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Point Cloud Based Path Planning for Tower Crane Lifting*

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ABSTRACT

This paper discusses automatic path planning for tower crane lifting in highly complex environments to be digitized using point cloud representation. A mathematical optimization technique is developed to identify the lifting path with GPU accelerated massively parallel genetic algorithm. A continuous collision detection method is designed for real time application of collision avoidance during the crane lifting process.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence** → **Planning and scheduling** → **Robotic planning** → **Evolutionary robotics**

KEYWORDS

Automatic lifting path planning, point cloud, complex environment, tower crane, genetic algorithm, collision check, rasterization, depth map

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1 INTRODUCTION

1.1 Background and Challenges

Tower crane lifting is commonly used in construction, petrochemical and pharmaceutical industries. Safety is always an issue, especially when lifting large and heavy equipment or pre-casted materials in highly complex plants or construction sites. Typically, plenty of planning procedures are required before the actual lifting is conducted in order to prevent hazards and improve productivity. Traditional lift planning is performed manually, which is time consuming and error-prone. Computer-aided lift planning techniques have been developed to assist the lifting process [1–4]. Often, they base their works on 3D models which are typically in the forms of Plant Design Management System (PDMS), SmartPlant, or Building Information Model (BIM). Different to such works, we are interested in lifting planning with highly complex and real environments. Typically, such environments have no existing 3D models or are very difficult, if not impossible, to build 3D models for the use of computer-aided lift planning. For instance, unlikely there are 3D models available with those process plants built several decades ago. Operational sites, which frequently serve as tentative storage spaces for pre-casts or other construction materials, usually keep changing and thus are not considered as parts of the BIM, PDMS or SmartPlant. To our knowledge, this is a challenging issue unaddressed. Instead of building 3D models of the lifting environment using Computer-aided Design (CAD) tools, our idea is to digitize the physical environments in point cloud form which can serve as an accurate and realistic representation of the highly complex and real plants or construction sites. By applying digital geometry processing technique, we can use the point cloud data effectively for the purpose of automatic lifting path planning.

1.2 Objectives

Our objective is to develop an automatic path planning system for highly complex environments in point cloud form to improve the safety and productivity for tower crane lifting. Safe, accurate and optimized lifting paths will be generated in near real-time.

1.3 State-of-the-art

Many research works have been done to improve the safety and productivity of crane lifting by taking advantage of computer technology. Different search algorithms have been exploited to tackle automatic lifting path planning. The initial trials rely on simple CAD models to represent the cranes and the environment [1–4]. Serial Genetic Algorithms (GAs) and heuristic searches are used in these works to solve the path planning problem. Among them, GA has been proved being able to achieve highly optimized paths. Their applications are, however, limited due to the intensive computations [2]. Other works include approximation algorithm [5] and Probabilistic Road Maps (PRMs) [6] for the purpose to quickly generate lifting paths. A comparison with the GA based method in [2] is conducted in [6]. The results indicate that GA is able to provide better solution quality but typically take much longer time to converge. [7,8] exploit GPU parallelization to accelerate the GA computing, and introduce a customized fitness function and reproduction operators to improve the search ability of GA.

2 OVERVIEW

2.1 Problem Statement

Safety and productivity are main concern for tower crane lifting in complex environments which have no 3D models. These complex environments can be very old plants constructed several decades ago or tentative space to keep pre-casts and other construction materials. We need to explore a solution to automatically output optimal and collision-free lifting path in such environment.

2.2 Proposed Solution

A recent effort [8] is made on automatic path planning for heavy lifting with mobile cranes in plants which are modeled in 3D using PDMS or SmartPlant. The work described in this paper is to further the research by developing novel techniques for automatic path planning of tower crane lifting in an environment which has no existing 3D model.

Two major issues need to be addressed in this paper. One is to deal with highly complex environments which have no 3D models available or are very difficult, if not impossible, to create 3D models. Another one is that tower cranes and mobile cranes are quite different. As such, we have to look into the details including the kinematics of the tower cranes aiming to establish a foundation for optimal planning of lifting.

We first digitize the environments into point cloud format by taking the advantages of laser scanning. In this paper, we propose a novel solution to handle automatic path planning of tower crane lifting in point cloud environment. For this, new collision avoidance technique needs to be developed in order to cater the discretized environments and tower cranes. In particular, digital geometry processing techniques using point cloud data based multi-level depth maps, kinematics of tower crane, hybrid C-space, and swept volumes based Continuous Collision Detection (CCD) will be investigated.

3 TOWER CRANE LIFTING IN POINT CLOUD ENVIRONMENT

Genetic algorithm (GA) is well recognized in achieving global optimization. The process of GA, including four functional modules (selection, mutation, crossover, and fitness evaluation), typically requires intensive computations. It is difficult to have fast GA optimization in serial platform. GPUs provide a highly parallel computing structure which enables various types of data processing. By embedding GA into the GPU platform, it is possible to achieve significant performance improvement.

To conduct the optimal planning of the crane lifting, some researchers developed a master-slave parallel genetic algorithm (MSPGA) based method to solve the problem [8]. They investigated the automatic path planning for mobile cranes in complex model-based environments in SmartPlant and PDMS format. In this paper, we briefly describe MSPGA and focus on the use of point cloud for automatic lifting path planning of tower cranes in complex environment.

The MSPGA uses CPU as the master processor for procedure control. The four functional modules of GA are assigned into GPU (slave processor) for parallel computing. These functional components harness the tremendous computational power of GPU parallelism to speed up the processes. They will be run successively during each iteration of GA computing. At the end of each GA iteration, the calculated fitness values will be examined against the termination criteria. If the fitness values meet the termination fitness value, the CPU will stop the GA procedure and output the best configuration as the lifting path planning solution.

4 POINT CLOUD BASED COLLISION DETECTION

The detection of collision between the environment structure and the crane's components (including load) plays an important role in the automatic lifting path planning. It serves as one critical factor in the fitness evaluation engine of MSPGA.

In order to balance the planning time and the pre-processing time and thus improve the efficiency of the collision detection module, we use the hybrid C-space strategy: since the tower crane has four degrees of freedom (DOFs) (see Section 4.2), we pre-compute the collision information for two DOFs of the crane and stored the information in the 2D C-space, whilst conduct the collision detection for the other two DOFs during the GA iterations. Due to the 2D C-space's simplicity, the hybrid C-space strategy is able to obtain the C-space in a short time and meanwhile decrease the time cost in the path planning.

To detect the collision between the environment structure and the tower crane's components (including load), we convert the structure of environment into depth map, and compare the position of the crane's parts with the depth map of the environment. The method to generate depth map of the environment is explained in Section 4.1. The tower crane kinematics provides essential information to compute the location of the components of tower crane (including load). Section 4.2 will discuss the kinematics of tower cranes. The hybrid C-Space and swept volumes will be presented in Section 4.3 and Section 4.4 respectively. The CCD outputs Boolean values which serve as a critical factor in the fitness evaluation function of MSPGA.

4.1 Rasterization of Point Cloud Environments

Once point cloud data for the environments have been acquired, they need to be processed into a histogram shaped depth map. Multi-level depth map used in 3D collision detection is highly suitable for GPU parallelization.

To rapidly generate the depth map from the original plant in point cloud form, we developed a GPU depth map generator based on rasterization. The size of the environment may be up to several square kilometers, and the number of points in point cloud plant model may be more than hundreds of millions. It would cost CPU much time to deal with such huge amount of data for the rasterization task. So, in order to speed up the rasterization process, we harness the tremendous computational power of GPU (Graphic Processing Unit) parallelism.

In the GPU depth map generator, parallel threads in the thread-grid of GPU are mapped into plant model's x-y ranges. Each GPU thread takes care of one pixel value in the x-y plane, finds in the point cloud model the points which correspond to the pixel, and records the Z values of these points. Thus, the multi-layer depth map is generated for the point cloud environment. Thousands of GPU threads work simultaneously to speed up the process.

Usually, components of the tower cranes, including the lifting targets, are not expected to move or operate underneath any environment objects. As such, the highest portions of the environment structures will determine a crane's frontier of contact with the environment objects. Therefore, in this paper, for practical purposes and for the concern of efficiency, we only take into consideration the maximum Z value for each pixel in the point cloud environment during collision detection.

4.2 Tower Crane Kinematics

Tower crane is essential tool for lifting tasks in construction sites and industrial plants such as petrochemical and pharmaceutical factories. For simplicity, here we use hammerhead tower crane as an example. Fig. 1 shows the kinematic information and degrees of freedom (DOFs) of hammerhead tower crane.

As shown in Fig. 1, the hammerhead tower crane has the following four degrees of freedom (DOFs):

(1) Swinging: the rotation of jib and counter-jib around Z axis (point B is the rotation center, Z axis is the direction along tower height), the rotation angle is denoted as α_{SW} .

(2) Trolley move in/out along the jib, the moving length is expressed as l_{MV} .

(3) Hoisting: the hoisting of load, the hoisting length is indicated as l_{HS} .

(4) Load rotation: the rotation of load around Z axis, the rotation angle is denoted as α_{LD} .

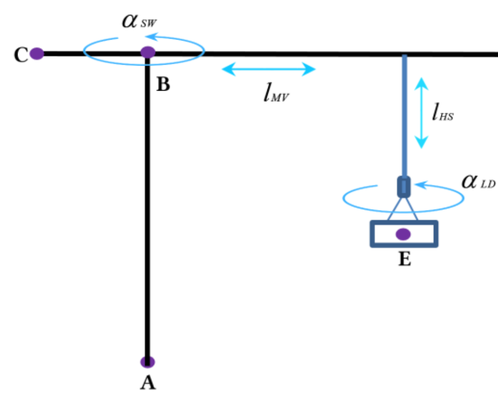

Figure 1: Kinematics and DOFs of Hammerhead Tower Crane.

Hammerhead tower cranes have five essential points: A, B, C, D, and E (Fig. 1). Point A is the center of the base of the tower crane. It will be determined once the tower crane is set up, and will not be changed during the lifting tasks. B is the Cockpit Rotation Pivot (CRP) around which the jib and counter-jib will rotate. Position of CRP will be determined by the location of the base (point A) and the height of the tower. Point C is the tip of counter jib, point D is the tip of the jib, and point E is the center of the load. Points C, D, and E will be calculated based on points A and B using vector operation.

The kinematics of tower crane is fundamental to the subsequent calculation, including the computation of hybrid C-space (see Section 4.3) and that of swept volumes (see Section 4.4).

4.3 Hybrid C-space

The 2D hybrid C-space is for the first two DOFs of the tower crane: swinging and trolley moving in/out. The computation of the hybrid C-space is conducted before the procedures of MSPGA. For each combination of the swinging angle α_{SW} and the distance of trolley moving in/out l_{MV} , the location of the jibs and counter-jibs is computed and then compared with the depth map of the point cloud environment to check whether there is any collision occurred. The collision information is then stored in the 2D hybrid C-space.

4.4 Continuous Collision Detection (CCD)

Continuous Collision Detection (CCD) is a technology that detects interference between the swept spaces of objects and the environment within continuous movement steps [4]. In our work, CCD is employed for the swept spaces constructed by the neighboring configurations in lifting paths.

When moving along the internal path between neighboring configurations, lifting target and the jibs (including counter-jibs) have the highest risk to contact with other objects in the environment. In the hybrid C-space strategy, we use hybrid C-space to check the collision between the environment structure and the swept space established by the movement of jibs (including counter-jibs), and apply swept frontier method (explained in the following paragraph) to detect the collision between the environment structure and the swept space constructed by the movement of the target.

During the crane's operation between neighboring configurations, the spaces which the load sweep through are denoted as swept volumes whose bottom surface are indicated as swept frontiers. It is the swept frontiers that will be used to conduct collision detection with the depth map of the environment structure. A unique swept frontier for each pair of neighboring configurations will always be acquired by applying certain pre-defined strategy of movement.

During the path planning, the system will perform searches in the hybrid C-space to check whether or not there is collision happened between the jibs (including counter-jibs) and the environment structure, and employ swept frontiers to conduct collision detection with the points in the environment structures' depth map. The results of the CCD are stored as Boolean values, and act as an important factor in the fitness evaluation function.

5 EXPERIMENT AND RESULT

To demonstrate the path planning for tower crane lifting in the point cloud environment, we conduct experiments on a real construction site with dimensions over 300m*150m, as shown in Fig .2 (see Section 5.3). The building constructed long time ago has no 3D models. The working sites are tentative storage space for pre-casts. Laser scanning can be used to digitize the environment in point cloud form. In the experiments, the target needs to be moved from the start position to the end position in the point cloud environment using a tower crane (in yellow). The inputs are the digital environment, as well as the start and end locations of the target. The output is the lifting path which should be collision-free and optimal.

After processing the raw scan data, the complete digital environment (in point cloud format) of the scanned construction site is obtained. Three sampling rates (1/9, 1/16, and 1/25) are chosen to test the performance of the path planner.

The experiments are run on a computer with Intel Core i7-4790 CPU and NVIDIA GeForce GTX660 GPU.

5.1 Rasterization Result

(1) Points in the Depth Map. The result shows that the output points (~23K) in depth map are much less than the points (~13M) in the point cloud file. This will help reduce the time spent on the collision detection; since the depth map points are used to compare with the crane's components for collision detection.

(2) Rasterization Time. It demonstrates that the speed to generate the depth map for point cloud environment is very fast (less than 1 second in all the case tested) and is not affected much by resolution of the depth map.

5.2 Performance of the Planner

We conduct three groups of experiments to test the GA performance for different resolutions of depth map at specific sampling rate of the point cloud file. The sampling rate is 1/9 for group1, 1/16 for group2, and 1/25 for group3. Using the complex environment as shown in Fig. 2, we take 50 times of execution for each resolution of depth map during each group of experiments.

(1) Success Rate and Convergence Speed. The experiments demonstrate that the success rate of GA is nearly 100% under different resolution of the depth map and different sampling rate of the point cloud. The speed of convergence is fast.

(2) Execution Time. The results illustrate that GA running time increases slowly with the rise of sampling rate from 1/25 to 1/9, but increases sharply with the raise of depth map's resolution from 100cm to 10cm. It means that the resolution of depth map has more influence on the GA running time than the sampling rate does.

(3) Scalability. The three groups' experiments show that the success rate is nearly 100% and the GA running time is always not more than 100 seconds under various combinations of resolution of depth map and sampling rate of the point cloud. This proves that the MSPGA proposed has good scalability in terms of the size of point cloud file and the resolution of the depth map.

5.3 The lifting path generated

One of the generated lifting paths is shown as Fig. 2. The target is first lifted up (dot line in blue) from the start location, trolley move out (dot line in green), swing (the circle in yellow), trolley move in (dot line in blue), lifted down (dot line in blue), and rotate the load (the fan area in orange), and reach the end location.

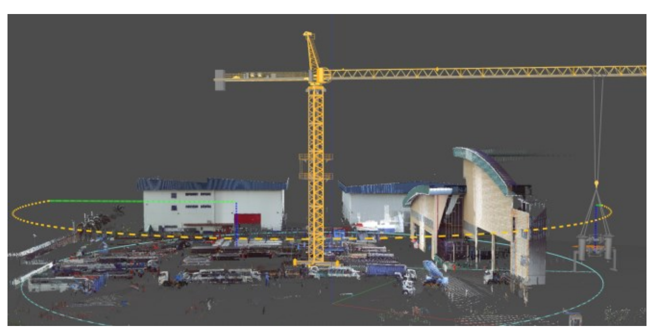

Figure 2: The generated lifting path.

6 CONCLUSIONS AND FUTURE WORK

Automatic path planning for tower crane lifting in highly complex environments is discussed in this work. We use laser scanning to capture real but old industrial plants or actual working sites in the point cloud form. This avoids the tedious or even painful modelling job if not impossible for the environments. The complete environments in point cloud is then rasterized to create a depth map of the environments. The depth map will be then used for various applications from collision detection to GA-based optimal path searching. Worth to mention, this depth map technique will make it possible to have the relevant application independent to complexity of the environments. In addition, the Genetic Algorithm implemented is highly parallelized which can significantly speed up the process of automatic path planning for tower cranes.

Presently, only a single crane is discussed in this paper. We are working on dual-cranes or multi-cranes problems for automatics path planning. In future, we will also look into more intelligent solution for depth map generation.

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