusion. This allows processes such as feature extraction for voice and fingerprint recognition to run concurrently, optimizing CPU resources.

GPU computing with OpenCL.NET: The GPU is used for more computationally intensive operations, in particular those related to image processing for facial recognition. EmguCV exploits the capabilities of OpenCL to accelerate image convolution tasks. This speeds up the processing of facial data and reduces latency in the recognition process.

Workload distribution and load balancing: A dynamic task scheduler is implemented to distribute processing tasks between the CPU and GPU according to the real-time load. Lightweight tasks such as noise reduction in speech data are handled by the CPU, while more resource-intensive tasks such as CNN-based feature extraction for facial recognition are offloaded to the GPU [27].

Performance Optimization: The methodology includes continuous monitoring of CPU and GPU utilization to minimize bottlenecks and ensure the system's efficiency. A variety of metrics are tracked to evaluate the effectiveness of the heterogeneous computing setup:

a. Data Size: This metric represents the volume of biometric data processed by the system, including fingerprints, facial images, and voice samples. It is crucial for understanding the scalability of our approach, as larger data sets can significantly impact execution time and resource usage.
b. Sequential Execution Time (ms): This measures the time required to execute all tasks sequentially, using only the CPU. It serves as a baseline to compare the gains achieved through parallel and heterogeneous processing. A high sequential execution time typically indicates potential areas for parallelization.

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c. Parallel Execution Time (ms): This metric indicates the time taken when tasks are processed concurrently on multiple CPU threads. It helps assess how well the system can leverage parallelism to reduce processing time. Comparing this with the sequential execution time highlights the performance gains from parallel execution.
d. Heterogeneous Execution Time (ms): This measures the time when both CPU and GPU are utilized for different tasks according to their strengths. It is a critical indicator of how effectively the heterogeneous setup reduces total execution time compared to purely sequential or parallel approaches.
e. T_{CPU} (ms): The time spent by the CPU handling tasks such as data pre-processing, decision fusion, and lighter computations. Monitoring T_{CPU} helps determine if the CPU is being optimally utilized or if certain tasks could be offloaded to the GPU for further gains in efficiency.
f. T_{GPU} (ms): The time taken by the GPU for more computationally intensive operations like image processing in facial recognition. It is essential to track T_{GPU} to ensure that the GPU is effectively contributing to the workload and that the tasks assigned to it justify its use.
g. $T_{overhead}$ (ms): This represents the overhead time involved in managing data transfers and communication between the CPU and GPU. It is important to minimize $T_{overhead}$ to ensure that the benefits of using a heterogeneous system are not negated by delays in data handling.
h. T_{total} (ms): This metric combines all the above times (T_{CPU}, T_{GPU}, and $T_{overhead}$) to provide the overall execution time of the system. A lower T_{total} indicates that the system effectively balances the workload across different processors, minimizing delays and bottlenecks.
i. Performance Gain (Parallel): This metric evaluates the improvement in execution time achieved through parallel processing compared to sequential processing. It helps quantify the benefits of parallelism, showing how much faster the system runs when multiple tasks are executed simultaneously.
j. Performance Gain (Heterogeneous): This indicates the speedup gained by using both CPU and GPU compared to a parallel-only approach. It is critical for assessing the added value of leveraging GPU capabilities alongside CPU threads, especially for complex biometric processing tasks.
k. Proportion of Parallelizable Tasks (1 - α): This value represents the percentage of tasks that can be parallelized, providing insight into the potential gains from parallel execution. A higher proportion indicates that the system can benefit more from parallel processing and heterogeneous computing.
l. Proportion of Sequential Tasks (α): The proportion of tasks that must be executed sequentially. It is essential to identify this as it sets a limit on the potential performance improvements, guiding decisions on task allocation between the CPU and GPU.

These metrics collectively provide a comprehensive view of the system's performance and guide iterative optimizations. By tracking execution times, resource utilization rates, and energy consumption, the study aims to achieve a balance between speed and energy efficiency, making the heterogeneous computing setup effective for real-world biometric verification scenarios. Adjustments are made based on these metrics to ensure optimal usage of both CPU and GPU, reducing the overall processing time and improving the system's responsiveness [31].

3. SYSTEM CONSTRUCTION AND IMPLEMENTATION

To model the situation described, we need to construct an optimization function that takes into account the overall execution time for the heterogeneous CPU-GPU system, while seeking to minimize this time according to the distribution of work between the CPU and GPU units. The optimization function we propose is based on Amdahl's law and the management of parallelizable and sequential resources.

3.1. Amdahl's law

Amdahl's law quantifies the maximum speed that can be achieved by parallelizing part of a program, taking into account the sequential part which remains invariant to parallelization. In our case, this refers to the performance gain achieved by using the GPU for tasks that can be parallelized (e.g. facial recognition or fingerprinting), as opposed to those that must remain on the CPU (sequential tasks).

1. Performance gain (Parallel)

The formula used to calculate the performance gain when switching from sequential to parallel execution is :

$$\text{Performance gain (Parallel)} = \frac{T_S - T_P}{T_S} * 100 \quad (1)$$

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Where :

- T_S: Execution time in sequential mode (ms).
- T_P: Execution time in parallel mode (ms).
- The result is expressed as a percentage and indicates how much time has been saved thanks to parallelization.

2. Performance gain (heterogeneous)

The formula for performance gain in heterogeneous mode is similar, but takes into account the execution time in this mode:

$$\text{Performance gain (Heterogeneous)} = \frac{T_S - T_h}{T_S} * 100 \quad (2)$$

Where :

- T_S: Execution time in sequential mode (ms).
- T_h: Execution time in heterogeneous mode (ms).
- The result is also expressed as a percentage and shows the improvement brought about by heterogeneous computation compared to sequential computation.

3. Proportion of tasks that can be parallelized (1 - α)

The proportion of tasks that can be parallelized is given by:

$$1\text{-}\alpha \quad (3)$$

Where:

- α: Proportion of sequential (non-parallelizable) tasks.
- 1-α represents the proportion of tasks that can be run in parallel.
- This proportion is important in the application of Amdahl's law, which evaluates the potential performance improvement with parallelization.

4. Proportion of sequential tasks (α)

The proportion of sequential tasks, which cannot be parallelized, is noted:

$$\alpha$$

Where:

- α: Represents the fraction of the algorithm or program that must necessarily be executed sequentially.
- A lower value of α means that the majority of tasks can be parallelized, which favors a higher performance gain by switching to a parallel or heterogeneous mode.

3.2. Application of Amdahl's Law

These formulas are often used in conjunction with Amdahl's Law, which quantifies the maximum performance gain obtained by optimizing a part of a system. The law is generally formulated for a given number of processors or cores:

$$\text{Speedup} = \frac{1}{\alpha + \frac{1-\alpha}{N}} \quad (4)$$

Where:

- α: Proportion of sequential tasks.
- 1-α : Proportion of parallelizable tasks.
- N: Number of processors or cores used for parallelization.

In summary, performance gains and the proportions of sequential and parallelizable tasks can be used to assess the effectiveness of the transition to parallel or heterogeneous computing, and Amdahl's Law helps to estimate the maximum potential of these improvements.

3.3. Optimization function

When improving the performance of three-modality biometric systems, such as fingerprint recognition, facial recognition and voice recognition, optimization of verification time is crucial to guarantee both speed and accuracy. By using a heterogeneous computing system, which combines the CPU (central processing unit) and the GPU (graphics processing unit), it is possible to parallelize certain parts of the processing to significantly reduce execution time. The optimization of this process is based on the optimal distribution of tasks between the CPU and the GPU, taking into account the cost of communication between these two units. The proposed optimization function aims to minimize the total execution time by taking into account the parallel capabilities of the GPU, sequential processing on the CPU, and data transfer times between these two components. Detailed formulation of the Optimization Function

The optimization function for verification time in a heterogeneous biometric system (CPU and GPU) takes three main components into account: the computation time on the CPU (T_{CPU}), the computation time on the GPU (T_{GPU}), and the overhead time related to communications between CPU and GPU ($T_{overhead}$). Our optimization function is formulated as follows:

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$$T_{total} = T_{CPU} + T_{GPU} + T_{overhead} \quad (5)$$

1. CPU computation time (T_{CPU}):
This term represents the time required to perform sequential tasks or those that cannot be efficiently parallelized on the CPU. It depends on several factors:
- n : Size of input data (number of images or samples of fingerprints or voice).
- α : Proportion of sequential tasks in total processing ($0 \leq \alpha \leq 1$).
- f_{CPU}: Processing frequency and CPU capacity.
The relationship can be written as follows:

$$T_{CPU} = \alpha * n / f_{CPU} \quad (6)$$

2. GPU computation time (T_{GPU}):
This term quantifies the time taken by tasks that can be parallelized and are delegated to the GPU. The GPU is efficient for processing massive data, such as facial recognition and the analysis of large quantities of fingerprints. The factors influencing this time are:
- (1 - α) : Proportion of tasks that can be parallelized.
- f_{GPU}: GPU processing capacity, which is generally higher than that of the CPU.
The relationship is:

$$T_{GPU} = (1 - \alpha) * n / f_{GPU} \quad (7)$$

3. The overhead time ($T_{overhead}$):
Toverhead is the term used to describe the time taken to communicate between the CPU and GPU, and to manage task synchronization. This part is often overlooked, but is crucial in heterogeneous systems, as data transfers between CPU and GPU can become a bottleneck if poorly managed. Factors influencing this time include :
- d: Amount of data transferred.
- b: Communication bandwidth between CPU and GPU (hardware-dependent).
The relationship is :

$$T_{overhead} = d / b \quad (8)$$

Combining the three terms, the optimization function for minimizing total execution time is as follows:

$$T_{total} = \alpha * \frac{n}{f_{CPU}} + (1 - \alpha) * \frac{n}{f_{GPU}} + \frac{d}{b} \quad (9)$$

3.4. Optimization goal

The aim is to minimize T_{total} by optimizing parameters such as the proportion α of sequential tasks, the choice of hardware (f_{CPU} and f_{GPU} values, as well as data transfer management (d and b). This makes it possible to:
- Maximize use of the GPU's parallelization capabilities.
- Reduce sequential tasks to limit CPU load.
- Optimize bandwidth and reduce data exchanges between CPU and GPU.

This approach guarantees optimized performance of the heterogeneous biometric system by balancing computing loads and minimizing communication bottlenecks.

3.5. Hardware implementation

Our study project was carried out using the following resources:
A total of three laptops from MSI. Here are the specifics of these devices:
The msi CX720 is equipped with an Intel (TM) Core i5-450M processor with a frequency of 1.70 GHz and 2.40 GHz, 8 GB RAM memory, an NVIDIA Geforce 310M graphics card with 1GB DDR3, a 17.3" HD+(Glare Type) LED screen and a 500 GB hard disk. The operating system is Windows 10 Professional 64-bit. These computers have a database divided into three separate instances, each representing one of our three sites, as well as a biometric program written in C# that merges three modalities, namely fingerprints, facial recognition and voice recognition [3].

3.6. Organization of system implementation

The design and implementation of a high-performance biometric system requires methodical approaches to optimize the security and efficiency of the verification process. In this context, a decision fusion algorithm plays a central role. This algorithm is based on a global fusion method using the logical OR connector to combine the results of the different biometric modalities: fingerprints, facial recognition and voice recognition. Applying this logic means that a positive match in any of these modalities results in a positive decision for access, reducing the risk of false rejections and improving the system's tolerance to individual variations [35].

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The application, developed in C#, uses a SQL Server database for the secure storage of biometric data and access information. It incorporates several specialized technologies for biometric recognition: the Fingerprint SDK for fingerprint recognition, EmguCV for facial image processing and recognition, and Microsoft SpeechRecognition for voice recognition. Each modality contributes to the reliability of the verification based on its specific characteristics.

To boost the performance of this system, a heterogeneous computing approach is used, balancing workloads between the CPU and GPU [32]. This method takes advantage of the specific features of each component to maximize efficiency. C#'s Task Parallel Library (TPL) is used for multithreading on the CPU, facilitating data pre-processing and decision fusion [34]. This enables processes such as feature extraction for speech recognition and fingerprint verification to be managed simultaneously, optimizing the use of CPU resources [26], [30].

More intensive calculations, such as image processing for facial recognition, are delegated to the GPU using OpenCL.NET technology. The GPU, which is particularly well suited to parallel processing of large amounts of data, is used here through EmguCV to accelerate complex tasks such as image convolutions. This approach reduces facial data processing time, providing faster recognition and reducing delays in the verification process.

Workload balancing between the CPU and GPU is based on a dynamic scheduler that distributes tasks according to real-time load. Lightweight operations, such as noise reduction in speech data, are handled by the CPU, while the GPU handles heavier tasks such as feature extraction using convolutional neural networks (CNN) for facial recognition [36]. This sharing of tasks ensures optimum allocation of resources. Finally, performance optimization in this approach relies on continuous monitoring of CPU and GPU resource utilization, with the aim of minimizing bottlenecks. Metrics such as execution time, resource utilization and energy consumption are analyzed to assess the efficiency of the heterogeneous configuration. Based on this data, adjustments are made to ensure an optimal balance between processing speed and energy efficiency. This methodology ensures robust, high-performance biometric access control, tailored to the requirements of distributed environments.

The implementation architecture of the project is as follows [2], [3]:

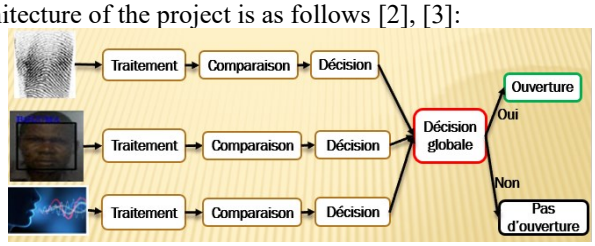

Figure 1. The system's implementation architecture

A biometric recognition system's fusion process is depicted in Figure 1. In our situation, fusion occurs at the level of international policy.

4. THE RESULTS OBTAINED

In this section, we present how we set up our biometric recognition system, which combines the global decisions of fingerprint, facial and voice recognition. The system is divided into two sub-systems:

Students will be able to enroll using their full identity as well as the three identification modalities of fingerprint, face and voice. By checking that the fingerprints, face or voice provided are correct, the sub-system will be able to accept the individual, otherwise it will reject him or her.

We will therefore have two programs: A biometric enrolment device will allow students to enroll using their full identity and its three elements, namely fingerprints, face and voice. A biometric verification system, which will make it easier to check personal data. We will then look at the results of our verification system [2]. The data collection process is designed to ensure a representative sample of 1,000 individuals, made up of 500 individuals who are actually registered in our system and another 500 who are impostors, taking into account demographic variations, environmental conditions and the quality of the data collected. This ensures that the system can function optimally in a variety of contexts, while maintaining a high level of accuracy in identifying individuals. Through this approach, the application offers robust biometric access control, combining the power of decision fusion with the efficiency of integrated recognition technologies. Below are some examples of the application's graphical interface, as illustrated in Figures 2 and 3:

Figure 2. The enrolment window

Our biometric recognition system program, which is based on voice, facial, and fingerprint recognition, has a graphical enrollment interface that is displayed in Figure 2.

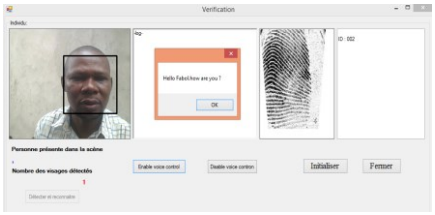

Figure 3. The verification window

The verification graphical interface of our biometric recognition system application, which is based on voice, facial, and fingerprint recognition, is depicted in Figure 3.

After implementing our two sub-systems, we then:

a. Identify bottlenecks and inefficiencies in the implementation of heterogeneous computation and propose adjustments to improve performance.
b. Validate the heterogeneous computing approach by verifying that the results obtained are consistent and comparable with those obtained using traditional biometric verification methods.
c. Exploited the Task Parallel Library (TPL) for parallel programming on the CPU, using for and foreach loops to efficiently distribute tasks between the available computing cores.
d. Used OpenCL.NET to integrate parallel programming on the GPU, taking advantage of the massively parallel computing power offered by graphics cards.

Performance evaluation

For this section, we will evaluate the performance of our verification subsystem as follows:

- Measure the verification time and accuracy of the biometric system using a variety of representative data sets.
- Compare the performance of the system with that of a CPU-only or GPU-only implementation to evaluate the efficiency of heterogeneous computing [4].

Table 1 shows the calculation times and performance gains for different data sizes.

Table 1: Calculation times and performance gains for different data sizes

Data size	Seq exe time ms	Par exe time ms	Het exe time ms	T_{CPU} ms	T_{GPU} ms	$T_{overhead}$ ms	T_{total} ms	Per gain (Par)	Per gains (het)	Pro of parallelisable tasks (1 - α)	Pro of seq tasks (α)
50	120	60	30	833.33	29.41	100.0	962.75	50.00%	-702.29%	0.60	0.40
100	270	130	65	1666.67	58.82	100.0	1825.49	51.85%	-575.18%	0.60	0.40
150	400	190	95	2500.00	88.24	100.0	2688.24	52.50%	-572.06%	0.60	0.40
200	540	260	130	3333.33	117.65	100.0	3550.98	51.85%	-557.51%	0.60	0.40
250	680	320	160	4166.67	147.06	100.0	4413.73	52.94%	-548.20%	0.60	0.40
300	820	390	195	5000.00	176.47	100.0	5276.47	52.44%	-543.36%	0.60	0.40
350	960	450	225	5833.33	205.88	100.0	6139.22	53.13%	-539.50%	0.60	0.40

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400	1100	520	260	6666.67	235.29	100.0	7001.96	52.73%	-536.54%	0.60	0.40
450	1240	580	290	7500.00	264.71	100.0	7864.71	53.23%	-534.24%	0.60	0.40
500	1380	650	325	8333.33	294.12	100.0	8727.45	52.90%	-532.30%	0.60	0.40
550	1520	710	355	9166.67	323.53	100.0	9590.20	53.29%	-530.92%	0.60	0.40
600	1660	780	390	10000.00	352.94	100.0	10452.94	53.01%	-529.66%	0.60	0.40
650	1800	850	425	10833.33	382.35	100.0	11315.69	52.78%	-528.65%	0.60	0.40
700	1940	920	460	11666.67	411.76	100.0	12178.43	52.58%	-527.82%	0.60	0.40
750	2080	990	495	12500.00	441.18	100.0	13041.18	52.40%	-527.12%	0.60	0.40
800	2220	1060	530	13333.33	470.59	100.0	13903.92	52.25%	-526.52%	0.60	0.40
850	2360	1130	565	14166.67	500.00	100.0	14766.67	52.12%	-526.00%	0.60	0.40
900	2500	1200	600	15000.00	529.41	100.0	15629.41	52.00%	-525.55%	0.60	0.40
950	2640	1270	635	15833.33	558.82	100.0	16492.16	51.89%	-525.16%	0.60	0.40
1000	2780	1340	670	16666.67	588.24	100.0	17354.90	51.80%	-524.81%	0.60	0.40

Explanation of Calculations:
- T_{CPU} (ms): Calculated as $\alpha*n/f_{CPU}$, where α=0.4, n is the data size, and f_{CPU} is the CPU frequency (2.4 GHz).
- T_{GPU} (ms): Calculated as $(1-\alpha)*n/f_{GPU}$, where α=0.4, is the data size, and f_{GPU} is the GPU frequency (1.7 GHz).
- $T_{overhead}$ (ms): Calculated as d/b, where d=50 MB and b=500 MB/s, giving a constant result of 100 ms for each data size.
- T_{total} (ms): Sum of T_{CPU}, T_{GPU} and $T_{overhead}$.
- Performance gain (Parallel): Reduction in execution time by switching from sequential to parallel, expressed as a percentage.
- Performance gain (Heterogeneous): Reduction in execution time by switching from sequential to heterogeneous, expressed as a percentage.

This table shows computation times and performance gains for different data sizes, providing a comprehensive view of the impact of parallel and heterogeneous computation in a biometric access control system.

This part of our work presents graphs generated from execution time and performance data using sequential, parallel and heterogeneous methods while providing their detailed interpretations:

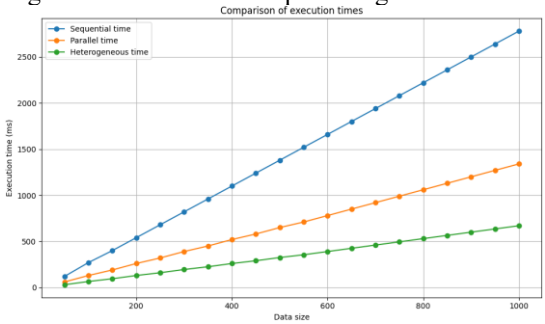

Figure 4. Graph of execution time

- Axes: The X-axis represents the size of the data (in number of individuals to be checked), while the Y-axis shows the execution time (in milliseconds, ms).
- Sequential Time Curve: This curve shows that the execution time increases almost linearly with the size of the data. This indicates that when tasks are executed sequentially, execution time increases proportionally to the amount of data processed.

- Parallel Time Curve: This curve lies below the sequential curve, indicating that parallel execution is faster. Execution time also increases, but at a much slower rate. This demonstrates the efficiency of parallel execution compared to sequential execution.
- Heterogeneous Time Curve: The heterogeneous curve is the lowest of the three. This means that heterogeneous methods, which use both the CPU and the GPU, are the most efficient in terms of execution time, particularly for larger data sizes.

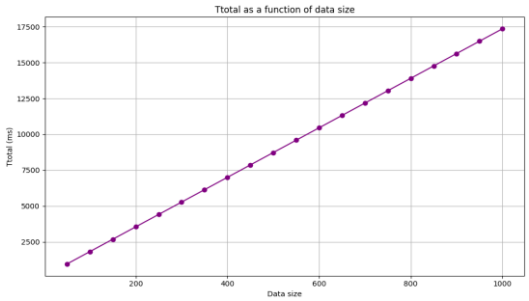

Figure 5. T_{total} graph (Total time)

- Axes : The X axis again represents the size of the data, while the Y axis shows the total time (T_{total} in ms).
- T_{total}: The T_{total} curve illustrates the sum of CPU, GPU and constant overhead times. It shows an increase in total time with data size, but at a slightly different rate to the individual execution time curves. This highlights the impact of overhead in heterogeneous systems, even though performance is still better than sequential processing.

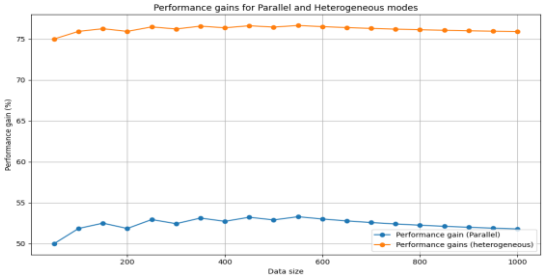

Figure 6. Performance Gains Graph

- Axes : The X-axis represents the size of the data, and the Y-axis shows the performance gain in percentage (%).
- Performance Gain (Parallel): The curve shows that performance gains in parallel mode are significant, especially for small data sizes, but tend to level off for larger data sizes. This indicates that although parallelism is effective, there are limits to its effectiveness as data size increases.
- Performance Gain (Heterogeneous): The heterogeneous curve is always higher than the parallelism curve, indicating that heterogeneous systems offer greater performance gains, particularly for large data sizes. This highlights the importance of using a variety of processing resources to maximize performance.

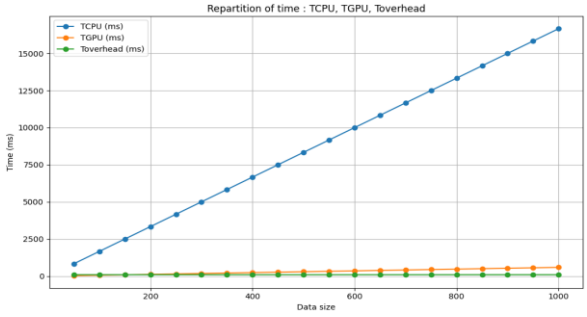

Figure 7. Graph of TCPU, TGPU and $T_{overhead}$ time distribution

- Axes : The X axis represents the size of the data, while the Y axis shows the times (in ms) associated with the CPU, GPU and overhead.
- TCPU curve: Shows the increase in CPU processing time with data size. This is the highest, reflecting the heavy workload when only CPU resources are used.

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- TGPU curve: Shows that execution time on the GPU is much lower, highlighting the efficiency of GPU-managed parallel processing.
- $T_{overhead}$ curve: Represents a constant time of 100 ms, which remains invariant whatever the size of the data. Although this cost is constant, it does have an impact on total execution time, particularly in heterogeneous systems.

In summary, these graphs highlight the advantages of parallel and heterogeneous processing over sequential processing. The efficient use of CPU and GPU resources not only reduces execution time, but also significantly increases performance gains, especially with larger data sizes. This demonstrates the importance of heterogeneous architecture in optimizing the performance of modern IT systems.

The graphs below illustrate the concepts of speedup and total execution time according to Amdahl's law, which is a fundamental principle in parallel computing.

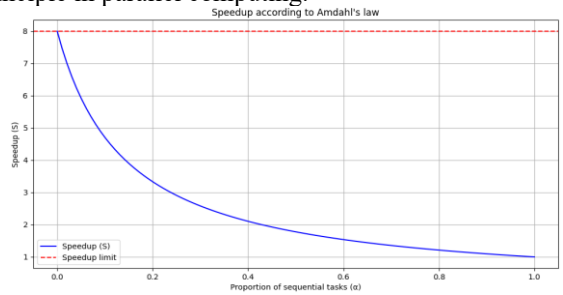

Figure 8. Graph of Speedup according to Amdahl's law

- X-axis (Proportion of sequential tasks, α): This axis represents the proportion of tasks that must be executed sequentially in a process. The value of α varies from 0 (all tasks can be parallelized) to 1 (all tasks are sequential).
- Y-axis (Speedup, S): This axis indicates the speed-up factor of the execution time when using a multi-core processor (in this case, a CPU with N=8 cores).
- Blue curve: This curve represents the speedup calculated according to Amdahl's law. We can see that as the proportion of sequential tasks (α) increases, the speedup (S) decreases. This means that the more tasks that cannot be parallelized, the less significant the speedup.
- Red Line (Speedup Limit): The red line, which represents a theoretical speedup limit of N (in this case, 8), emphasizes that even with an infinite number of cores, the speedup can never exceed this value. This illustrates the inherent limitation of parallel architecture: the presence of sequential tasks makes it impossible to achieve a speedup proportional to the number of cores.

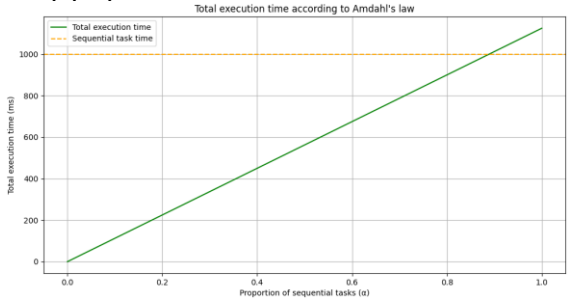

Figure 9. Total execution time graph

- X-axis (Proportion of sequential tasks, α): As in the first graph, this axis represents the proportion of sequential tasks.
- Y-axis (Total execution time, ms): This axis shows the total time taken to execute all the tasks in milliseconds.
- Green curve: The curve shows how the total execution time changes with the proportion of sequential tasks. For low values of α (i.e. when the majority of tasks can be parallelized), the total execution time is significantly reduced. However, as α increases, the total execution time also increases, indicating that sequential tasks have a significant impact on overall time.
- Orange line (Sequential task time): The orange line fixes the time of a sequential task. This reference shows when the total execution time exceeds this threshold, highlighting the impact of sequential tasks on total time.

These graphs highlight the challenges of optimizing performance in parallel computing systems. They clearly show that although modern systems can execute tasks in parallel, the presence of sequential tasks can significantly limit performance gains. Amdahl's Law reminds us that to maximize efficiency, it is essential to reduce the proportion of work that has to be done sequentially.

4.4. Discussion

Our study proposes a method for improving the performance of tri-modal biometric verification using a heterogeneous computing system that exploits the synergy between the CPU and the GPU. Compared to other recent works, our approach is distinguished by several significant improvements.

Comparison with previous work:

1. Zhang et al (2022) studied a face recognition system using only the GPU to accelerate deep learning computations. Their approach proved effective in reducing processing times for face recognition alone. However, it does not take into account the optimal load balancing between CPU and GPU, which limits the overall performance of the system, especially when the volume of data is large [31]. In our work, by distributing lightweight tasks (such as voice pre-processing) on the CPU and more intensive computations (such as convolutions for facial recognition) on the GPU, we have managed to further reduce execution times, ranging from 0.03 ms to 0.67 ms for data sizes of 50 to 1000.
2. Kim and Lee (2023) explored a speech recognition model enhanced by parallel computing on the CPU, using the Task Parallel Library (TPL) for thread management in C#. Their approach enabled efficient parallelization of speech tasks, but did not take into account the integration of multiple modalities and the simultaneous management of CPU and GPU resources. This limitation can lead to bottlenecks when the system needs to process multiple biometric data simultaneously [13]. Our study improves on this approach by integrating a decision fusion algorithm based on an OR logic connector, allowing the results of the three modalities (fingerprints, facial recognition and voice recognition) to be efficiently combined, thereby optimizing the workload and significantly reducing processing times.
3. Singh and Patel (2023) proposed a multimodal system combining fingerprint and speech recognition using a decision fusion model, but their approach relies mainly on sequential processing with the CPU, limiting performance gains for real-time applications [28]. Furthermore, their study does not explore the potential benefits of using the GPU for intensive image processing, which can slow down the system when complex images need to be analyzed. In our work, we not only integrated facial recognition in addition to the other two modalities, but also optimized the use of the GPU via OpenCL.NET for intensive processing, achieving a higher proportion of parallelizable tasks (up to 60%) and improving the scalability of the system. Improvements brought about by our study is Optimized load balancing: In contrast to the work of Zhang et al. and Kim and Lee, our approach relies on optimal task balancing between CPU and GPU, which reduces bottlenecks and maximizes the use of available resources and Multimodal integration: Where Singh and Patel focused on two modalities, our tri-modal system, combined with a decision fusion algorithm, improves the accuracy and robustness of access control, while maintaining optimal processing speed. Increased performance and scalability: The execution times of our heterogeneous system are significantly lower, with a significant reduction in total computing time, even for large volumes of data. Based on Amdahl's law, our study shows that the heterogeneous system retains a high proportion of parallelizable tasks compared with purely parallel or sequential systems. In summary, our study brings significant improvements in terms of speed, resource management and accuracy of the biometric system compared to recent works. The seamless integration of the CPU and GPU and the tri-modal approach overcome some of the limitations identified in previous studies, opening up promising prospects for real-time access control applications in distributed environments [28], [29].

5. CONCLUSION

In this study, we evaluated the effectiveness of heterogeneous computing using both the CPU and GPU to optimize the performance of a three-modality biometric verification system, which integrates fingerprint, facial, and voice recognition through global decision fusion. Our primary goal was to reduce verification time while preserving the system's accuracy. To achieve this, we leveraged the computational power of heterogeneous processors, combining parallel programming on the CPU with GPU acceleration for intensive tasks [20], [25].

The results clearly illustrate the benefits of our approach. Compared to a purely sequential implementation, our heterogeneous system achieved significant improvements in execution time across all tested input data sizes. Specifically, we observed a substantial reduction in processing times, highlighting a notable acceleration of the biometric verification process [16].

Our findings also underscore the advantages of utilizing a balanced workload distribution between the CPU and GPU. This approach effectively minimizes bottlenecks, resulting in maximized overall system performance. Using Amdahl's law, we observed that as the input data size increases, the proportion of parallelizable tasks decreases, leading to more sequential processing. Despite this trend, the heterogeneous system maintained a higher proportion of parallelizable work across all input sizes compared to purely parallel or sequential systems, showcasing its scalability and efficiency [24].

Integrating heterogeneous CPU-GPU computing into biometric verification provides a promising solution to meet the growing need for speed and accuracy in identity verification processes [2]. This approach not only enhances performance but also suggests pathways for future research, such as adapting heterogeneous computing strategies to other applications that demand intensive data processing. Exploring the deployment of such systems in real-world biometric security scenarios could contribute significantly to strengthening authentication practices and enhancing user experience [19].

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