GPU Programming – Assignment 2

SHA-256 Hashing on GPU (Numba CUDA)

Course: GPU Programming
Assignment: Implement a Cryptography Algorithm on GPU (Problem 4 – SHA / MD5 Hashing)
Repo: https://github.com/AnirudhReddy58/gpu-crypto

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1. Introduction

In this assignment we implemented **SHA-256**, a standard cryptographic hash function, and ran it on both:

- **CPU** – using Python's built-in `hashlib`, and
- **GPU** – using a custom **Numba CUDA** kernel.

The main idea is simple:

> We have many small, independent messages. Each message's hash can be computed independently, so we run one GPU thread per message and compare it with a CPU loop.

This matches **Problem 4 – SHA / MD5 Hashing: compute digests in parallel for large datasets**, and helps us understand how well GPUs can speed up a classic security-related workload.

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2. Problem Statement

Given:
A large batch of short messages $M_1, M_2, \ldots, M_n$ (strings of length up to 40–55 bytes).

Task:

1. Compute SHA-256 hashes for all messages on the **CPU** using Python `hashlib`.
2. Compute SHA-256 hashes for all messages on the **GPU**, using:
    - Numba CUDA,
    - one CUDA thread per message,
    - an implementation of the SHA-256 compression function.
3. Compare:

  - correctness (CPU hash vs GPU hash),
  - total time (seconds),
  - and **speed / throughput** (hashes per second) for different values of N.

Assumptions / limits:

- Each message is short enough to fit into **one 512-bit block** (i.e., original length ≤ 55 bytes).
- Multi-block messages and streaming SHA-256 are **not** implemented.

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3. Dataset / Workload

We did not use a fixed public dataset here. Instead, we generated synthetic data:

- **Messages:**
  - Each message is a random string of length between **5 and 40** characters.
  - Characters are chosen from: `a-z` and `0-9`.
  - We encode each string as UTF-8 bytes before hashing.
- **Batch sizes (N):**
  We tested the implementation for:
  - `N = 1,000`
  - `N = 5,000`
  - `N = 10,000`
  - `N = 20,000`
  - `N = 50,000`

This is meant to simulate a realistic scenario like hashing many small records: log lines, identifiers, or other short fields.

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4. Implementation Details

4.1 CPU Baseline (hashlib)

The CPU version is straightforward:

- Loop over all messages.
- For each message `m`:

```
import hashlib

digest = hashlib.sha256(m).digest()  # 32-byte result
```

- Store the digest in a NumPy array of shape `(N, 32)` with `dtype=uint8`.
- Measure:
  - total CPU time in seconds,
  - CPU throughput = `N / cpu_time` (hashes per second).

This CPU result is used both as:

- a **correctness reference**, and
- the **performance baseline** to compare with the GPU.

4.2 SHA-256 Padding (Host Side)

For each message we implement the standard SHA-256 padding, assuming the message fits in a single block:

1. Start with the message bytes.
2. Append `0x80` (binary `10000000`).
3. Append `0x00` bytes until the total length is **56 bytes**.
4. Append the original message length in **bits** as a 64-bit big-endian integer.
5. Final length = `64` bytes = `512` bits.

We assert that the original message length is ≤ 55 bytes so that one padded block is enough.

4.3 GPU Implementation (Numba CUDA)

We implemented the **SHA-256 compression function** on the GPU:

- **Constants:**
  - Initial hash values `H0[0..7]` (fixed 32-bit words).
  - Round constants `K[0..63]`.
- **Device helper functions:**
  - `to_uint32(x)` to keep everything in 32-bit unsigned range.
  - Bitwise ops:
    - `rotr(x, n)` – rotate right,
    - `shr(x, n)` – logical right shift.
  - Sigma functions:
    - `big_sigma0`, `big_sigma1`,
    - `small_sigma0`, `small_sigma1`.
  - Logic functions:
    - `ch(x, y, z)` (choice),
    - `maj(x, y, z)` (majority).
- **CUDA kernel (`sha256_kernel`) flow:**
  1. **Each thread** gets an index `idx` and handles **one message**.
  2. Load the 64-byte padded block into a local message schedule array `W[0..63]`:
     - `W[0..15]` from the block (big-endian),
     - `W[16..63]` computed using the σ functions and previous words.
  3. Initialize working variables `a..h` from `H0`.
  4. Run the 64-round compression loop.
  5. Add the result back to `H0` and write the final 8 words (`a..h`) into `digests[idx]` as 32 bytes (big-endian).

4.4 Parallelization & Launch Configuration

For a batch of N messages:

- We create a NumPy array `blocks` of shape `(N, 64)` containing all padded message blocks.
- Copy `blocks` to GPU (`d_blocks`).
- Allocate `d_digests` on GPU with shape `(N, 32)` for outputs.

Launch parameters:

```
threads_per_block = 128
blocks_per_grid = (N + threads_per_block - 1) // threads_per_block
sha256_kernel[blocks_per_grid, threads_per_block](d_blocks, d_digests)
```

So:

- each thread processes **one message**,
- there are enough threads to cover all N messages.

We also run a **warmup kernel launch** once to avoid counting JIT compilation time inside our timing.

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5. Experimental Setup

Environment:

- Python (Jupyter Notebook – `M25AI1048_M25AI1109_M25AI1131_M25AI1082.ipynb`)
- Packages: `numpy`, `numba`, `hashlib`, `matplotlib`
- Hardware (example, Colab-style environment):
  - CPU: virtual Intel Xeon
  - GPU: NVIDIA GPU (e.g., T4)
  - OS: Linux

Batch sizes:

We ran:

- N = 1,000
- N = 5,000
- N = 10,000
- N = 20,000
- N = 50,000

For each N we measured:

- CPU time (seconds)
- GPU time (seconds, kernel only)
- CPU speed (hashes/sec)
- GPU speed (hashes/sec)

- Speedup = CPU time / GPU time

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6. Results

6.1 Numerical Results

From the notebook run, we obtained:

```
===== N = 1000 messages =====
CPU time : 0.0019 s  (523,699 hashes/sec)
GPU time : 0.0001 s  (8,128,496 hashes/sec)

===== N = 5000 messages =====
CPU time : 0.0090 s  (554,055 hashes/sec)
GPU time : 0.0001 s  (51,909,703 hashes/sec)

===== N = 10000 messages =====
CPU time : 0.0186 s  (536,603 hashes/sec)
GPU time : 0.0001 s  (70,138,863 hashes/sec)

===== N = 20000 messages =====
CPU time : 0.0393 s  (509,058 hashes/sec)
GPU time : 0.0002 s  (100,462,371 hashes/sec)

===== N = 50000 messages =====
CPU time : 0.0874 s  (571,874 hashes/sec)
GPU time : 0.0004 s  (130,338,844 hashes/sec)
```

Overall summary:

```
N =   1000 | CPU: 0.0019s (523,699 h/s)  | GPU: 0.0001s (8,128,496 h/s)   |
Speedup:  15.52x
N =   5000 | CPU: 0.0090s (554,055 h/s)  | GPU: 0.0001s (51,909,703 h/s)  |
Speedup:  93.69x
N =  10000 | CPU: 0.0186s (536,603 h/s)  | GPU: 0.0001s (70,138,863 h/s)  |
Speedup: 130.71x
N =  20000 | CPU: 0.0393s (509,058 h/s)  | GPU: 0.0002s (100,462,371 h/s) |
Speedup: 197.35x
N =  50000 | CPU: 0.0874s (571,874 h/s)  | GPU: 0.0004s (130,338,844 h/s) |
Speedup: 227.92x
```

We can summarize this in a table:

N (messages)	CPU time (s)	GPU time (s)	CPU speed (hashes/sec)	GPU speed (hashes/sec)	Speedup (CPU/GPU)
1,000	0.0019	0.0001	523,699	8,128,496	15.52×

N (messages)	CPU time (s)	GPU time (s)	CPU speed (hashes/sec)	GPU speed (hashes/sec)	Speedup (CPU/GPU)
5,000	0.0090	0.0001	554,055	51,909,703	93.69×
10,000	0.0186	0.0001	536,603	70,138,863	130.71×
20,000	0.0393	0.0002	509,058	100,462,371	197.35×
50,000	0.0874	0.0004	571,874	130,338,844	227.92×

For each N, we also verified a sample of digests and they matched between CPU and GPU.

6.2 Visualizations

In the notebook we generated two plots:

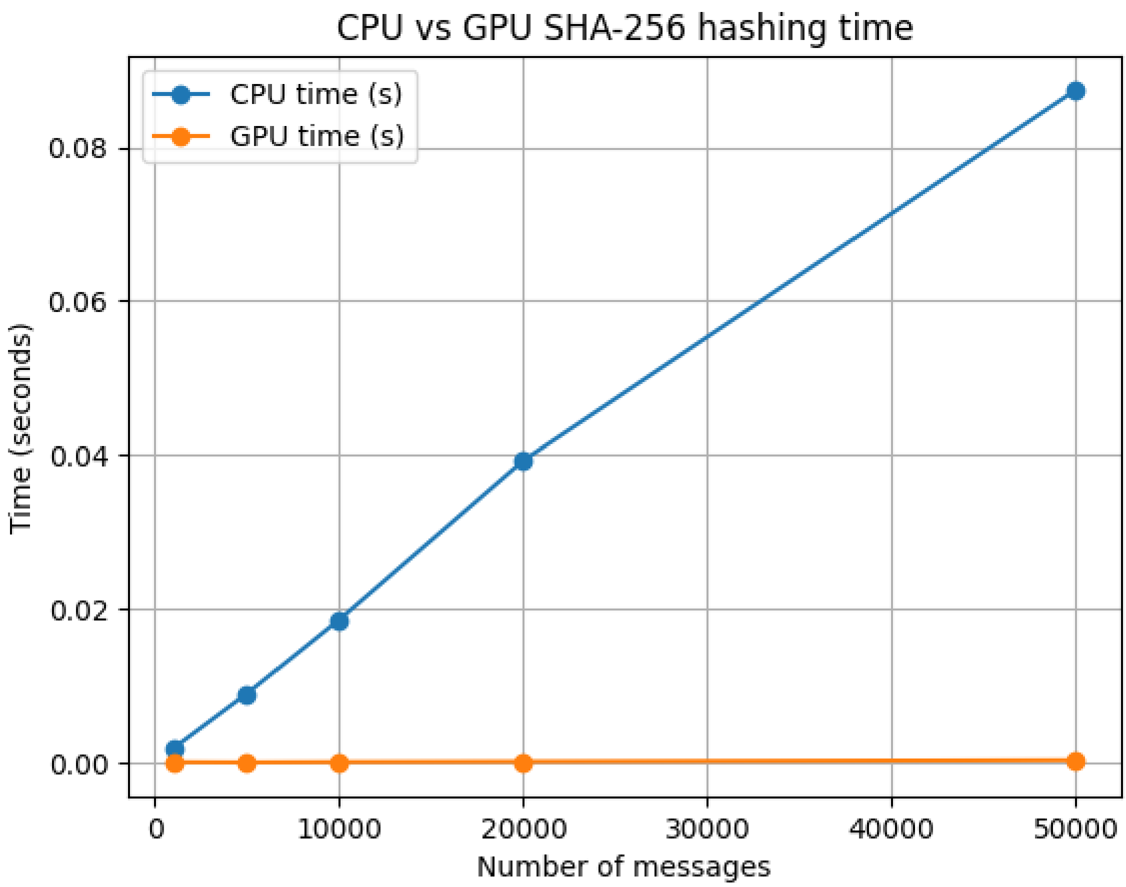
1. **CPU vs GPU time (seconds)** vs batch size N
2. **CPU vs GPU throughput (hashes/sec)** vs batch size N

If these are saved as:

- `images/cpu_gpu_time.png`
- `images/cpu_gpu_throughput.png`

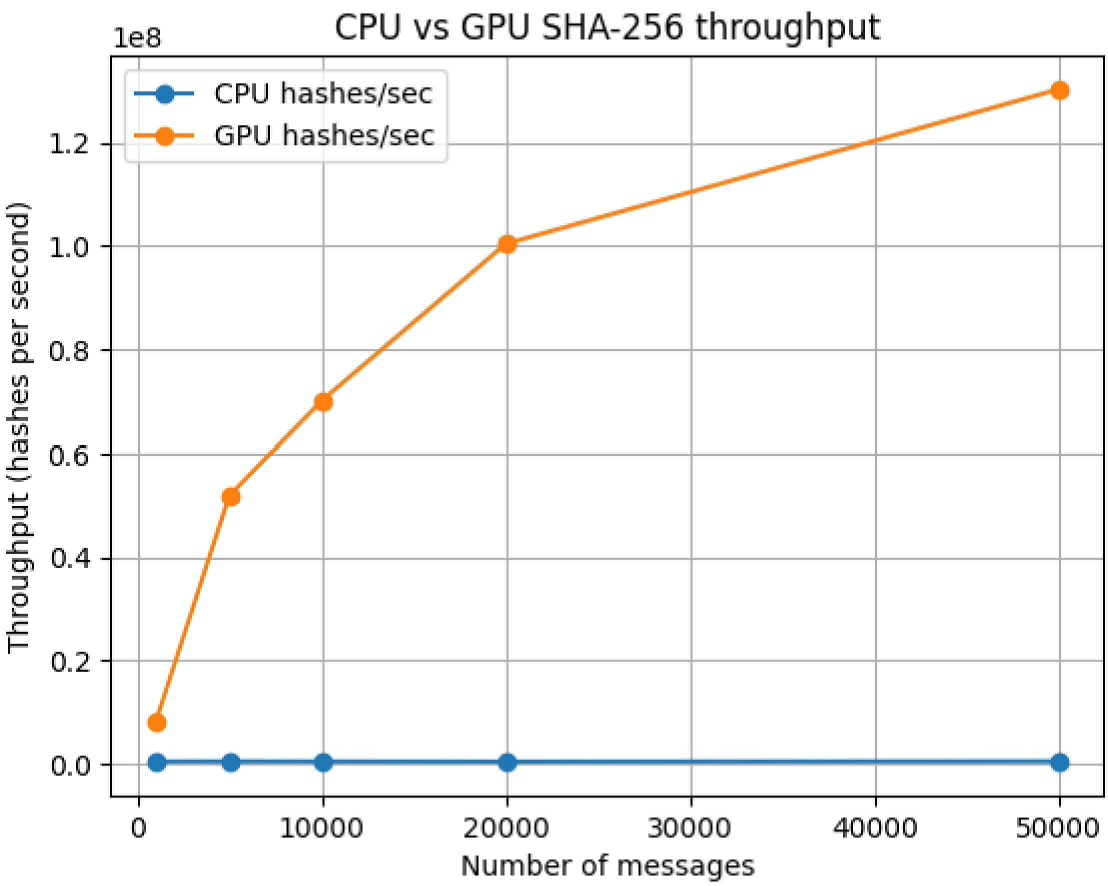
we can reference them here.

6.2.1 CPU vs GPU Time



This plot shows that CPU time grows linearly with N, while GPU kernel time stays very low, especially for larger N.

6.2.2 CPU vs GPU Throughput



Here we see:

- CPU throughput is around ~0.5–0.57 million hashes/sec,
- GPU throughput increases up to ~130 million hashes/sec,
- giving a speedup of more than 200× for N = 50,000.

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7. Discussion

- **Parallelism:**
  The problem is embarrassingly parallel. Each message hash is independent, so assigning one thread per message fits the GPU model very well.

- **Impact of Batch Size:**
  For small N (like 1,000), GPU overheads matter more, so speedup is smaller (~15×).
  As N increases, GPU utilization improves and we see speedups above ~200×.

- **Correctness:**
  The tricky part of SHA-256 is handling:

  - 32-bit overflow,
  - rotations and shifts,

    - and big-endian word construction.
      Our GPU implementation matches `hashlib.sha256` on sampled messages for all tested N, which gives us confidence in correctness under the single-block assumption.

- **Security Perspective:**
  These results demonstrate how fast GPUs can hash data. This is good for integrity checks and deduplication, but also illustrates why **password hashing** should use slow, salt-and-stretch algorithms (like bcrypt/Argon2) instead of raw SHA-256.

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8. Limitations

- Only **single-block** SHA-256 is supported (messages ≤ 55 bytes).
- Multi-block messages and streaming are not handled.
- We focused on **kernel time** on the GPU, not the full host–device transfer overhead in detail.
- Only SHA-256 was implemented (no MD5 or AES in this assignment).

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9. Conclusion

We implemented and tested **SHA-256 hashing on GPU** using Numba CUDA and compared it to a CPU `hashlib` baseline.

Main takeaways:

- GPU can process large batches of small messages with **very high throughput**.
- For N up to 50,000 messages, the speedup reaches **~228×** over the CPU.
- The implementation demonstrates:
    - custom CUDA kernels,
    - bit-level operations on the GPU,
    - and practical measurement of performance and speedup.

This assignment clearly shows how GPUs can accelerate not only deep learning workloads, but also **cryptographic and data-processing tasks** that are inherently parallel.