Multi-View 3D Geometry Reconstruction: Exploiting Massive Parallelism

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Abstract

3D geometric reconstruction from digital images captured from consumer cameras is an inexpensive, but computationally demanding application. In this experimental study, we have explored parallelism in the best known public domain software (Bundler and PMVS2) and found that massive parallelism exists at various levels that can be exploited on various computer architectures (such as multi-cores, distributed memory and GPU machines). Although in this report, we present results for multi-core and distributed memory machines, but we believe that similar results could be obtained on vector machines and GPU architectures as well. We have tested our MPI codes on a large clusters of 500 Linux nodes. Having shown almost linear scalability, we stress upon the need of improvements in sequential algorithms to enhance the quality of generated models.
1 Introduction

3D geometric reconstruction from images from digital camera is very attractive technique because digital consumer cameras are now a days quite inexpensive, extremely portable and have reasonably high resolution. Commercial large laser scanners, although provide extremely high quality triangulated models, are limited in usage because of their high cost, bulkiness and non-portability.

Another driving force for developing this technology is Internet Imagery. Internet is perhaps the biggest repository of images where millions of photographs of well known buildings, statues and structures can be downloaded. The major characteristic of Internet images is the diversity in every sense which provides both opportunities and challenges in the development of Internet imagery a killer future application. It is possible to find a large number of images of every conceivable viewing direction and environment conditions( sunny, cloudy, night etc ). Diversity in image resolutions, exposure setting and image quality provides additional information that can be exploited to reconstruct high quality 3D models.

One of the major obstacle in reconstructing 3D models from images is high computational cost per image in the set. Depending on the image sizes and number of images, it could take many hours or days to produce acceptable quality despite using the best known algorithms on a single processor machines. In this project, we have explored parallelism ( both fine grained and coarse grained ) in the existing, well known public domain software that can be exploited on various computer hardware.

2 Exploiting Parallelism

In many applications, parallelism exists at many levels. Fine grain parallelism occurs at loop levels or instructions level. Such parallelism are hard to exploit and many modern compilers can automatically detect and parallelize the code. On the other hand, coarse grain or task parallelism are application dependent, simpler to implement and reason about. In many applications, coarse grained parallelism provide unlimited scalability. Fortunately, in this application both fine grains and coarse grain parallelism exists that can be exploited on modern computer hardware very efficiently.

3 Literature Survey

There is large collection of papers on the 3D reconstruction and stereo matching. But this project is influenced by Building Rome in a Day[3]. In addition, we refer Modeling the World from Internet Photo Collection [4] for algorithms and techniques used in the reconstruction process.
### Table 1: Parallelism in different modules of 3D reconstruction

<table>
<thead>
<tr>
<th>Module</th>
<th>Fine Grain Parallelism</th>
<th>Coarse Grain Parallelism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature Detection</td>
<td>pixel level operations are independent</td>
<td>every image is independent so each image run on different processor</td>
</tr>
<tr>
<td>Feature Matching</td>
<td>Parallel KD Tree</td>
<td>Each image is matched against all others</td>
</tr>
<tr>
<td>SFM</td>
<td>Parallel Linear Algebra</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Parallel RANSAC</td>
<td></td>
</tr>
<tr>
<td>Dense Point Cloud</td>
<td>Each Patch is independent and each patch is run by independent thread</td>
<td>Each patch is independent each patch run on different processor</td>
</tr>
<tr>
<td>Surface Reconstruction</td>
<td>Domain Decomposition</td>
<td>Domain Decomposition</td>
</tr>
<tr>
<td>Mesh Processing</td>
<td>Domain Decomposition</td>
<td>Domain Decomposition</td>
</tr>
</tbody>
</table>

### 4 Public Domain Software

Instead of developing software from scratch, we have used best known public domain software which have been provided for research purpose.

- **SIFT** is a feature detector (Lowe 2004) which provides good invariance to image transformation.

- **Bundler** Bundler takes a set of images, image features, and image matches as input, and produces a 3D reconstruction of camera and (sparse) scene geometry as output. The system reconstructs the scene incrementally, a few images at a time, using a modified version of the Sparse Bundle Adjustment package of Lourakis and Argyros as the underlying optimization engine.

- **PMVS** is a multi-view stereo software that takes a set of images and camera parameters, then reconstructs 3D structure of an object or a scene visible in the images. Only rigid structure is reconstructed, in other words, the software automatically ignores non-rigid objects such as pedestrians in front of a building. The software outputs a set of oriented points instead of a polygonal (or a mesh) model, where both the 3D coordinate and the surface normal are estimated at each oriented point.
Figure 1: Pipeline of 3D model reconstruction

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Images</th>
<th>Image Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Middlebury: Temple</td>
<td>359</td>
<td>640x480</td>
</tr>
<tr>
<td>Middlebury: Dino</td>
<td>363</td>
<td>640x480</td>
</tr>
<tr>
<td>Ponce: GreenDragon</td>
<td>24</td>
<td>3104x2072</td>
</tr>
<tr>
<td>Ponce: Armor</td>
<td>48</td>
<td>3504x2336</td>
</tr>
<tr>
<td>UW: BascomHall</td>
<td>150</td>
<td>1645x970</td>
</tr>
<tr>
<td>Madison: Capitol</td>
<td>246</td>
<td>1649x970</td>
</tr>
</tbody>
</table>

Table 2: Dataset used in the experiments

5 Results

We have implemented two most time consuming operations i.e. Feature Detection and KeyMatching using Message Passing Interface (MPI) and tested the codes on Intel Eight cores machines and a cluster of 64 nodes at Engineering Physics department at the University of Wisconsin, Madison. PMVS is already available as multithreaded code so we did not modify it. Two of the dataset are from Middlebury benchmark and two are from Ponce Research group. These four dataset have been used to compare the results with other group. We have taken large number of images of Bascom Hall and Capitol building at Madison and these two dataset are primarily used to study parallelization issues.
### Table 3: SIFT Features in the dataset

<table>
<thead>
<tr>
<th>DataSet</th>
<th>Min Features</th>
<th>Max Features</th>
<th>Mean Features</th>
<th>Total Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temple</td>
<td>445</td>
<td>1144</td>
<td>869</td>
<td>314426</td>
</tr>
<tr>
<td>Dino</td>
<td>66</td>
<td>248</td>
<td>156</td>
<td>58654</td>
</tr>
<tr>
<td>Dragon</td>
<td>6928</td>
<td>9546</td>
<td>8194</td>
<td>198050</td>
</tr>
<tr>
<td>Armor</td>
<td>11919</td>
<td>55417</td>
<td>27764</td>
<td>1408775</td>
</tr>
<tr>
<td>BascomHall</td>
<td>3673</td>
<td>69907</td>
<td>15120</td>
<td>2317129</td>
</tr>
<tr>
<td>Capitol</td>
<td>144</td>
<td>28597</td>
<td>13700</td>
<td>3103375</td>
</tr>
</tbody>
</table>

### Table 4: Features Detection on Intel Eight-Core Machine

<table>
<thead>
<tr>
<th>DataSet</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temple</td>
<td>12/1.0</td>
<td>6.0/2.0</td>
<td>3.0/4.0</td>
<td>2.20/5.45</td>
</tr>
<tr>
<td>Dino</td>
<td>538/1.0</td>
<td>271/1.98</td>
<td>138/3.89</td>
<td>95/5.66</td>
</tr>
<tr>
<td>Dragon</td>
<td>831/1.0</td>
<td>432/1.92</td>
<td>237/3.50</td>
<td>173/4.80</td>
</tr>
<tr>
<td>BascomHall</td>
<td>4492/1.0</td>
<td>2270/1.97</td>
<td>1163/3.86</td>
<td>776/5.78</td>
</tr>
<tr>
<td>Capitol</td>
<td>7757/1.0</td>
<td>3902/1.98</td>
<td>1967/3.93</td>
<td>1366/5.67</td>
</tr>
</tbody>
</table>

### 6 Conclusions

From the results of the experiments we can conclude that

- There is almost linear scaling on the two most time consuming operations in the 3D reconstruction pipeline i.e. Feature detection and Feature matching on both Multi-Core and distributed memory machines using MPI. The parallelization of these two module is trivial task with MPI.

- Presently PMVS2 is multi-threaded and there is good scope to improve both the algorithm and the implementation on distributed memory machines.

- The point cloud generated after the PMVS2 has many outliers and has sampling errors which make it difficult for the surface reconstructor to generate watertight triangulated mesh.

### 7 Future Work

We firmly believe that 3D reconstruction with images has great potential for future applications. But in the entire pipeline of reconstructions, it seems the
<table>
<thead>
<tr>
<th>DataSet ↓</th>
<th>NumThreads →</th>
<th>1</th>
<th>4</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temple</td>
<td>113m 10s</td>
<td>29m</td>
<td>16m 41s</td>
<td></td>
</tr>
<tr>
<td>Dino</td>
<td>5m 25s</td>
<td>4m 15s</td>
<td>3m 38s</td>
<td></td>
</tr>
<tr>
<td>Dragon</td>
<td>5m 25s</td>
<td>1m 39s</td>
<td>1m 7s</td>
<td></td>
</tr>
<tr>
<td>Armor</td>
<td>105m 54s</td>
<td>26m</td>
<td>16m 5s</td>
<td></td>
</tr>
<tr>
<td>BascomHall</td>
<td>6h 46m</td>
<td>1h 45m</td>
<td>62m 31s</td>
<td></td>
</tr>
<tr>
<td>Capitol</td>
<td>14h 58m</td>
<td>3h 50m</td>
<td>137m 3s</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Features Matching on Intel Eight-Core Machine

<table>
<thead>
<tr>
<th>DataSet →</th>
<th>BascomHall</th>
<th>Capitol</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumProcs ↓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>18514s</td>
<td>34688s</td>
</tr>
<tr>
<td>4</td>
<td>9257s</td>
<td>17258s</td>
</tr>
<tr>
<td>8</td>
<td>3675s</td>
<td>8682s</td>
</tr>
<tr>
<td>16</td>
<td>2520s</td>
<td>4300s</td>
</tr>
<tr>
<td>32</td>
<td>1249s</td>
<td>2334s</td>
</tr>
<tr>
<td>64</td>
<td>841s</td>
<td>1416s</td>
</tr>
</tbody>
</table>

Table 6: Features Matching on 64 Node Intel Cluster

Quality of an acceptable model is primarily dependent on (1) Better feature detection (2) Dense point cloud generation. At present, the dense point cloud produced by PMVS2 has lots of scope for improvement. In many cases, it still generates large number of holes which are difficult for surface reconstructors.

In order to generate photo realistic models, it is important to apply texture mapping on the model. In future we would like to investigate applying image texture on the reconstructed models.

One of the limitations of the present algorithm is that they can not reconstruct 3D models if the model’s surfaces are shiny and reflective. Probably using High Dynamic Range imaging, we can avoid input images to have shiny spots. In future, We would to explore use of HDR imaging in 3D model reconstruction.
8 MPI Source Code: KeyMatching with Load Balancing

```c
#include <assert.h>
#include <time.h>
#include <string.h>
#include <sstream>
#include <fstream>
#include "keys2a.h"
#include <deque>
#include <boost/lexical_cast.hpp>

using namespace std;

#ifdef PARALLEL
#include <mpi.h>
#endif

int main(int argc, char **argv)
{
    char *list_in = ".\list.txt";
    char *file_out = "matches.init.txt";
    double ratio;
    ratio = 0.6;
    int myid = 0, numprocs = 1;
```
int start_proc_id = 0;

#ifdef PARALLEL
    MPI_Init(&argc,&argv);
    MPI_Comm_rank(MPI_COMM_WORLD,&myid);
    MPI_Comm_size(MPI_COMM_WORLD,&numprocs);
    double tstart = MPI_Wtime();
#endif

unsigned char **keys;
int *num_keys;

/* Read the list of files */
std::vector<std::string> key_files;

FILE *f = fopen(list_in, "r");
if (f == NULL) {
    printf("Error opening file %s for reading\n", list_in);
    return 1;
}
Load Balancing on Distributed Memory Machine
Module: KeyMatching; Capitol Dataset

Figure 5: Dynamic load balancing on 64 nodes distributed memory machine

```c
char buf[512];
while (fgets(buf, 512, f)) {
    /* Remove trailing newline */
    if (buf[strlen(buf) - 1] == '
')
        buf[strlen(buf) - 1] = 0;
    string fname = std::string(buf);
    size_t pos = fname.find(".jpg");
    if( pos != string::npos) {
        fname = fname.substr(0, pos);
        fname = fname + ".key";
        key_files.push_back( fname );
    }
}
fclose(f);

int num_images = (int) key_files.size();
```
keys = new unsigned char *[num_images];
num_keys = new int[num_images];

/* Read all keys */
for (int i = 0; i < num_images; i++) {
    keys[i] = NULL;
    num_keys[i] = ReadKeyFile(key_files[i].c_str(), keys+i);
}

string ofilename = file_out + boost::lexical_cast<string>(myid);
ofstream ofile(ofilename.c_str(), ios::out);
assert( !ofile.fail() );

int numPieces = num_images/numprocs;
int numindex = 0;

int imgid, work_requester, num_images_processed = 0;
MPI_Status mpi_status;
if( myid == 0)
{
    deque<int> imgQ;
    for( int i = 0; i < num_images; i++)
        imgQ.push_back( num_images-i-1 );

    for( int i = 1; i < numprocs; i++) {
        imgid = imgQ.front(); imgQ.pop_front();
        MPI_Send( &imgid, 1, MPI_INT, i, 0, MPI_COMM_WORLD);
    }

    while( !imgQ.empty() ) {
        MPI_Recv( &work_requester, 1, MPI_INT, MPI_ANY_SOURCE, 0,
                  MPI_COMM_WORLD, &mpi_status);
        imgid = imgQ.front(); imgQ.pop_front();
        MPI_Send( &imgid, 1, MPI_INT, work_requester, 0, MPI_COMM_WORLD);
    }

    for( int i = 1; i < numprocs; i++)
        MPI_Recv( &work_requester, 1, MPI_INT, MPI_ANY_SOURCE, 0,
                  MPI_COMM_WORLD, &mpi_status);

    int stop_signal = -1;
    for( int i = 1; i < numprocs; i++) {
        MPI_Send( &stop_signal, 1, MPI_INT, i, 0, MPI_COMM_WORLD);
    }
}
else {
    while(1 ) {
        MPI_Recv( &imgid, 1, MPI_INT, 0, 0, MPI_COMM_WORLD, &mpi_status);

        if( imgid == -1) break;
    }
}
int i = imgid;
if (num_keys[i])
{
    num_images_processed++;

    /* Create a tree from the keys */
    ANNkd_tree *tree = CreateSearchTree(num_keys[i], keys[i]);

    for (int j = 0; j < i; j++) {
        if (num_keys[j] == 0) continue;

        /* Compute likely matches between two sets of keypoints */
        std::vector<KeypointMatch> matches =
            MatchKeys(num_keys[j], keys[j], tree, ratio);

        int num_matches = (int) matches.size();

        if (num_matches >= 16) {
            /* Write the pair */
            ofile << j << " " << i << endl;

            /* Write the number of matches */
            ofile << matches.size() << endl;

            for (int i = 0; i < num_matches; i++)
                ofile << matches[i].m_idx1 << " " << matches[i].m_idx2 << endl;
        }
    }

    delete tree;
}

MPI_Send( &myid, 1, MPI_INT, 0, 0, MPI_COMM_WORLD);

/* Free keypoints */
for (int i = 0; i < num_images; i++) {
    if (keys[i] != NULL)
        delete [] keys[i];
}

delete [] keys;
delete [] num_keys;

ofile.close();

#ifdef PARALLEL
    double tend = MPI_Wtime();
    double elapsetime = tend-tstart;
#endif
cout << myid << " Elapsed Time " << elapsetime << endl;

if( myid == 0 )
{
    vector<double> proctime(numprocs);
    vector<int> imagecounter(numprocs);

    proctime[0] = elapsetime;
    imagecounter[0] = 0;
    for( int i = 1; i < numprocs; i++ ) {
        MPI_Recv( &num_images_processed, 1, MPI_INT, i, 0, MPI_COMM_WORLD, &mpi_status);
        imagecounter[i] = num_images_processed;
        MPI_Recv( &elapsetime, 1, MPI_DOUBLE, i, 1, MPI_COMM_WORLD, &mpi_status);
        proctime[i] = elapsetime;
    }

    string file2 = "proctime" + boost::lexical_cast<string>(numprocs) + ".dat";
    ofstream ofile2(file2.c_str(), ios::out);
    cout << " ProcID " << " # of Images Processed " << endl;
    for( int i = 0; i < numprocs; i++ ) {
        ofile2 << i << " " << proctime[i] << endl;
        cout << i << " " << imagecounter[i] << endl;
    }
} else {
    MPI_Send( &num_images_processed, 1, MPI_INT, 0, 0, MPI_COMM_WORLD);
    MPI_Send( &elapsetime, 1, MPI_DOUBLE, 0, 1, MPI_COMM_WORLD);
}

MPI_Barrier( MPI_COMM_WORLD );

tend = MPI_Wtime();

MPI_Finalize();

if( myid == 0 )
{
    cout << "Total Execution time for KeyMatching : " << (tend - tstart) << endl;
}
#endif

return 0;
}

References

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