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Automatic Object Recognition and Registration of Dynamic Heavy Equipment Using a Hybrid LADAR System

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by

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Automatic Object Recognition and Registration of Dynamic Heavy Equipment Using a Hybrid LADAR System

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It has been a challenging subject to recognize dynamic objects from a scattered work environment because large and complex 3D site data obtained by a laser scanner makes it difficult to process itself in real or near real time. This thesis introduces a model-based automatic object recognition and registration framework, Projection-Recognition-Projection (PRP), to assist heavy equipment operators in rapidly perceiving 3D working environment at dynamic construction sites. In this study, a digital camera and a hybrid laser scanner were used to rapidly recognize and register dynamic target objects in a 3D space by separating target object's point cloud data from a background scene for a quick computing process. A smart scan data updating algorithm has been developed which only updates the dynamic target object's point cloud data while keeping the previously scanned static work environments. Extracted target areas containing 3D point clouds were orthographically projected into a series of 2D planes with a rotation center located in the target's vertical-middle line. Prepared 2D templates were compared to these 2D planes by extracting SURF (Speeded Up Robust Feature) features. Then, point cloud bundles of the target were recognized, and followed by the prepared CAD model's

registration to the templates. The field experimental results show that the proposed PRP framework is promising and can significantly improve heavy construction equipment operations and automated equipment control by rapid modeling dynamic target objects in a 3D view.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION

Safe construction and operation of heavy construction equipment such as cranes, excavators, and concrete pump trucks has been considered a very important subject in construction fields. It would be helpful for the operators if the accurate 3D position of the target objects and surroundings are readily available. One of the intensively used methods to obtain 3D position of the objects is based on 3D laser scanner (Tang, et al. 2010; Huber, et al. 2010), which, however, has several disadvantages, such as low speed and low object recognition rates (Kim et al. 2011). Also, it has been a challenging subject to recognize specific objects from a 3D point cloud in unstructured construction environments. This is because the 3D point cloud data obtained by a laser scanner is quite large and complex so that it is difficult to separate the target area from other interferences in a short period of time. In addition, the surrounding objects like trees, people, and common stuffs, cause interferences to the recognition process, so it is necessary to develop a specific method to exclude such interferences and to keep only the scenes needed for the faster target object recognition and registration process.

Currently, many researchers are working on the subjects to obtain position of the objects, and proposed varieties of methods, such as context-based modeling (Antonio et al. 2011; Xiong and Huber 2010), which was able to automatically model and identify the main structural components in an indoor environment. However, most of the studies emphasized on the components with primitive shapes, such as a rectangle and a circle; few works have been done on the recognition of objects with irregular shapes, such as heavy equipment. Meanwhile, the registration process is time-consuming (Shih and Wang 2004; Bosche 2010; Son and Kim 2010). In addition, there were studies that employed methods projecting models to images. Lowe (1992) projected a model into an image plane. Correspondences were determined by analyzing image features that were close to a projected visible model entity. A probabilistic approach was used to select the best match in his research. Once correspondences were established, numerical minimization was used to determine object's rotation and translation values. However, when computing the perspective projection of a three dimensional model, occlusions had to be taken into account. In the method proposed by Wunsch (1996), a CAD model was registered into images by iterative inverse perspective matching. However, there was not distance metric relating 3-D point coordinates to 2-D image coordinates, so Wunsch could not apply the closest point principle to the registration of a 3-D model to a perspective image.

The main objective of this research is to propose a model-based automatic object recognition and registration methodology to assist heavy equipment operators in rapidly perceiving 3D working environment at dynamic construction sites. The sub-objectives of this research are:

(1) To rapidly collect the data, specifically, to develop a hybrid LADAR (Light Detection and Ranging) system, including hardware, firmware, software, algorithms and GUI-based user-interfaces, to rapidly collect 3D data of the working environment with heavy equipment. Mounted on a moving platform, the LADAR system is set up in the

blind area of heavy equipment like crane, and assists the equipment operators by transferring and presenting real-time 3D scene data via wireless technologies.

(2) To rapidly model workspace in 3D, specifically, to design and create the Projection-Recognition-Projection (PRP) framework utilizing the developed hybrid LADAR system, implement automatic object recognition and registration, and rapidly model workspace in 3D. Equipment operators can access to the 3D scene data of the construction sites including 3D point clouds and registered CAD models, which are produced by the developed LADAR system through employing the proposed PRP framework.

(3) To present the data to the operators in real time, specifically, to develop a wireless demonstration system using network technologies to present the 3D data to equipment operators in real time. A real-time visualization method was proposed based on the developed LADAR system, to simultaneously assist multiple heavy equipment operators in perceiving 3D working environments at dynamic construction sites.

In this study, a new framework called PRP was developed in order to automatically recognize complex objects from a 3D laser point cloud scene. A CCD camera was used to initially recognize a target object and an area containing the target object. To rapidly process recognition and registration of target object in a 3D space, a point cloud in the target area was separated from other background point clouds. The separated point cloud of target object was projected onto different 2D planes from multiple different views. By finding matching views from the previously built 3D model library, the position and orientation of the target was determined and the target's CAD model was registered to the point cloud data. The whole process can be summarized in the three steps, projection, recognition and projection (PRP).

The following sections will firstly present a brief literature review of automatic object recognition and registration of dynamic heavy equipment in construction job sites. Then the developed methodologies will be presented, including an introduction of the proposed LADAR system, visual target recognition and tracking method, bounding area extraction process from point clouds, projection illustration from projected 2D planes, 3D position calculation flows, and point cloud and CAD model registration method. Finally, demonstration of the experimental results will be given, and followed by conclusions and future work.

CHAPTER 2 LITERATURE REVIEWS

The construction industry suffers high rate of injury and fatality in terms of its dynamic and unstructured nature at jobsites. According to statistics from Occupational Safety and Health Administration (OSHA), approximately 75% of struck-by fatalities involve heavy equipment such as trucks and cranes. The interactions between workers, equipment, materials on ground easily create vision-related accidents. This vision blocked problems lead to serious collision contacts without pro-active warning. Lack of full visibility is one of the major contributing factors for accidents at construction site, which brings out a number of vision-aid techniques. Many researches have studied to detect blind areas or blind lifts around heavy equipment, and provide real-time tracking or warning system to operators using sensor readings, images, videos, or 3D point clouds. Existing technologies include radar, infrared sensors, tag-based detection, GPS, stereovision system, LADAR, etc. (Ruff 2007). More prevalent approaches integrate two or more technologies mentioned above for less processing time and more accuracy.

2.1 RFID and GPS

In the early stage, Radio Frequency Identification (RFID) and ultra-wideband were adopted in tag-based system to detect moving objects. Global Positioning System (GPS) and web-based technologies were implemented to track vehicles and detect collision at outdoor environments (Oloufa et al. 2003; Navon and Shpatnitsky 2005; Caldas et al. 2006). There are also some attempts to combine RFID with GPS technology, and transfer data between detectors and receivers (Ergen et al. 2007; Andoh et al. 2012).

However, GPS has drawbacks such that it works ineffectively without direct line of sight from the satellites, and it is expensive to install on every moving objects.

2.2 Vision-based Methods

Vision-aid systems are more practical in real construction sites that transmit images to operators' cabin to resolve blind lift of cranes (Everett and Slocum 1993; Lee et al. 2006; Shapira et al. 2008). Commercially available products such as video streams and time-lapse photography have been applied in equipment's cabin to monitor backing motion. A camera system consisting of one camera on the rear axle of the truck, and one camera on the front of truck, and a video monitor in cab can provide visual check of front and rear blind areas (Ruff 2007).

2.3 Laser Scanner Based Methods

Laser scanning technology offers a rapid and non-intrusive methodology of scanning that does not require any contact with surface materials or structure. Since it is a non-contact, non-intrusive technique, laser scanner has been extensively utilized to automatically obtain the "as-built" condition of an existing building, or to classify and capture a complex heavy equipment operation as it happens and to provide automating feedback to those conducting the operations (Cheok, et al. 2001; Arayici 2007; Gai, et al. 2012; Im, et al. 2012). Lee et al. (2009) proposed an automated lifting-path tracking system of tower crane by receiving and recording data from laser device. Teizer et al. (2010) used a laser scanner inside of equipment cab to detect blind spots from 3D point clouds. Bosche and Hass (2008) registered 3D-CAD objects to laser scanned point cloud data, which can be utilized to efficiently assess dynamic construction process. By imposing point cloud data with existing equipment CAD models, operators can distinguish obstructions from real-time 3D point cloud.

The research in point cloud based target recognition has advanced significantly in the past few years (Cheok and Stone 1999; Gordon, et al 2003; Gordon and Akinci 2005; Arayici 2007; Frédéric 2010), and many research initiatives presented different types of system using laser scanners. Local surface descriptors named spin-images (Johnson and Hebert 1999) were used in the system proposed by Gordon et al. (2003) to recognize the shapes of target objects. In the system, the pose and position of 3D targets with arbitrary shapes were determined; similarly shaped regions were identified using a localized measure of surface shape between the 3D scene and the target model (Gordon, et al 2003).

Contrary to point cloud, many researchers were using digital imaging based methods for construction target recognition (Lukins and Trucco 2007; Ibrahim, et al 2009; Memon, et al 2005; Song 2007; Goldparvar-Fard, et al 2009; Vexcel Corporation 2003). In these strategies, a series of images were gathered initially, which are registered in order to build a 3D model. Construction job site images were compared to the 3D model using virtual images generated from the model (Goldparvar-Fard, et al 2009; Song 2007; Vexcel Corporation 2003) or using pictures gathered in the first step (Lukins and Trucco 2007; Ibrahim, et al 2009).

The main challenge from the process of object recognition in this study is to extract the shapes from projected 2D planes and compare the corresponding shapes with the prepared templates in the database. Several methods based on distance transforms have been presented by researchers. Gavrila and Philomin (1999) introduced a shape-based target recognition method using distance transforms, specifically, offline template hierarchy was prepared and trained through stochastic optimization techniques; and online target matching with the template was processed, together with a simultaneous coarse-to-fine approach. Besides the distance transforms based methods, Amit et al. (1997) introduced an algorithm to construct classification trees which were used to determine the separate particular shapes. In their method, every possible geometric array was conrresponding to specific features, and the coarse constraints was described by distances and angles. Because of randomization and being aggregated in a common way, the array are denpendent weakly. The SIFT local descriptor (Lowe 1999; Lowe 2004) proposed by David Lowe, which can provide robust matching across a substantial range of illumination change, noise, viewpoint and distortion, was intensively used to determine key identical points and got a well performance.

2.4 Point Cloud and CAD Model Registration

In this study, prepared CAD models are one by one corresponding to the prepared point cloud templates, which means the registration process between point cloud and corresponding CAD model is based on the result of the object 3D position calculation. Point cloud registration is defined as registering multiple point clouds scanned from different viewpoints into one common coordinate system. The current state-of-the-art approach is to find at least three common points between two overlapped point clouds, and then calculate 3D rigid transformation matrix based on these three common points.

Many types of commercial software are now available to realize the registration function by manually assigning three common points. However, this manual process is time-consuming and inaccurate when the data sets are huge and complicated. To automate the registration process, typically there are two approaches target-based and target-free.

For the target-based registration, Akca (2003) used a customized 2D planar target as a landmark, 3-D coordinates of which were measured with a theodolite in a ground coordinate system before the scanning process. Then the proposed registration algorithm can automatically recognize all the targets using radiometric and geometric information (shape, size, and planarity). Franaszek et al. (2009) developed a fast automatic registration algorithm using sphere targets. Two point cloud data sets can be registered by finding three matching points which are the centers of the spheres. Using 3D targets, the laser scanner can capture the same point cloud from different viewpoints. There is no need to re-orient the targets, not like using 2D targets, if the targets are properly placed. It could give users more flexibility and save more time on locating and setting up the equipment. Becerik-Gerber et al. (2011) tested three different types of targets (fixed paper, paddle, and sphere) with two different types of laser scanners (phased-based and time of flight). The authors conclude that the sphere target with time of flight scanner yields the best results in terms of accuracy. It was also stated that scanning, setting up, and acquiring the targets were the three most time-consuming processes for target-based methods.

The limitations of target-based registration are that the extra time is needed for setting up and adjusting the targets during each scan and the target is not always allowed to be installed in the sites such as construction jobsites. With the development of image processing and computer vision technology, target-free registration has been widely used to eliminate the limitations. Currently, target-free registration can be categorized into three main types: 1) ICP-based, 2) feature-based, and 3) geo-referencing based. ICP (Iterative Closest Point) algorithm (Besl and Mckay 1992) has been widely applied in 3D point cloud registration. It uses the closest points in two different scans as relative control points. Then an error function is built between relative points, and the algorithm is constantly iterated until the result satisfies the requirements of the error function. A considerable amount of work on improving ICP algorithm has been conducted over the past few decades. Li and Wang (2008) introduced weighted value to the process of finding relative control points to improve the accuracy. Geometric Primitive ICP with the RANSAC (GP-ICPR) was proposed by (Bae and Lichti 2008) using the change of geometric curvature, approximate normal vector of the surface, and neighborhood search to improve the efficiency and accuracy. Parallel computing of MapReduce was presented by (Liu and Xie 2011) to improve the efficiency of computing. Men et al. (2011) integrated Hue value with ICP algorithm to develop a 4D ICP algorithm, in which the Hue value was calculated according to RGB data captured by a digital camera. With the assistance of the Hue value, the ICP algorithm can be improved by getting higher accuracy and faster convergence. ICP-based registration is time consuming due to the heavy computation load. Also the accuracy depends on the size of the overlapping areas and the selection of initial starting points. It can perform better as having more overlapping areas.

Recently many researchers have been working on automatic recognition of common local features (e.g., planes, lines, surface patches, curvatures) to both 3D point clouds (Franaszek et al., 2009). Johnson (1997) developed a spin image algorithm to automatically register two point clouds through regional surface matching. Discrete and continuous optimization methods were combined to construct a globally consistent model from a set of pairwise registration results (Huber 2003). Rabbani and Heuvel (2005) proposed a method by doing a constrained search for finding the corresponding objects and using them as targets. In this method, the point clouds are processed to recognize all the possible planar and cylindrical objects and create 3D models out of them. Then the two point cloud can be registered by matching common 3D models based on the properties of the 3D model (dimension, shape, and orientation). The proposed algorithm needs less overlapping area than ICP algorithm, while requires more time to recognize the objects and create them. Dold and Brenner (2006) introduced a registration method by recognizing and matching two corresponding patches in two overlapping scans. The digital image data captured from an additional image sensor was also utilized in their method to improve the result. The matrix transformation can be obtained through the calculation of the correlation between corresponding patches. Barnea and Filin (2008) extracted keypoints which could be corners and edges from 2D intensity image, and then calculated the transformation matrix by matching the keypoints. A robot platform, equipped with a PTU, a 2D SICK laser scanner, a PMD time-of-flight camera, and a digital camera, was built by (Huhle et al. 2008) to collect colored 3D point clouds. Then registration of Colored 3D Point Clouds was conducted with a Kernel-based Extension to the Normal Distributions Transform (NDT). Theiler and Schindler (2012) introduced another method of matching virtual tie points generated by intersecting planar surfaces recognized from point clouds. Thomas (2012) developed a method using local distribution of albedo on the surface to define discriminative attributes based on range image information, and then do surface matching. Eo et al. (2012) also utilized the feature points extracted from 2D intensity images using Scale-invariant feature transform (SIFT) algorithm. However, this method heavily depends on the size of overlapping area. In their test, 12 scans were collected for registering one corner of the building. The accuracy of transformation matrix was within 0.005–0.069 m. Feature-based registration can be realized without knowing initial starting points, and utilize the 2D image processing technology to assist the recognition of feature points. However, more scans are needed to achieve better performance, and also the methods using image feature are not fully independent on the illumination so that the performance accuracy can somehow be affected by the environment. The heavy computation load is the other limitation for feature-based registration. Thousands of feature points can be extracted from each scan based on geometry or image information, while most of them will not be filtered out because of the wrong or low accuracy match.

Geo-referencing based registration has also been utilized using the information collected from other sensors. Olsen et al. (2011) did the registration with knowing the location of each view point obtained from GPS. This method is mainly used in outdoor survey, and the accuracy could be bad due to the low accuracy of the GPS device. As for indoor registration, Valero et al. (2012) developed an automatic construction of 3D basic-semantic models of inhabited interiors using laser scanners with the help of RFID technologies. This method is only suitable for indoor open space situation, and the laser scanner needs to set up closely to the objects, otherwise it won't be able to recognize the RFID tags due to its small size. It can be seen that the geo-referencing based registration cannot fit all the situations because of the limitation of the geo-sensors. Therefore, there is a need for rapid and accurate registration method suitable for complex scanned point clouds.

CHAPTER 3 METHODOLOGIES

This thesis developed a model-based automatic object recognition and registration framework, Projection-Recognition-Projection (PRP), to assist heavy equipment operators in rapidly perceiving 3D working environment at dynamic construction sites. The framework of the proposed PRP method is illustrated in Figure 1.

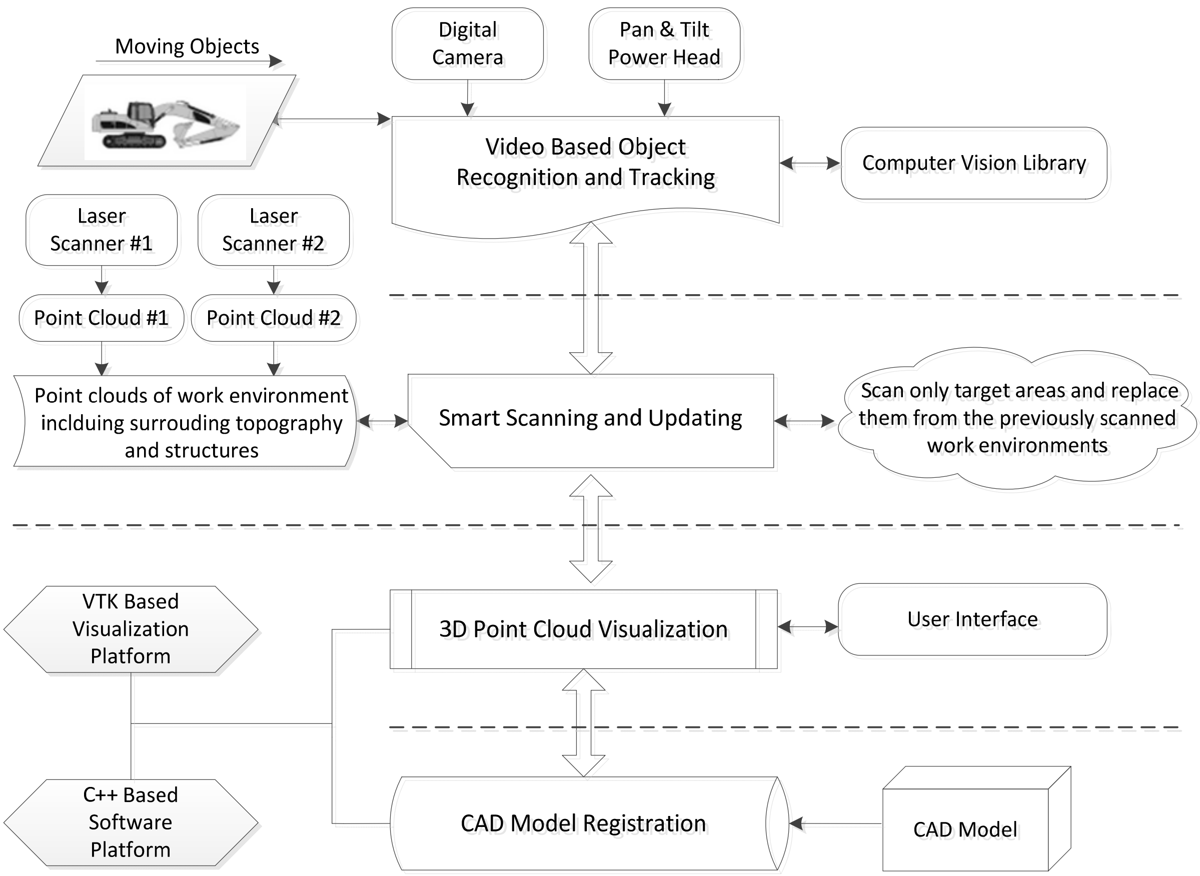


Figure 1. The frame of the proposed PRP method

This framework is mainly composed of four steps: video-based object recognition and tracking, point cloud-based smart scanning and updating, 3D point cloud visualization, and CAD model registration. Digital camera and pan & tilt units are utilized to provide 2D consequential images of moving objects. The bounding area containing specific moving objects used to be tracked is defined through the user interfaces by the equipment operators, from which Surf features are extracted based on the Open Source Computer Vision Library (OpenCV). 2D consequential images with Surf features extracted are simultaneously compared to the selected bounding area and generated common SURF (Speeded Up Robust Feature) features; as a result, 2D target area is stretched from and updated in the images. In this study, topographies and structures of surroundings are automatically scanned by two commercial 2D line laser scanners through smart scanning and updating process. Only 3D bounding area corresponding to the 2D target region obtained in the last component is scanned in the following rounds and replaced from the previously scanned work environments.

Based on open source VTK library and software implementation platform built by C++, 3D point clouds of the working environment together with the target area are updated simultaneously. Friendly user interfaces are developed to provide a pathway of User-Machine-Interaction. Extracted target areas containing 3D point clouds are projected to a series of 2D planes with a rotation center located in the target's vertical-middle line. Prepared 2D templates containing the selected objects are compared with 2D planes by extracting their SURF features respectively. Point cloud bundles of the target are among the comparison results, followed by the prepared CAD model corresponding to the templates aligned to the target area. In this thesis, several different types of equipment were tested as examples in order to verify the robustness of the proposed methodology.

3.1 3D LADAR System

In this study, an innovative robotic hybrid LADAR system was developed, consisting of two 2D line LADAR scanners (40 and 80 meters working ranges at 100Hz scan speed; Up to 2.5 sec / 360º scan; 190º for vertical line), a digital video camera (2592 x 1944 at 17Mbps/VBR), and a digital camera (1280 x 720 pixels at 30 fps), as is shown in Figure 2. A graphical user interface (GUI) was built using Visual C ++. The GUI controls the LADAR scanner and the three cameras, and visualizes the captured 3D point clouds.

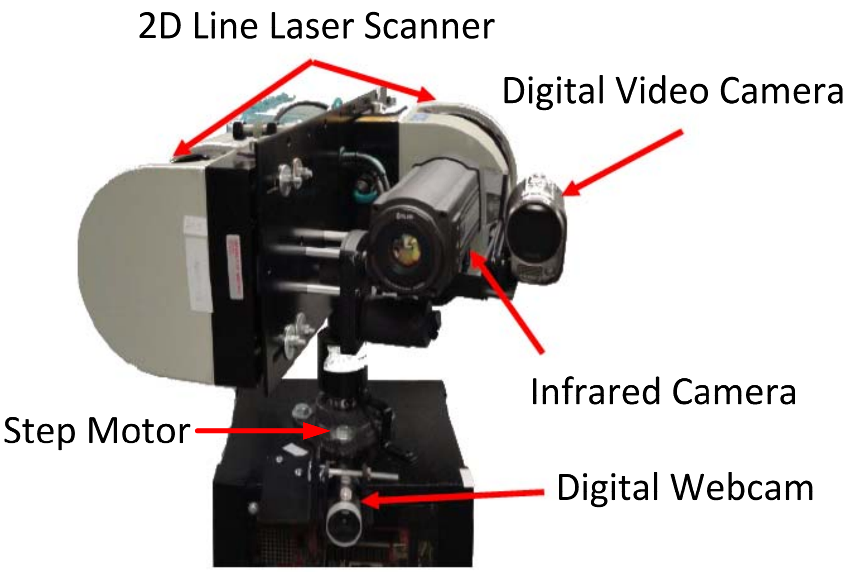


Figure 2. Prototype hybrid LADAR system

From the previous research efforts (Gai, et al. 2012; Im, et al. 2012; Cho and Martinez 2009; Gai and Zhao 2010; Dang et al. 2010; Shao et al. 2010; Li et al. 2008; Liu 2012), it was proven that the customized 3D LADAR system had provided more flexibility in hardware control and software programming than a commercial LADAR scanner. Based on the current mounting configuration, multiple degree-of-freedom (DOF) kinematics was solved to obtain x-y-z coordinates from the LADAR, and real-time digital image data were obtained from the web camera simultaneously. The transformation matrices for the LADAR and the web camera share the same base-coordinate, located in the axle center of the step motor. This kinematics frame allows more sensors, such as digital video camera and infrared camera, to be added. The LADAR system equipped with two laser scanner (laser #1: 40 meter scan distance; Laser #2: 80 meter scan distance) with a back-to-back relationship provides longer scan distance (80 meter) and double the scan resolution than using a single laser, as is shown in figure 3.

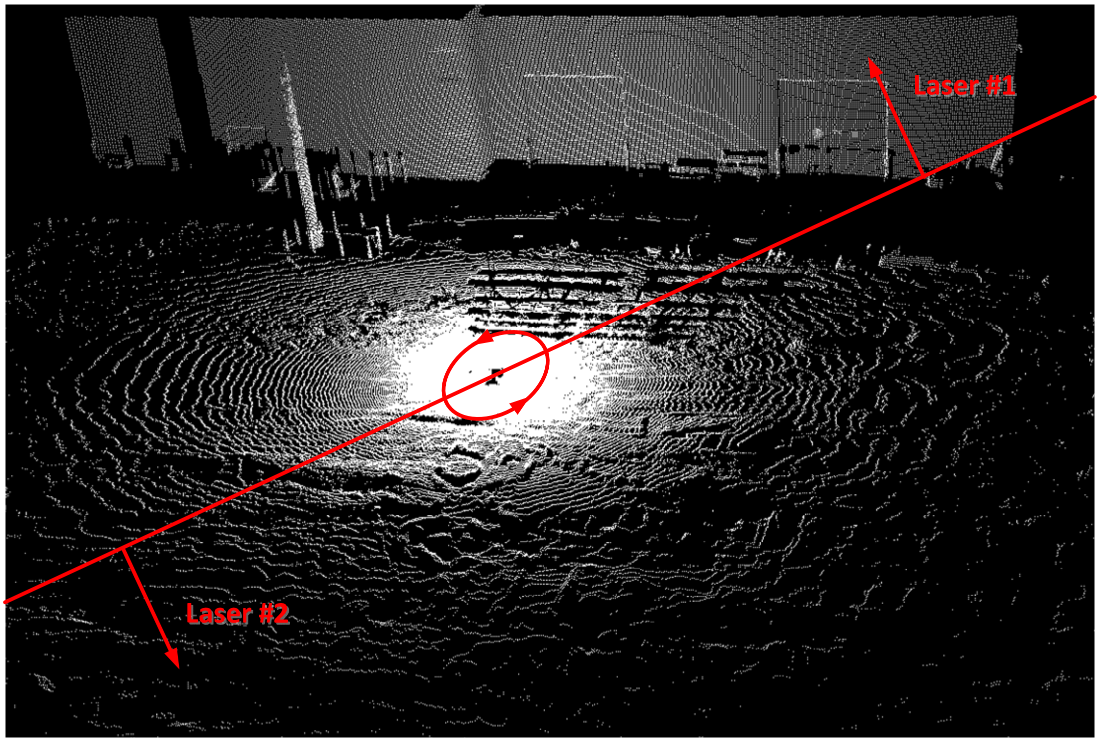


Figure 3. Point clouds obtained by two laser scanners

Proposed hybrid LADAR system scans with a fixed resolution (0.25 degree) in the vertical direction and a flexible resolution (0.0072 degree minimum) in the horizontal direction, shown in Figure 4. Two laser scanners rotate around the axle located in the axle center of the step motor, producing different qualities of point clouds with different resolution, shown in Table 1. When two laser scanners are used, the angular resolutions become half of the current minimum degrees by filling vertical and horizontal gaps of point grids.

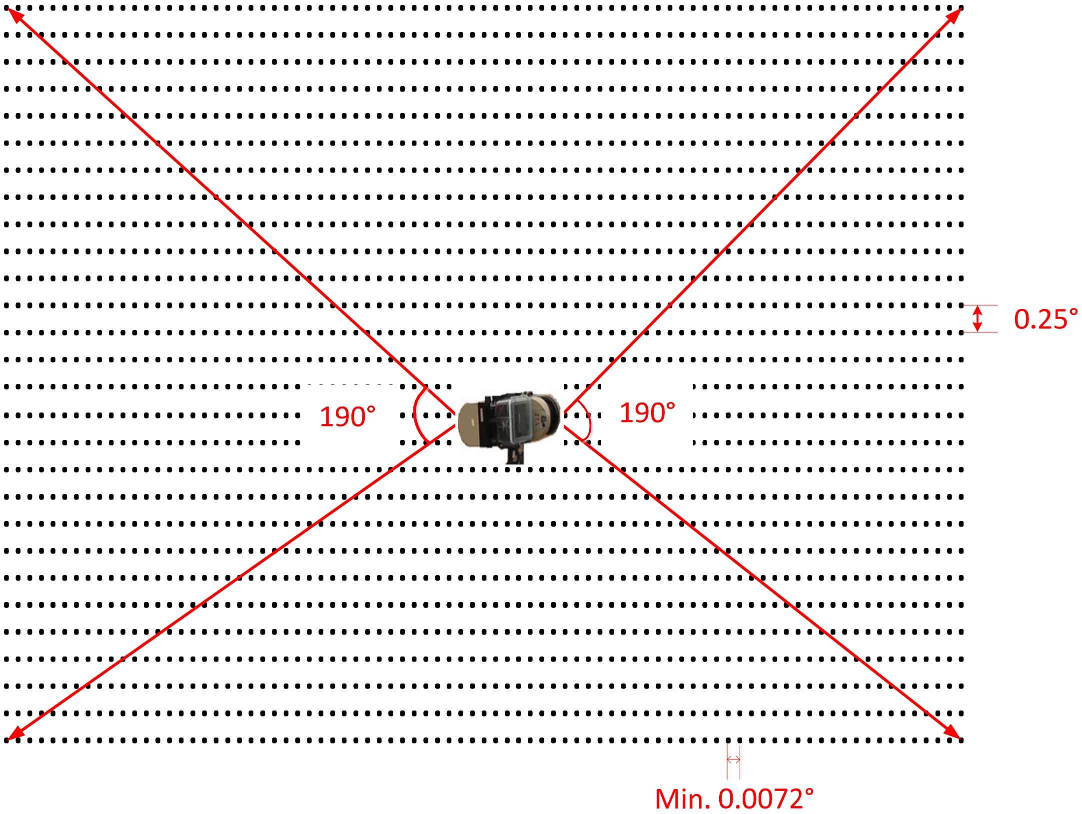


Figure 4. Scan range of the laser scanner

Table 1. Rotation speed, scan resolution and angle of the LADAR system

Rotation Speed (degree/sec)	Resolution in horizontal direction (degree)	Resolution in horizontal direction (10 m)	Resolution in horizontal direction (40 m)	Resolution in horizontal direction (80 m)
0.001	0.0072	6.28E-04	2.51E-03	5.03E-03
1.08	0.18	0.0157	0.0628	0.1256
10.8	1.25	0.109	0.436	0.872
21.6	2.7	0.236	0.944	1.888
43.2	5.8	0.507	2.028	4.056
86.4	12.1	1.059	4.236	8.472
100	15.5	1.361	5.444	10.888

3.2 Visual Target Recognition and Tracking

Figure 5 illustrates the user interface and the process of image based target recognition and tracking.

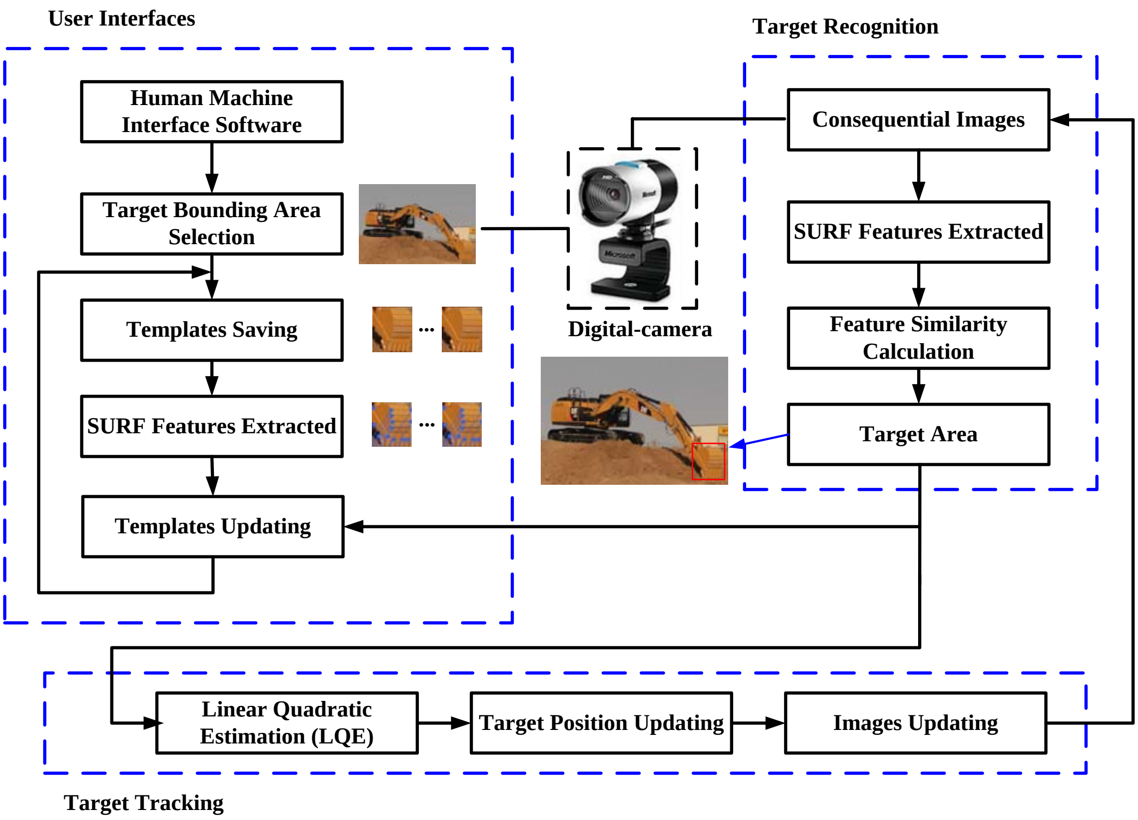


Figure 5. User interface and image based target recognition and tracking

2D consequential images were provided by a digital camera mounted on a pan & tilt head. Human machine interface software based on visual c++ platform interacted with the equipment operator via real-time software interface, shown in Figure 6. The SURF descriptor was utilized for visual object recognition, based on the results of which the algorithm Kalman filter(Steffen 1981; Steffen 2002), named for Rudolf (Rudy) E. Kálmán, also known as linear quadratic estimation (LQE), was used in the object tracking phase to produce estimates of unknown variables that are more precise than those based on a single measurement.

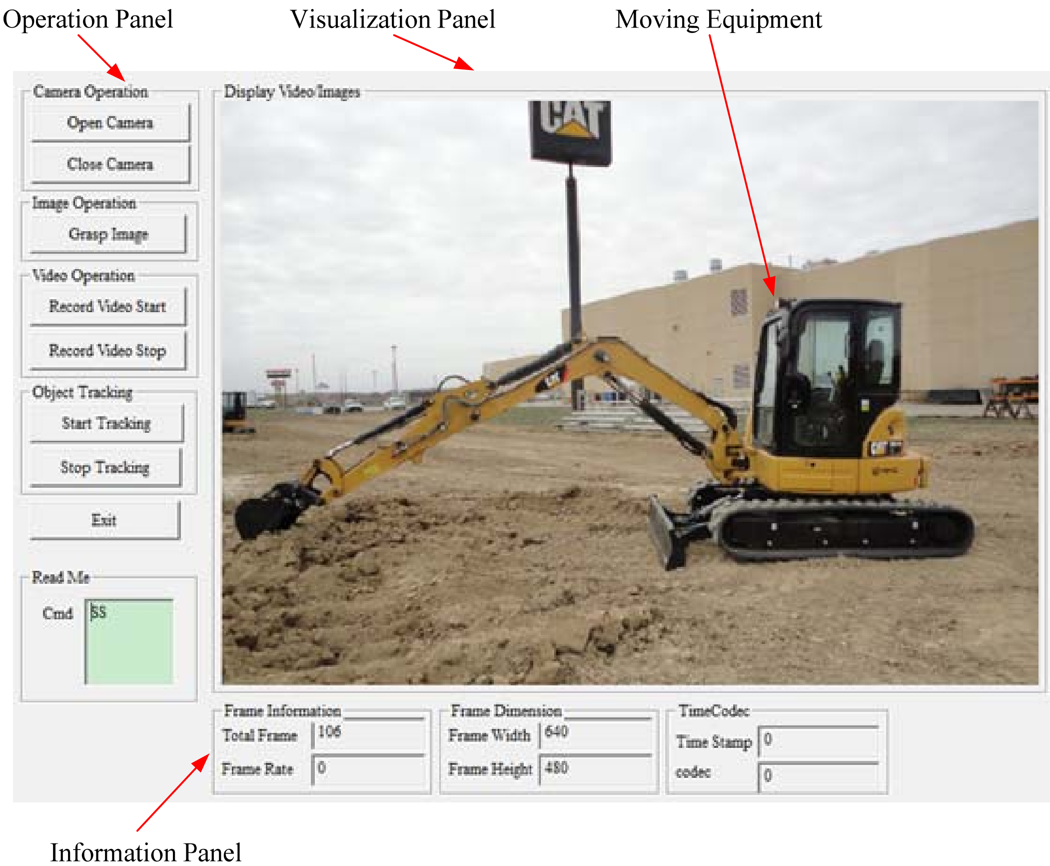


Figure 6. User Interface used for user-machine interaction

The software interface is mainly composed of three panels: operation panel for user-machine interaction, information panel for dynamic information displaying and visualization panel for presenting video of heavy equipment together with the working environment from a digital camera. The bounding area containing specific moving objects (heavy equipment) was defined and stored as templates through the user interfaces, from which SURF features were extracted via Open Source Computer Vision Library (OpenCV). 2D consequential images, from which SURF features were extracted simultaneously, were provided by digital camera, compared to the templates and produced the common SURF features, as shown in Figure 7; as a result, a 2D target area was defined and updated from the images. Also, the target area was further used to update the template set and used for the next round recognition. Based on the recognition results, the Kalman filter (linear quadratic estimation), was used in the object tracking phase to produce estimates of unknown variables, and followed by updating the dynamic target position (Figure 8).

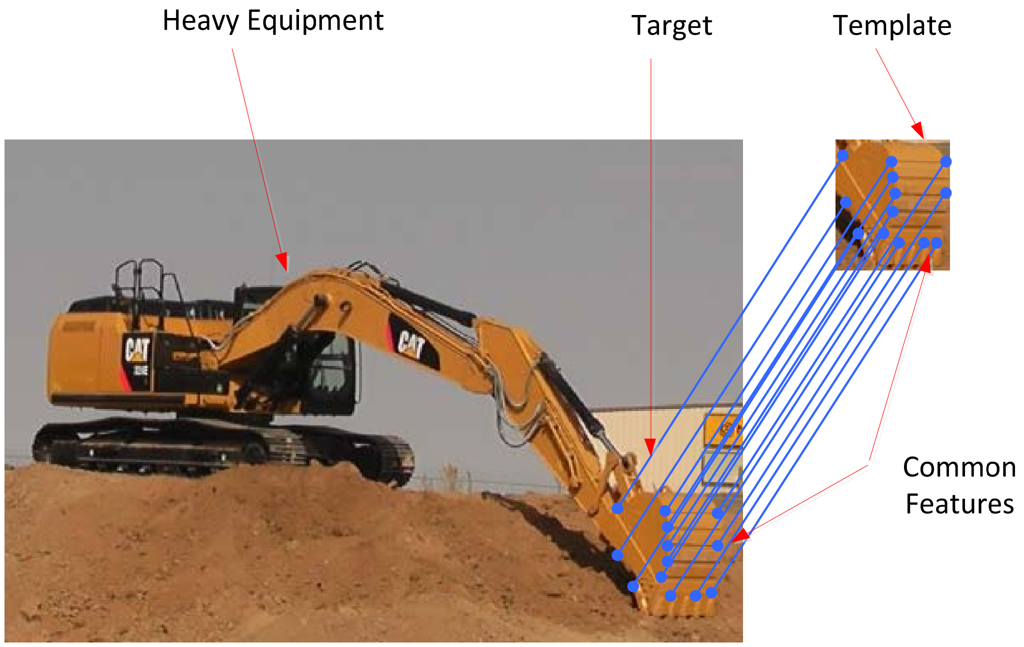


Figure 7. SURF features comparison between an equipment target and a template

Figure 8. Recognition and tracking heavy equipment's dynamic component by a digital camera

3.3 Bounding Area Extraction from point clouds

A digital camera captures 2D images of target object and the background area (x-y plane) containing the target; while a laser scanner obtains 3D point cloud data of the whole surroundings (x-y-z-axis 3D space). The scan depth can be optionally measured from the point clouds in the obtained area around the target (z-axis direction). The laser scanner automatically scans around the created bounding box by excluding other unimportant features. Or, pre-scanned data can be filtered later based on the measured area volume information. The proposed data filtering method is useful when it is necessary to exclude unimportant background surroundings from the scanning process, thus increasing a scanning speed and reducing a scanned data size and data processing time. Figure 9 illustrates the process of filtering a data acquisition zone based on the data obtained from the hybrid 3D LADAR system (Figure 2), where D0 is the mean distance value from the LADAR system to the target in data acquisition zone, corresponding to the 2D target bounding area as a output of target tracking process. D1 is the depth scope in z-axis direction defined according to the heavy equipment's dimension. For example, the transport width of the CAT hydraulic excavator 324E is 3.2m (Long Undercarriage – 600 mm Shoes), D1 is set as 3.5 m, approximate 300mm more, which makes sure the data acquisition zone can cover the whole body of equipment.

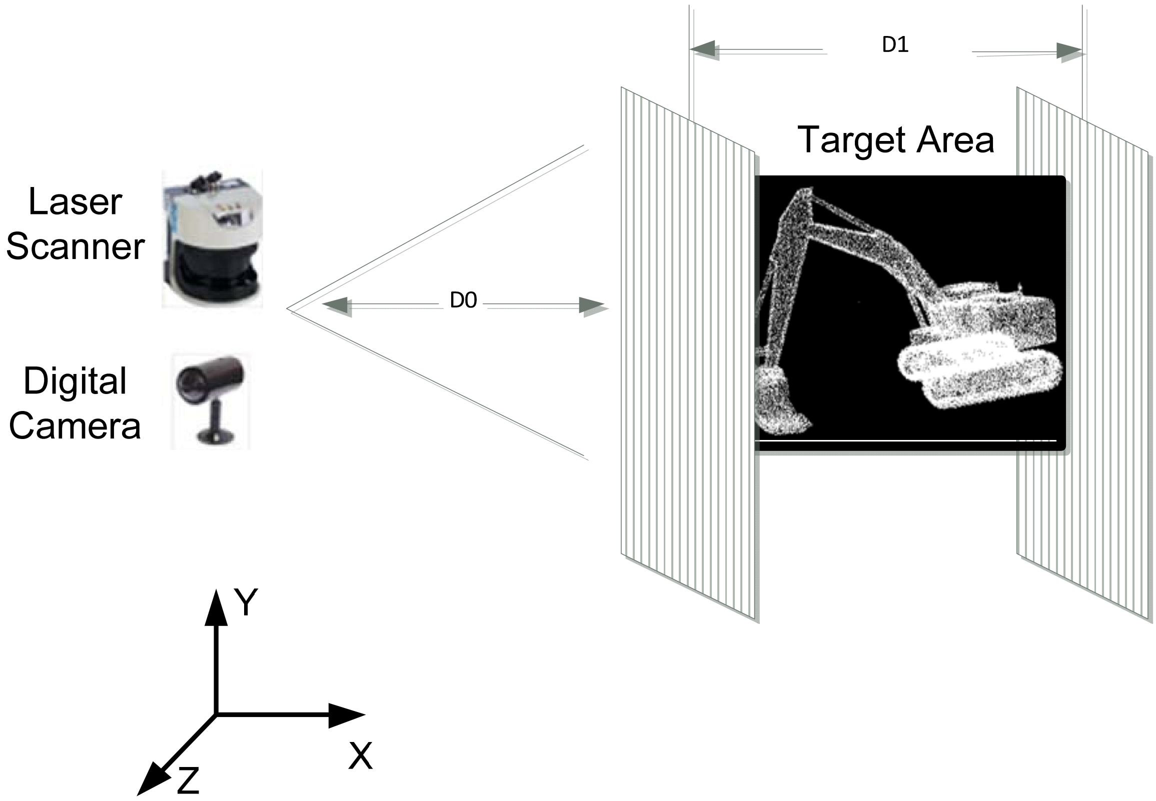


Figure 9. Illustration of filtering a data acquisition zone

Figure 10 takes a forklift as an example and illustrates the extraction process of a bounding area from point clouds. Figure 10 (a) shows a forklift with the object “box”, which is scanned by the developed LADAR system; (b) provides the point cloud data; (c) illustrates the object’s bounding area extracted from the point cloud and (d) shows the extracted point cloud.

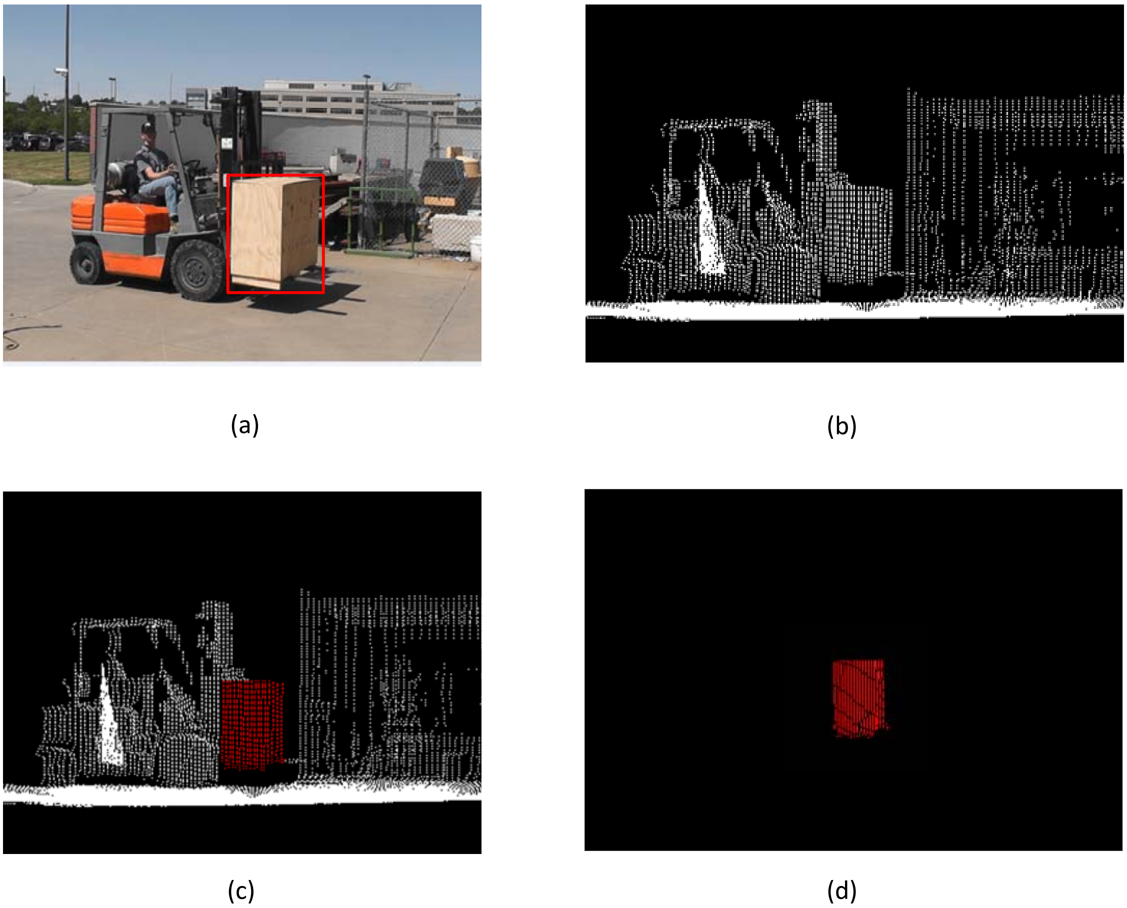


Figure 10. Example of bounding area extracted from point clouds: (a) job site with forklift (b) point cloud of the forklift with the object “box” (c) bounding area extracted from the point cloud (d) extracted point cloud of the object

3.4 Projection from 3D Point Cloud to 2D Planes

Orthographical projection from 3D to 2D introduced in this study is a process of mapping three-dimensional point cloud to a two-dimensional plane, which is used to recognize and localize the target in a 3D view. Orthographical projection has a long history and was intensively used in engineering, drawing and computer graphics (Snyder

1993). Gathered by the hybrid laser system, the 3D point cloud is orthographically projected into different 2D planes from different directions, of which the principle is shown in Figure 11.

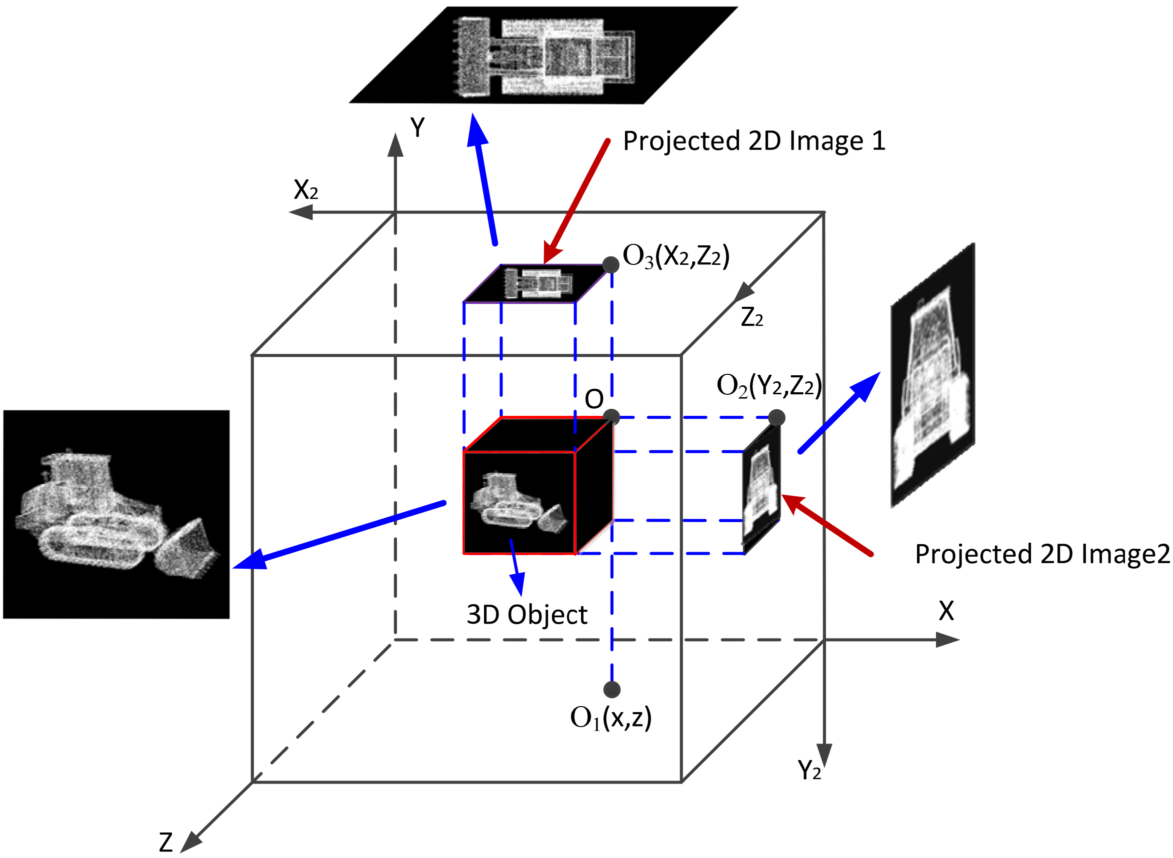


Figure 11. Process of 3D to 2D transmission

In Figure 11, as an example, a track loader is located in the center, and different projection angles are randomly selected from the laser scanning direction (e.g., 90 degree or 45 degree). Assume point O (O_x, O_y, O_z) is orthographically projected onto 2D points

$O_1(O_{1x}, O_{1z})$ parallel to the y axis, the coordinate values of point O_1 can be calculated as follows,

$$\begin{bmatrix} O_{1x} \\ O_{1z} \end{bmatrix} = \begin{bmatrix} m_x & 0 & 0 \\ 0 & 0 & m_z \end{bmatrix} \begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} + \begin{bmatrix} n_x \\ n_z \end{bmatrix} \qquad \text{(Equation 1)}$$

where m is an arbitrary scale factor and n is an arbitrary offset factor, both of which can be used to align the projection viewport. For example, set a projection angle from the laser scanning direction as 90 degree, which means the factor m=1, n=0, then the coordinate values $O_{1x} = O_x$, $O_{1z} = O_z$. Here, a distance value is also obtained from the 3D point cloud to the 2D projection plane, based on which 2D image data are collected and displayed. The projection results include the 3D point cloud data and the 2D projection planes of the loader.

3.5 Recognition from Projected 2D Planes

Many previous research initiatives presented different types of system using laser scanners. Local surface descriptors named spin-images (Johnson and Hebert 1999) were used in the system proposed by Gordon et al. (2003) to recognize the shapes of target objects. In the system, the pose and position of 3D targets with arbitrary shapes were determined; similarly shaped regions were identified using a localized measure of surface shape between the 3D scene and the target model (Gordon, et al 2003). Based on previous research (Cho and Martinez 2009), another system was proposed (Wang, et al and Gai, et al 2012), integrating a 3D LADAR scanner, a digital camera and an IR camera. This lightweight 3D LADAR system was more flexible in hardware control and software programming than a commercial LADAR scanner. Window and building outline recognition was implemented based on the point cloud data obtained by this system.

Figure 12 illustrates the process of object recognition from 2D projected planes proposed in this study.

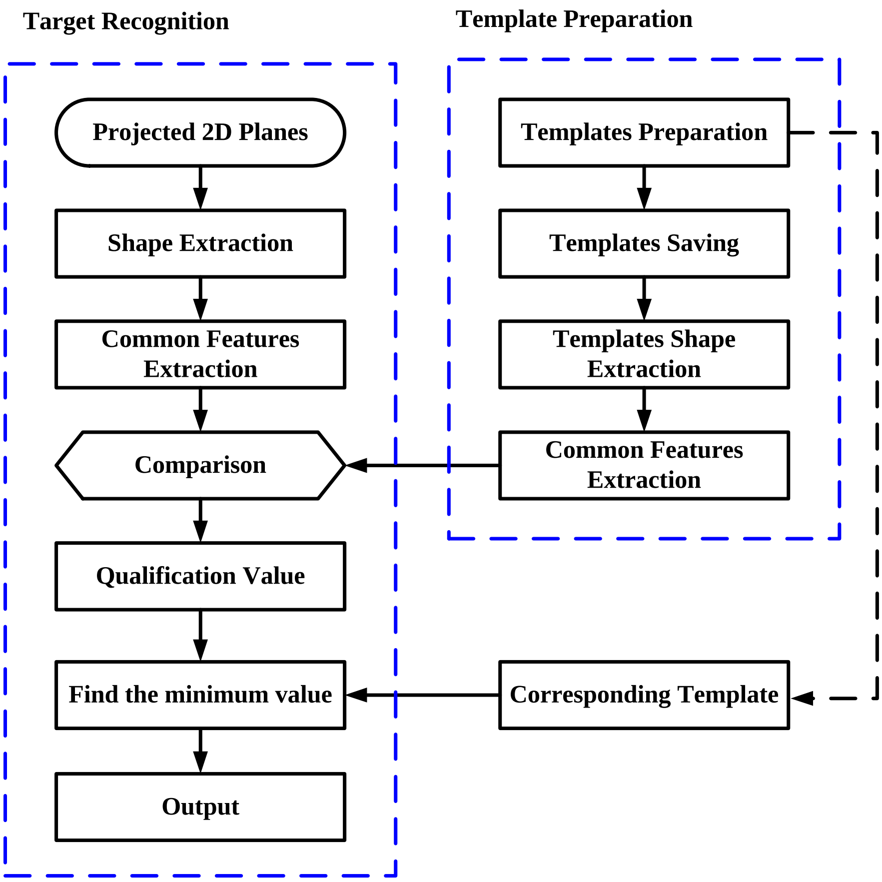
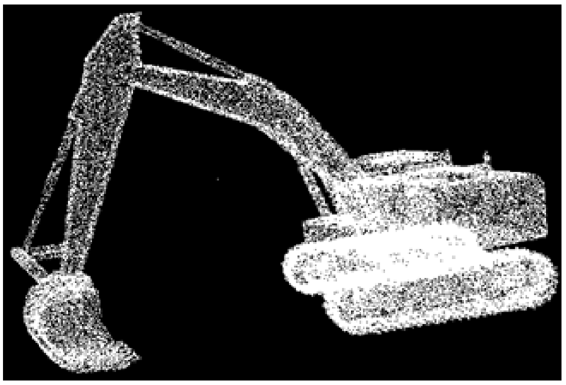


Figure 12. Process of object recognition from 2D planes

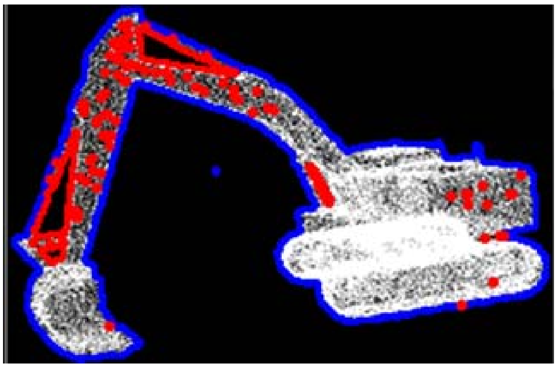
Offline templates of the target were prepared based on different projection angles, which were stored in the local software database. Each template's shape was generated one by one and followed by common features were extracted from the corresponding shape. Projected 2D planes as input of the target recognition component were online processed and corresponding shapes and common features were generated from them. Similarity comparison between common features from projected 2D planes and the ones from templates database was implemented. As a result, comparison qualification values were generated, of which the template corresponding to the minimum one was chosen as the process result. The main challenge from the process of object recognition in this study is to extract the shapes from projected 2D planes and compare the corresponding shapes with the prepared templates in the database. Several methods based on distance transforms have been presented by researchers. Gavrila and Philomin (1999) introduced a shape-based target recognition method using distance transforms, specifically, offline template hierarchy was prepared and trained through stochastic optimization techniques; and online target matching with the template was processed, together with a simultaneous coarse-to-fine approach. Besides the distance transforms based methods, Amit et al. (1997) introduced an algorithm to construct classification trees which were used to determine the separate particular shapes. In their method, every possible geometric array was conrresponding to a group of features, which coarse constraints was presented on the distances and angles. Because of randomization and being aggregated in a common way, the array are denpendent weakly. The SIFT local descriptor (Lowe 1999; Lowe 2004) proposed by David Lowe, which can provide robust matching across a substantial range of illumination change, noise, viewpoint and distortion, was intensively used to determine key identical points and got a well performance. This study employed another local descriptor SURF (Bay et al. 2006) and the methodology process provided by

Mikolajczyk (Mikolajczyk, et al 2003) to perform the target shape recognition from 2D planes. The whole system was mainly composed of two stages, reducing ambiguity by clustering via a local transformation firstly, and implementing object detecting by estimating a global transformation (Mikolajczyk, et al 2003). Take hydraulic excavator of CAT as a recognition target, as is shown in Figure 13, the target edge was extracted based on the Open Source Computer Vision Library (OpenCV) and followed by image filtering process to remove the noises. Several moving components of the hydraulic excavator were disassembled and separate templates were prepared and trained for them, as is shown in figure 14.

(a)

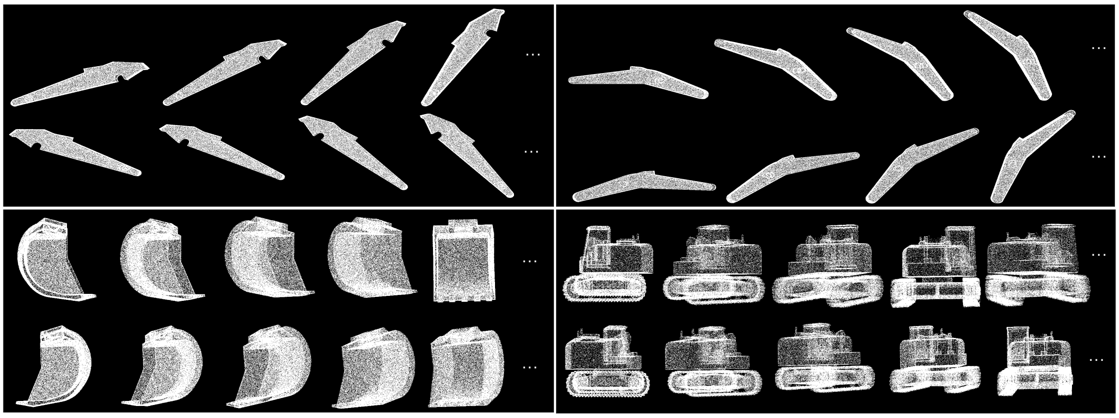


(b)

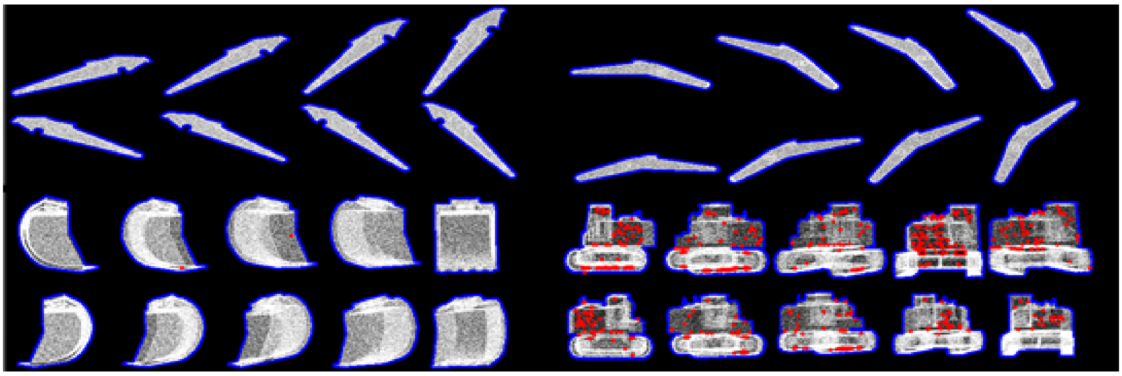


(c)

Figure 13. Hydraulic excavator picture (a), point cloud (b), and extracted contours (c)



(a)



(b)

Figure 14. Offline prepared component Templates (a) and contours (b) of the Hydraulic Excavator

3.6 Point Cloud and CAD Model Registration

A series of 2D planes, projected from extracted target areas containing 3D point clouds with a rotation center located in the target's vertical-middle line, were employed from which object contours were extracted, and followed by a filtering process to remove the outliers from the corresponding SURF features. In order to filter the extracted features contaminated by outliers, many researchers proposed methodologies with promising results, such as the Random Sample Consensus (RANSAC) algorithm (Fisher and Bolles 1981). It is an iterative algorithm which aims to estimate mathematical model's parameters from a set of feature data array with outliers, producing a reasonable result with a certain probability. Inliers (features which are consistent with the relation) and outliers (features which are not consistent with the relation) are simultaneously classified according to the relationship between the data set and an estimated global relation (Fisher and Bolles 1981). Based on the RANSAC algorithm, there have been a number of researchers who were trying to improve RANSAC's verification and sampling performance, such as Matas and Chum (2004) and Capel (2005). These efforts aimed to optimize the model verification and sampling process to generate much more meaningful hypotheses. In particular, Nister (2003) proposed a system aiming to perform robust estimation and find the best solution from a set of hypothesis, together with a preemptive scoring based on an inlier-outlier model. However, inherent non-adaptive performance on the data array becomes a limitation and for low contamination problem, this framework seems slower than the standard RANSAR (Rahul, et al 2008).

In this study, a triangle relationship based filtering method was used to remove the outliers from the feature data array. Figure 15 (a) gives an example of common features and their corresponding relationship and Figure 15 (b) illustrates two triangles with relation: $A_1A_2A_3$ and $B_1B_2B_3$. The employed method implements the filtering function as is shown below.

Triangle relationship based filtering method

Initialization
ARRSAC algorithm implementation
Set output data array of common features extracted process as the input

1. Generate random triangles using corresponding common features
   N = total number of triangles generated in the initial stage

2. Triangle similarity evaluation
   For i = 1 to N do
      Set A_{1i} A_{2i} A_{3i} as the T_{base};
      Set B_{1i} B_{2i} B_{3i} as the T_{base+1};
      Calculate the normal vectors of both triangles;
      Let A_{1i} move to the point of B_{1i};
      Calculate separation angle α of the planes containing both triangles separately;
      Rotate T_{base+1} according to the separation angle α, the two planes are parallel;
      Rotate line $B_{1i}B_{2i}$ till to be parallel with line $A_{1i}A_{2i}$;
      Calculate the angle between line $A_{1i}A_{3i}$ and line $B_{1i}B_{3i}$ = A_i;
   end for

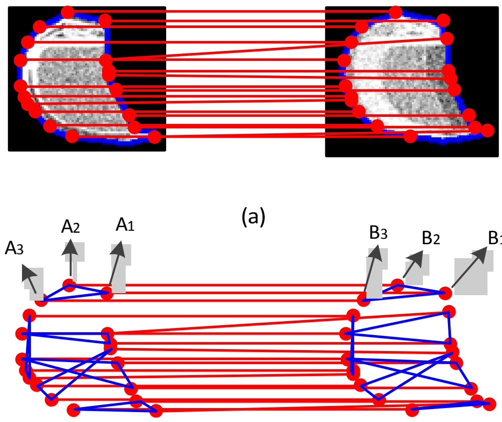
3. Separation angle sorting and minimum & maximum finding
   For i = 1 to N do
      Set minimum = A_0;
      Set maximum = A_0;
      if A_i > maximum then maximum = A_i;
      if A_i < minimum then minimum = A_i;
      Put the maximum one to the end of the data array;
   end for

4. Justify the performance of data array obtained in step 3
   For i = 1 to N do
      Set minimum = A_0-A_1;
      Set maximum = A_0-A_1;
      if A_i -A_{i+1} > maximum then maximum = A_i -A_{i+1};
      if A_i -A_{i+1} < minimum then minimum = A_i -A_{i+1};
      Put the maximum one to the end of the data array;
   end for
   Set the middle value as the base;
   Compare the base with all the data array, and find the outlier value;
5. Remove the outlier value/values

The output data array performs a reverse calculation process of 3D point cloud to 2D planes after the outliers are removed from the original contaminated features. 3D position calculation is the reverse projection process from 3D point clouds to 2D planes, as is shown in Figure 11. The object is located in the projection center of coordinate system, and different projection angles can be randomly selected from the laser scanning direction (e.g., 90 degree or 45 degree). In the projection process discussed above, point O (O_x, O_y, O_z) is orthographically projected onto 2D points O_1(O_{1x}, O_{1z}) parallel to the y axis, the coordinate values of point O_1 can be calculated through the equation 1. The calculation process of the object's 3D position is to figure out the value of point O (O_x, O_y, O_z) based on the known points such as O_1(O_{1x}, O_{1z}), O_2(Y_2, Z_2) and O_3(X_2, Z_2). Take the projected point O_1(O_{1x}, O_{1z}) to O (O_x, O_y, O_z) as an example, the equation is given as following Equation 2,

$$\begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} = \begin{bmatrix} m_x & 0 & 0 \\ 0 & 0 & m_z \end{bmatrix}^{-1} \left(\begin{bmatrix} O_{1x} \\ O_{1z} \end{bmatrix} - \begin{bmatrix} n_x \\ n_z \end{bmatrix} \right) \qquad \text{(Equation 2)}$$

where m is an arbitrary scale factor and n is an arbitrary offset factor, both of which can be used to align the projection viewport. For example, set a projection angle from the laser scanning direction as 90 degree, which means the factor m =1, n =0, then the coordinate values $O_{1x} = O_x$, $O_{1z} = O_z$. Here, a distance value is also obtained from the 3D point cloud to the 2D projection plane, based on which 2D image data are collected and displayed.



(b)

Figure 15. Extracted Common features (a) and the established triangle relationship (b)

In this study, prepared CAD models are one by one corresponding to the prepared point cloud templates, which means the registration process between point cloud and corresponding CAD model is based on the result of the object 3D position calculation. Based on the 3D coordinate value of the object contour, an existing CAD model from a database, which has same dimension with the object, is aligned according to the coordinate values of the object in a 3D view. Figure 16 illustrate the registration process of point cloud and CAD model, Figure 17 provides the test environment and heavy equipment, and an example of alignment result is shown in Figure 18 (side view), Figure 19 (bird's eye view) and Figure 20 (front view). Figure 21 takes a yellow robot as the object, and shows the alignment results in multiples positions.

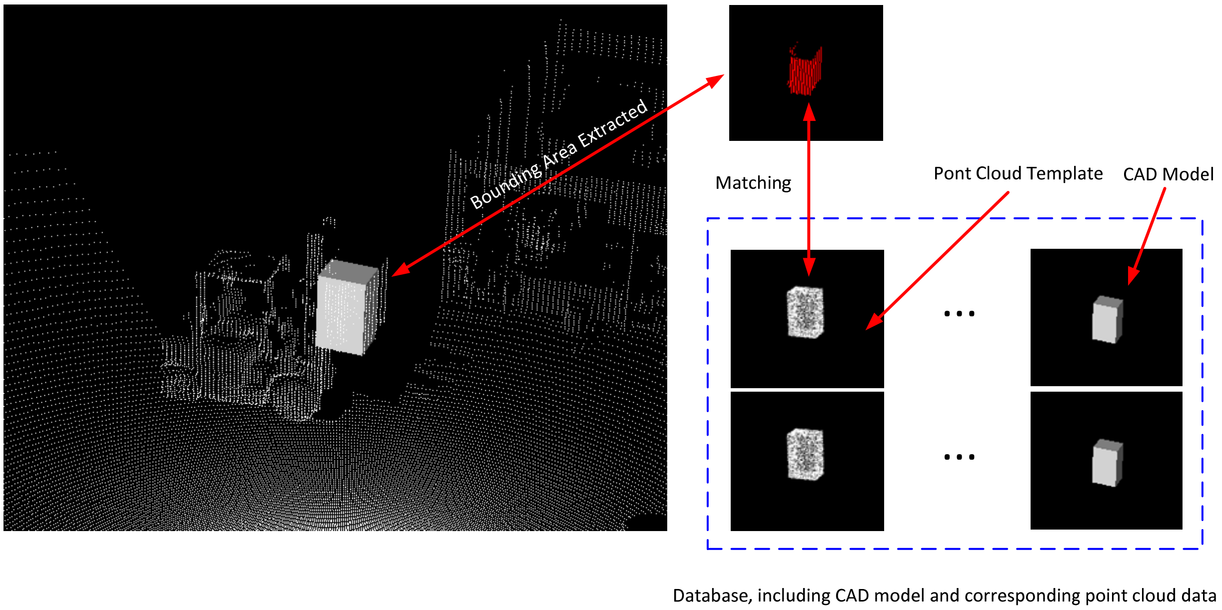


Figure 16. Point cloud and CAD model registration process

Figure 17. Equipment and test environment

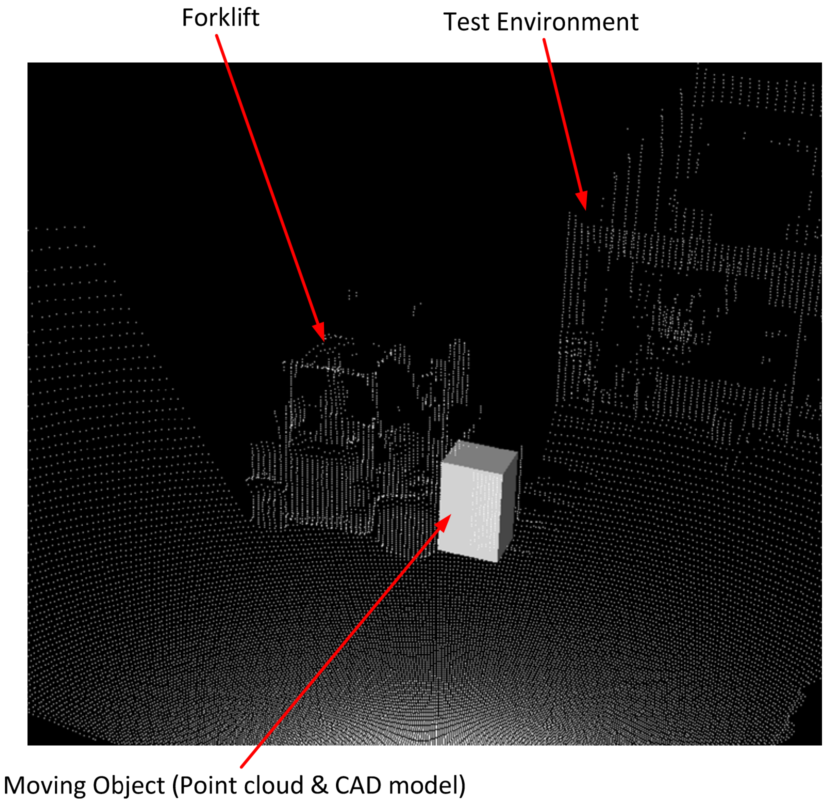


Figure 18. Results of aligning a 3D CAD model to a single scan point cloud (Side view)

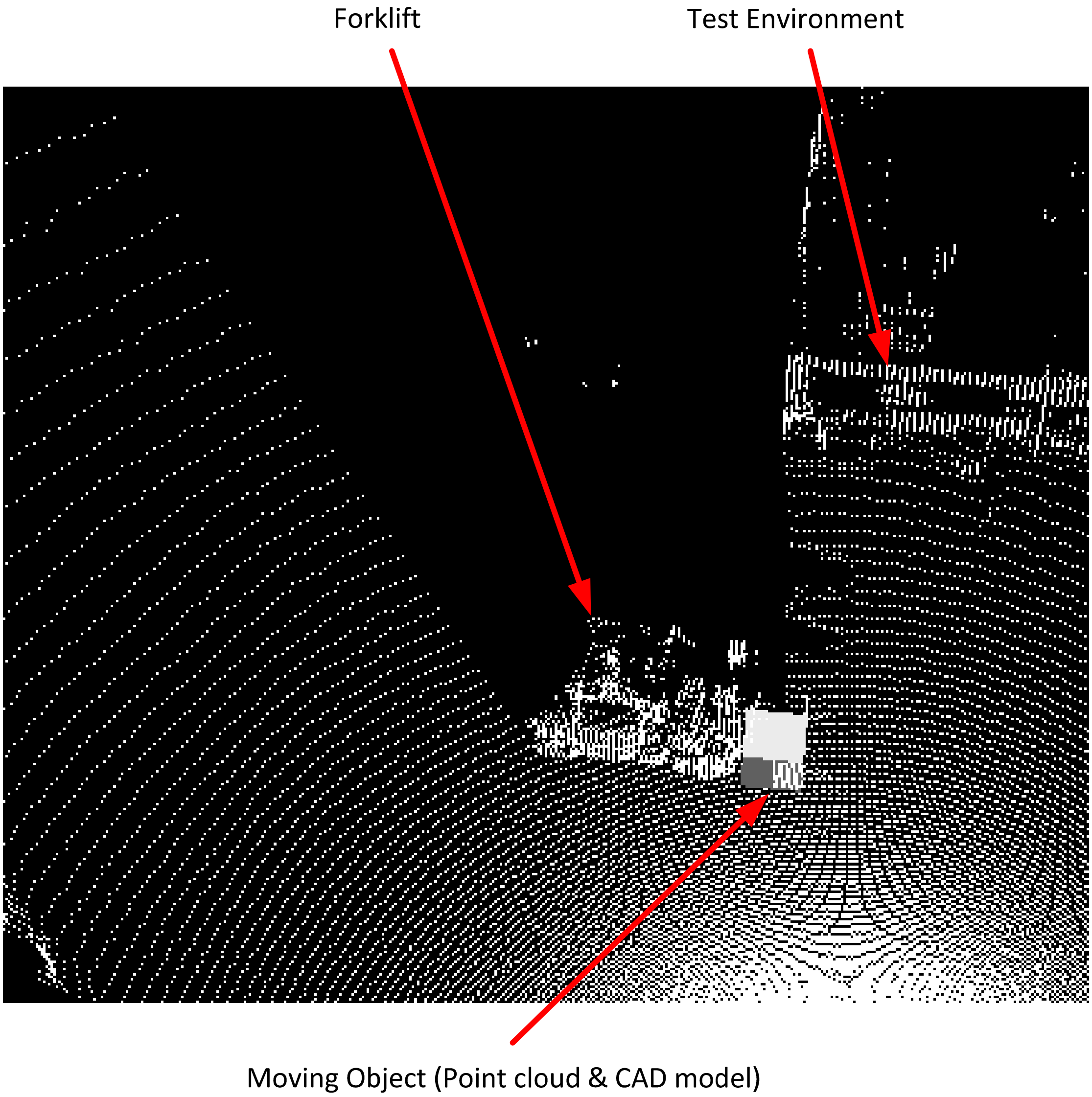


Figure 19. Results of aligning a 3D CAD model to a single scan point cloud (Bird's-eye view)

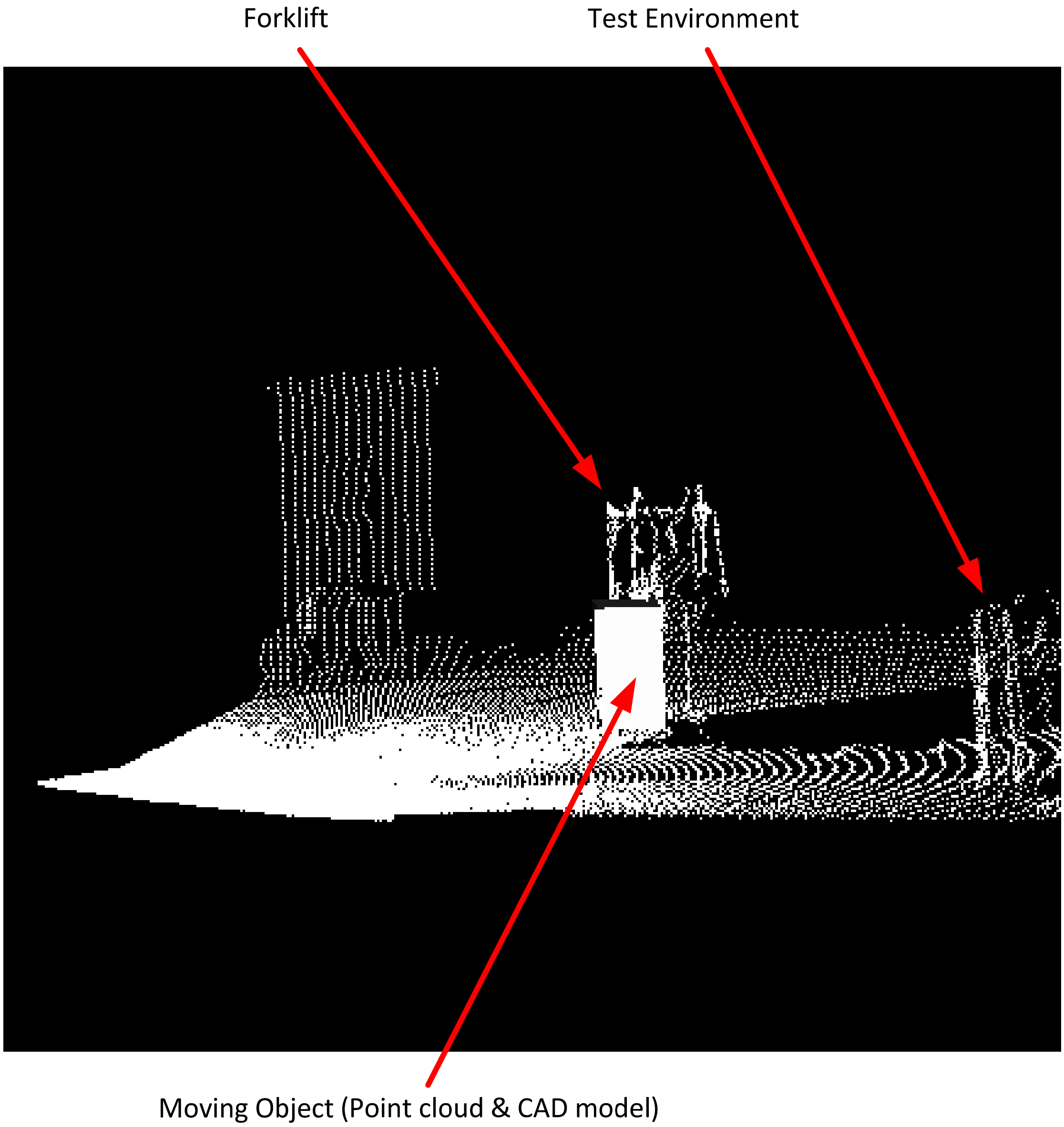


Figure 20. Results of aligning a 3D CAD model to a single scan point cloud (Front view)

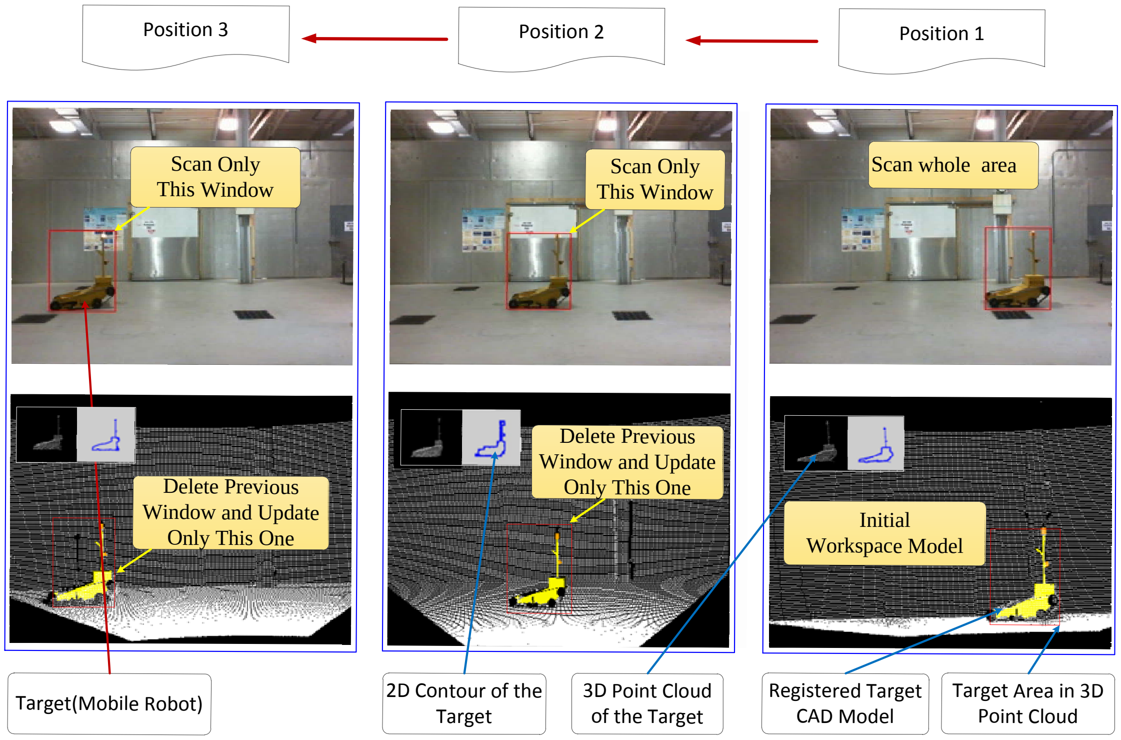


Figure 21. Results of aligning a 3D CAD model to a single scan point cloud (multiple steps, multiple positions)

CHAPTER 4 RESULTS DEMONSTRATION

This section introduces a real-time visualization method based on a LADAR system, to simultaneously assist multiple heavy equipment operators in perceiving 3D working environments at dynamic construction sites. Figure 22 illustrates the system configuration, including hybrid laser system, data server, router and terminals.

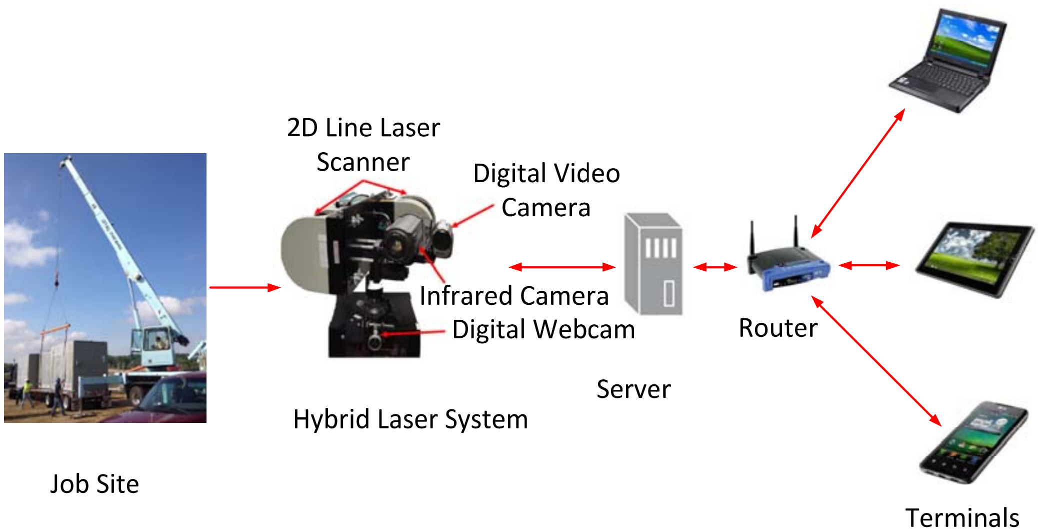


Figure 22. System configuration

The hybrid LADAR system obtained 3D point cloud data, which were transferred into data streams and uploaded to a remote operator's computer screen simultaneously. The data streams can be accessed by different equipment operators through local wireless or global networks such as Wi-Fi and 4G, and be further presented in dynamic 3D views. Strategies to rapidly update 3D point cloud scenes are discussed in this study. An earthmoving site with multiple pieces of construction equipment has been tested with promising results. The introduced 3D visualization method for equipment operations at dynamic working environments can significantly reduce blind working spots and even casualties while improving productivity.

Mounted on a mobile platform, the proposed hybrid laser system gathers point clouds with digital images of the job site which contains different types of heavy equipment. A separate data server connected to the hybrid laser system automatically stores the scanned data set from dynamic working environments and shares the data through a wireless router. Different mobile terminals can access the data server across the wireless router and present real-time 3D scenes of the job site. A wireless communication technology is preferred for data transmission. This study focuses on employing two types of wireless communication technology – Wi-Fi and Fourth generation of wireless (4G). Wi-Fi communication was recognized by IEEE in 1998 as the 802.11 standard that is a framework around local area network (LAN) (Amy and Samuel 2013). Users can receive data at their workstation such as PC or laptop within the local area network. The fourth generation of wireless (4G) communication is the latest communication technology that provides secure mobile access to smartphones, IP-based wireless modems and mobile devices. Remote users can access the 3D point cloud data from smartphones or any mobile device at their convenience. Figure 23 shows the scene that the hybrid LADAR system worked in a job site.

Figure 23. Hybrid LADAR system and outside view of the equipment

Figure 24 mainly illustrates the inside view of the heavy equipment. Equipment operators can access the data produced by the LADAR system via mobile terminals and investigate the real-time situation of the surroundings.

Figure 25 gives an example of the point cloud data gathered in the job site. In this experiment, the data transferring speed between LIDAR system and terminals is around 25M/bps, the rotation speed of the LIDAR system is 7.2 Degree/sec, the resolution in horizontal direction for two laser scanner is 0.42 (0.84/2) degree, the resolution in vertical direction is 0.25 degree, scan angle in horizontal direction is 360 degree, and scan angle in vertical direction is 190 degree.

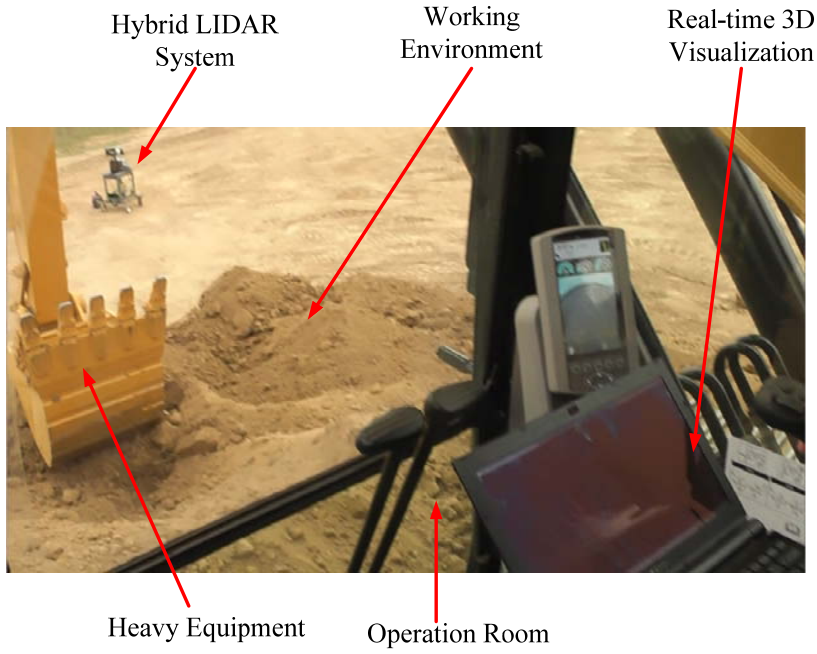


Figure 24. Hybrid LADAR system and inside view of the equipment

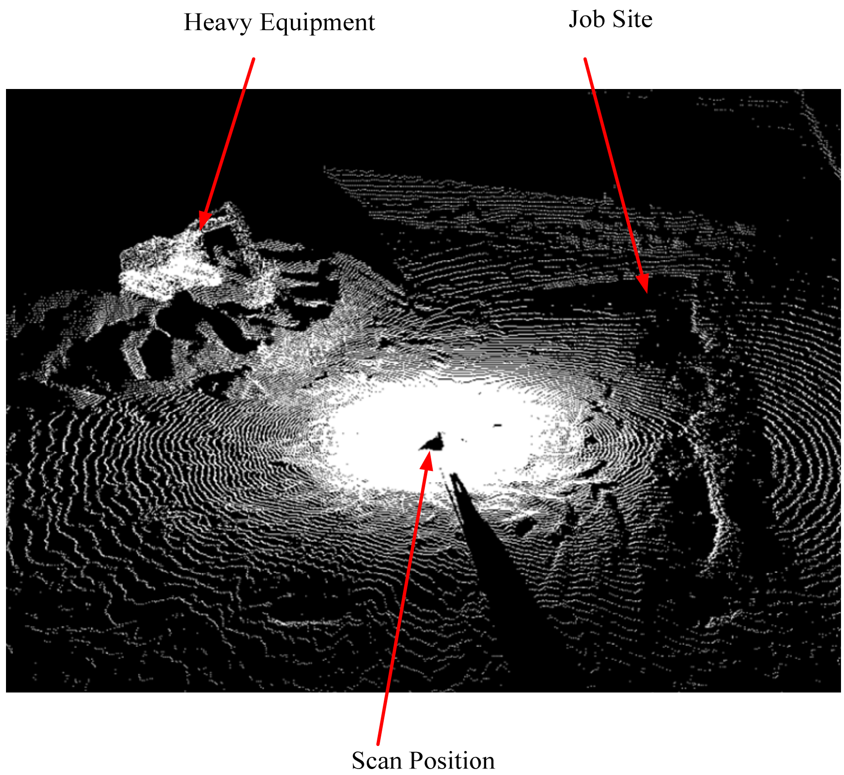


Figure 25. Example of 3D scene on the screen

CHAPTER 5 CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

A hybrid LADAR system and a model-based automatic object recognition and registration method, Projection-Recognition-Projection (PRP), were developed and tested successfully to assist heavy equipment operators in rapidly perceiving 3D working environment at dynamic construction sites.

In the developed hybrid LADAR system, a digital camera and a hybrid laser scanner were utilized to collect the point cloud data with digital images. Two laser scanners were used to speed up the data collection and increase the scan resolution. Two laser scanners can scan 360 degree in horizontal direction and 190 degree in vertical direction in 15 seconds. The resolution is 0.125 degree in vertical direction and 0.18 degree in horizontal direction, with a rotation speed of 1.08 degree per second.

A new framework, Projection-Recognition-Projection (PRP), was developed and tested successfully. A digital camera and a hybrid laser scanner were used to rapidly recognize and register dynamic target objects in a 3D space by separating target object's point cloud data from a background scene for a quick computing process. A smart scan data updating algorithm has been developed which only updates the dynamic target object's point cloud data while keeping the previously scanned static work environments. Extracted target areas containing 3D point clouds were orthographically projected into a series of 2D planes with a rotation center located in the target's vertical-middle line. Prepared 2D templates were compared to these 2D planes by extracting SURF features. Point cloud bundles of the target were recognized based on the defined qualification values among the comparison results, and followed by the prepared CAD model's registration to the templates aligned to the target area. Finally, the collected 3D data with registered CAD model were transferred and presented to the equipment operators through local network successfully.

Field demonstration was introduced for validation. Vision-based object recognition and tracking was implemented in real time. 3D data were transferred through local network rapidly. The outdoor field experimental results show that the proposed PRP method is promising and can significantly improve heavy construction equipment operations and automated equipment control by rapidly modeling dynamic target objects in a 3D view.

In conclusion, the proposed hybrid LADAR system and PRP framework successfully assist heavy equipment operators in rapidly perceiving 3D working environment at dynamic construction sites, and improve construction equipment operation safety and productivity by providing 3D dynamic workspace in real time.

5.2 Future Work

Future work will focus on the improvement of (1) the LADAR system resolution, optimization of the (2) image based target recognition and tracking, and training more (3) templates for object recognition from 2D planes.

(1) LADAR system resolution: In the dynamic construction job sites, it is required to update the environment in real time frequently; while with the increase of rotation speed, the scan resolution is decreasing accordingly. Lower resolution is supposed to bring more noises and errors, and also means lower system working robustness. Therefore, a smart scanning mode with flexible speed is necessary to developed in the future work.

(2) Robustness of image based target recognition and tracking: challenges from complex dynamic environments have existed for a long time in image based object recognition and tracking fields. Illumination changes, object shadows, obstacles and shape flexibility make the robustness of object recognition and tracking becomes lower. Although SURF descriptor based tracking methodologies have been employed by many researchers, there is still a long way to go, particularly in the quick dynamic environments. Future work will try to optimize the algorithms used in this system and more experiments will be implemented.

(3) Template based object recognition from 2D planes: 3D point cloud data are projected into 2D planes, and objects are recognized from these planes through template

based methodology. The volume of template database has direct effectiveness on the recognition performance, namely, templates in the database are more comprehensive, and there will be more opportunities to implement object recognition well.

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