T06: OpenMP - Write a parallel code to perform two NxN Matrix Multiplication - Each element of the matrix is double precision number.

CS24M1005 – SINDHIYA R

Write a parallel code to perform two NxN Matrix Multiplication - Each element of the matrix is double precision number. Consider N values sufficiently larger number at least 10000.

Assumption: 3000 matrix size is taken as input because 10000 input matrix size took 15000 seconds for execution which is roughly 2.5hrs. Attached image for your reference.

9992 9993 9994 9995 9996 9997 9998 9999 Serial Execution Time: 15332.328169 seconds sindhiya@MSI:/mnt/c/SEM_02/HPC/t06\$

1) Serial Code - 5 Marks

```
#include <iostream>
#include <stdio.h>
#include <stdlib.h>
#include <time.h>
using namespace std;
#define N 3000 // Matrix size
// Function to allocate a matrix
double ** allocate_matrix(int n) {
  double** matrix = (double**)malloc(n * sizeof(double*));
  for (int i = 0; i < n; i++) {
    matrix[i] = (double*)malloc(n * sizeof(double));
  return matrix;
// Function to initialize a matrix with random values
void initialize_matrix(double** matrix, int n) {
  for (int i = 0; i < n; i++) {
    for (int j = 0; j < n; j++) {
       matrix[i][j] = (double)rand() / RAND MAX;
}
// Serial Matrix Multiplication
void serial matrix mult(double** A, double** B, double** C, int n) {
  for (int i = 0; i < n; i++) {
```

```
// cout<<i<" ";
    for (int j = 0; j < n; j++) {
       C[i][j] = 0;
       for (int k = 0; k < n; k++) {
         C[i][j] += A[i][k] * B[k][j];
       }
    }
  }
}
int main() {
  double** A = allocate_matrix(N);
  double** B = allocate matrix(N);
  double** C = allocate matrix(N);
  initialize matrix(A, N);
  initialize_matrix(B, N);
  clock_t start = clock();
  serial matrix mult(A, B, C, N);
  clock_t end = clock();
  printf("Serial Execution Time: %f seconds\n", (double)(end - start) / CLOCKS PER SEC);
  // Free memory
  for (int i = 0; i < N; i++) {
    free(A[i]); free(B[i]); free(C[i]);
  free(A); free(B); free(C);
  return 0;
```

Output:

```
sindhiya@MSI:/mnt/c/SEM_02/HPC/t06$ g++ mul.cpp -o mul -fopenmp
sindhiya@MSI:/mnt/c/SEM_02/HPC/t06$ ./mul
Serial Execution Time: 254.150323 seconds
```

2) Parallel Code - 5 Marks

```
#include <stdio.h>
#include <stdlib.h>
#include <omp.h>

#define N 3000 // Matrix size
```

```
// Function to allocate a matrix
double** allocate matrix(int n) {
  double** matrix = (double**)malloc(n * sizeof(double*));
  for (int i = 0; i < n; i++) {
     matrix[i] = (double*)malloc(n * sizeof(double));
  return matrix;
}
// Function to initialize a matrix with random values
void initialize_matrix(double** matrix, int n) {
  for (int i = 0; i < n; i++) {
    for (int j = 0; j < n; j++) {
       matrix[i][j] = (double)rand() / RAND MAX;
    }
}
// Parallel Matrix Multiplication using OpenMP
void parallel_matrix_mult(double** A, double** B, double** C, int n) {
  #pragma omp parallel for collapse(2)
  for (int i = 0; i < n; i++) {
    for (int j = 0; j < n; j++) {
       C[i][j] = 0;
       for (int k = 0; k < n; k++) {
         C[i][j] += A[i][k] * B[k][j];
       }
    }
}
int main() {
  double** A = allocate_matrix(N);
  double** B = allocate matrix(N);
  double** C = allocate matrix(N);
  initialize matrix(A, N);
  initialize matrix(B, N);
  int threads[] = {1, 2, 4, 6, 8, 10, 12, 16, 20, 32, 64};
  int num tests = sizeof(threads) / sizeof(threads[0]);
  for (int t = 0; t < num tests; t++) {
     omp set num threads(threads[t]);
```

```
double start = omp_get_wtime();
    parallel_matrix_mult(A, B, C, N);
    double end = omp_get_wtime();
    printf("Parallel Execution with %d threads: %f seconds\n", threads[t], end - start);
}

// Free memory
for (int i = 0; i < N; i++) {
    free(A[i]); free(B[i]); free(C[i]);
}
free(A); free(B); free(C);
return 0;
}</pre>
```

Output:

```
sindhiya@MSI:/mnt/c/SEM_02/HPC/t06$ g++ mul_p.cpp -o mul_p -fopenmp
sindhiya@MSI:/mnt/c/SEM_02/HPC/t06$ ./mul_p
Parallel Execution with 1 threads: 261.819542 seconds
Parallel Execution with 2 threads: 124.467051 seconds
Parallel Execution with 4 threads: 63.176933 seconds
Parallel Execution with 6 threads: 44.522700 seconds
Parallel Execution with 8 threads: 38.269970 seconds
Parallel Execution with 10 threads: 36.955305 seconds
Parallel Execution with 12 threads: 32.439435 seconds
Parallel Execution with 16 threads: 31.529269 seconds
Parallel Execution with 20 threads: 32.671955 seconds
Parallel Execution with 32 threads: 31.242556 seconds
Parallel Execution with 64 threads: 31.632853 seconds
```

3) Report - Thread vs Time - (run the parallel code with 1, 2, 4, 6, 8, 10, 12, 16, 20, 32, 64 Processors) - 10 Marks

Threads	Execution Time	
1	261.819542	
2	124.467051	
4	63.176933	
6	44.5227	
8	38.26997	
10	36.955305	
12	<mark>32.439435</mark>	
16	<mark>31.529269</mark>	
20	<mark>32.671955</mark>	
32	<mark>31.242556</mark>	
64	<mark>31.632853</mark>	

Observation:

- Beyond **12 threads**, the **performance gain is minimal**, indicating a **saturation point**.
- CPU and memory bandwidth bottlenecks limit further improvement.
- After 12 threads, increased contention for cache and RAM bandwidth prevents further speedup.
- **Synchronization overhead** and **thread management** costs increase at 20+ threads, leading to no significant speedup.
- Threads beyond available **physical cores (hyperthreading)** do not contribute much to performance.

4) Plot Speedup vs Processors - 5 Marks

Threads	Execution Time	Speedup
1	261.819542	1
2	124.467051	2.103525
4	63.176933	4.144227
6	44.5227	5.880585
8	38.26997	6.841384
10	36.955305	7.084762
12	32.439435	<mark>8.071027</mark>
16	31.529269	<mark>8.304016</mark>
20	32.671955	<mark>8.013587</mark>
32	31.242556	<mark>8.380222</mark>
64	31.632853	<mark>8.276824</mark>

MATRIX MULTIPLICATION - Speedup vs Processors



5) Inference - 5 Marks

1. Near-Linear Speedup Up to 12 Threads

- Speedup improves significantly up to 12 threads (8.07× speedup).
- This indicates that **matrix multiplication is highly parallelizable**, benefiting from multithreading.

2. Performance Saturation Beyond 12 Threads

- The improvement flattens after 12-16 threads, suggesting a hardware bottleneck.
- This is caused by memory bandwidth limitations and cache conflicts.

3. Memory Bandwidth Becomes the Limiting Factor

- Beyond 12 threads, the processor struggles to fetch data from memory efficiently.
- Large matrices require high memory throughput, leading to contention among threads.

4. Synchronization and Overhead Reduce Efficiency

- At 20+ threads, execution time fluctuates, showing diminishing returns.
- Thread creation, scheduling, and data synchronization introduce significant overhead.

5. CPU Hyperthreading Provides Minimal Gains

- Increasing threads beyond available physical cores (16 in modern i7 CPUs) does not improve speedup.
- Hyperthreading only helps if computations involve frequent memory stalls.

6. Matrix Size Plays a Crucial Role in Parallel Performance

- For very large matrices (N ≥ 10,000), multi-threading is highly effective.
- However, for smaller matrices, overhead dominates, making parallelization inefficient.

7. Tiling and Cache Optimization Can Improve Performance

- Using cache-aware optimizations like tiling (block matrix multiplication) reduces cache
 misses.
- This can improve performance even when increasing threads beyond 12-16.

8. GPU Acceleration Would Be More Effective

• GPUs are optimized for massively parallel operations, unlike CPUs, which suffer from thread contention.

9. Thread Scheduling and Load Balancing Affect Performance

- Uneven work distribution among threads can cause some to remain idle while others work harder.
- Dynamic scheduling may improve performance in some cases.

10. Parallel Matrix Multiplication is Memory-Bound, Not Just Compute-Bound

• While matrix multiplication involves intense computation (O(N³)), memory access is a major bottleneck.

Note

1.All the calculation are done in excel and it is attached for your reference.

2. All the code files with output are in github link and they are attached for your reference.