

EXHIBIT 1012

Ship Identification Algorithm Based on 3D Point Cloud for Automated Ship Loaders

Chao Mi[†], Yang Shen^{†*}, Weijian Mi[†], and Youfang Huang[†]

[†]Container Supply Chain Tech. Engineering Research Center
Shanghai Maritime University
Shanghai 200000, China

[‡]Higher Technical College
Shanghai Maritime University
Shanghai 200000, China



www.cerf-jcr.org



www.JCRonline.org

ABSTRACT

Mi, C.; Shen, Y.; Mi, W., and Huang, Y., 2015. Ship identification algorithm based on 3D point cloud for automated ship loader. In: Mi, W.; Lee, L.H.; Hirasawa, K., and Li, W. (eds.), *Recent Developments on Port and Ocean Engineering*. Journal of Coastal Research, Special Issue, No. 73, pp. 28-34. Coconut Creek (Florida), ISSN 0749-0208.

With the development of bulk port automation, the ship loader as the main quayside machine of bulk terminal is required for transformation from manual operation to automation. The ship identification method is a key inspection technique for automated ship loaders. In this paper, a fast ship identification algorithm was formulated based on the 3D point cloud of the ship, as generated by the Laser Measurement Systems (LMS) mounted on the ship loader. To meet the requirement of real-time computing for the automated ship loader, the 3D point cloud was first processed to reduce its dimensions from 3D point cloud into a 2D image. A projection method was then applied to locate and identify all bulk cargo holds in the ship. Finally, a group of experiments on ship identification was conducted using this algorithm in the Coal Terminal of Tianjin Port. The results showed that the computing time for a whole ship was lower than 200 ms and the error of the algorithm was lower than 10%, meeting the requirement of automated ship loaders.

ADDITIONAL INDEX WORDS: *Automated ship loader, bulk terminal, point cloud, target identification, automation, crane, LiDAR.*

INTRODUCTION

Nowadays, with the development of economic globalization, there are increasing demands in port handling capacity. In order to meet the requirements of port machinery to achieve high-speed operational capability, in more and more ports the transformation from manned mechanized ones to unmanned intelligent ones is being realized. Many engineers and researchers are developing intelligent control systems to achieve automation of port machinery. And the development of international container port automation is relatively mature. Currently, the Euromax terminal, in Rotterdam, the Netherlands, has reached the world's highest degree of automation. Its handling equipment consists of the semi-automated double trolley quayside container cranes. The horizontal transport equipment is 20 m/s automatic guided vehicle (AGV), and the yard equipment is automatic rail-mounted container gantry cranes (ARMG) (Zhen *et al.*, 2012; Tang, Huber, and Akinci, 2010).

However, automation in bulk terminals has developed at a slower pace. It is different from the container terminals as the operation environment is poorer and more complex in bulk terminals (Hyla, 2012). For example, the cranes can locate the containers in the yard just by conventional encoders because the shapes and positions of containers are standard. However, it is very difficult to locate the operation targets in bulk terminals, because the shapes of the bulk materials, ships and yards are all anomalous (Barrosa *et al.*, 2011; Rong and Grunow, 2009).

Due to its poor operation environment, uncertainties of bulk materials, and complex shapes of operation targets, the development of automated bulk terminal has lacked behind and there is rarely machinery for fully automated bulk solutions worldwide. To promote the development of automation in bulk terminals, the first problem to be solved is how to detect the operation targets. Recently, more and more engineers and researchers have begun to find a way to implement the target identification by machine visions.

In the beginning, a digital camera has been used as the image sensor and the three-dimensional coordinates of objects are calculated by image-marking. Jung *et al.* (2012) used a smart vision camera to measure spreader motion; Chen, Peng, and Singhose (2009) utilized a downward pointing Siemens Simatic VS723-2 intelligent camera mounted on the trolley to provide relative positional measurement of the hook. Lee, Huang, and Shih (2011) tried to build a visual feedback control system with a 30 frames per second (fps) CCD camera; Kawai, Choi, and Kim (2008) proposed a position measurement system placed on the trolley of a crane with an image sensor, containing a CCD camera and an image processor. The above methods can all successfully track the targets, but the digital camera-based identification methods are not real-time, so it is not suitable for fast identification in automated bulk terminals. Meanwhile, these methods require at least one color target installing in the scene for correct camera parametric inference. However, it is not easy and sometimes even impossible to install color targets in bulk terminals. Even if the color targets can be correctly installed, the bulk dust can cover those targets in a short time and make them ineffective.

Therefore, multiple cameras were used to replace single cameras without color targets to be identified. Mrovlje and

DOI: 10.2112/SI73-006.1 received 15 August 2014; accepted in revision 16 November 2014.

*Corresponding author: kingdows@gmail.com

© Coastal Education & Research Foundation, Inc. 2015

Vrancic (2012) presented a simple method for automatic detection of the truck position using stereo vision system consisting of two cameras. This system enhanced the automation grade of the unloading process and improved the overall productivity of port container terminals. But this method required complex equipment installation, and required long computation time for the corresponding points matching between two images. In bad weather conditions, it also showed lower calculation accuracy, although multiple cameras still performed better than single cameras. Yoon, Hwang, and Cha (2010) proposed the method of container detection and depth extraction using stereo vision for real-time container auto-landing systems. However, it was only verified in the indoor environment objectively and the errors of depth estimation increased with the distance. Although multiple cameras could lead to self-parametric inference, the calculation time was much longer than that of single cameras. It is because the algorithm of multiple cameras matrix needs more computing steps than that of single cameras. In addition, multiple cameras have some other disadvantages: smaller field of view, difficult stereo matching and larger system structure, which drives the visual system to be unstable (Angeloudis and Bell, 2011).

The detection technique of the operation targets based on image identification is mainly realized by analyzing the images collected through cameras. It is passive recognition and can be greatly affected by the environment. When it comes to heavy rain or heavy fog, the detection will be more difficult. In more unfavorable conditions, the visual system may lose the ability to work. To deal with images under such complex background, the algorithm is more complicated in the implementation because the images contain a lot of interference factors. Accordingly, the detection speed will be slower, and otherwise the identification accuracy cannot meet the needs of the automation of normal operation. So the image identification method is unreliable for bulk terminals with a complex background environment. In view of the above weakness, some other researchers began looking for a new approach to achieve the operation target identification. As a result, an active vision system using radar for data acquisition was then proposed. Its signal can penetrate the heavy rain and fog and will not be influenced by the environment, color, etc.

Zhou, Zou, and Wu (2007) adopted millimeter wave FMCW radar to replace traditional distance measurement method in the crane crash—preventing system design. Since this radar is insensitive to environmental variations and it could be used in the high-precision measurement of short distance, Yi *et al.* (2011) used the linear frequency modulation continuous wave (LFMCW) radar sensor to determine the distance from the subject vehicle to the target vehicles. FMCW has mainly been used for distance and speed detection. But if it is used for target detection, errors will be larger since it cannot correctly describe the surface of the target with single point scanning. Hence, the study focus has shifted to Light Detection and Ranging (LiDAR). FMCW and LiDAR have no essential difference in terms of the working principle. But compared with microwave radar, laser beam is used in LiDAR, which has a high efficiency to obtain higher resolutions of angle, distance and speed. Moreover, the scanning coverage is so wide that it can form a fan to provide more data for the target detection.

Kim *et al.* (2013) used LiDAR laser radars to detect the distance between the radar and the target. Lee, Lim, and Park (2011) used the terrestrial laser scanner to measure and record the change of the beach. Shimoni *et al.* (2011) presented a four-step process that combined high resolution LiDAR and hyperspectral data to classify shadow areas, segment vehicles in LiDAR data, detect spectral anomalies and improve vehicle detection. It has overcome the limitations of small target detection in complex urban scene and obtained good detection effect in semi and deep shadow areas. Natale, Tutwiler, and Baran (2010) used a commercial 3D Flash LiDAR camera to accomplish the detection, segmentation, and tracking of human sized objects with a combination of fundamental point cloud processing algorithms. By using point cloud, multi-view stereo 3D models can be directly generated to circumvent the problems associated with structure in motion.

In conclusion, LiDAR is the most reliable method in vision detection. It obtains the point cloud data in each cross section at first, and reconstructs the data in space according to the relative motion information to perform surface display of the entire target. This method has a simple structure and fast response, and is independent of environment, and its performance is determined by how the three-dimensional point cloud data are processed, which is the key to LiDAR target detection (Sampath and Shan, 2007; Sithole and Vosselman, 2004).

Tang, Huber, and Akinci (2010) used Laser scanners to capture dense 3D measurements of a facility's as-built condition and converted the resulting point cloud data into surface data in the form of a triangular surface mesh to create an as-built BIM. However, it is difficult to forecast the performance of this method due to more complex and real data sets, which is to say, a full context must be considered when this method is used for bulk cargo wharf with complicated environment. Woo, Kang, and Wang (2002) proposed a new method for segmenting the point cloud data. They handled a large amount of unordered sets of point data with the octree-based 3D-grid method. This method can extract edge-neighborhood points while considering the geometric shape of a part. Its performance was fine for simple-structured objects. However, if the measured object is large with a complex structure, it would take a long time to deal with a refinement process and iterative sub-division of cells using the normal values of points, leading to a poor instantaneity. Kirchhof, Jutzi, and Stilla (2008) found that the use of the estimated surface response from the surface normal can increase the response of the matched filter for feature extraction. They proposed a method for iterative knowledge-based processing of terrestrial laser scanning data by full waveform analysis. This method can not only improve the point density and accuracy of the range values, but also allow closing gaps in partly occluded surface regions. But it was based on the use of prior knowledge of the surface, so without it, the calculation cost would be high. So far, there have been no data on automatic target detection to support this method. Hence, it has not been further studied considering the high security of the automation process.

In conclusion, no processing methods of 3D Point Cloud data based on LiDAR can be applied to target detection in bulk terminal automation, because such processing methods are too complex and do not meet the real-time control requirements of

automated ship loaders. The objective of this paper is to formulate an algorithm to process the 3D point cloud of the whole ship and identify the bulk cargo holds in real-time. Experimental results would show that this algorithm is suitable for automated ship loaders.

SHIP IDENTIFICATION ALGORITHM

At the beginning of the loading operation, the bulk ship berths align alongside at a rough position. The automated ship loader should firstly search for the ship position and locate the bulk cargo holds on the ship. And then, the slip barrel of the ship loader can be guided into the bulk cargo hold. The bulk materials can be loaded from the slip barrel into the bulk cargo hold. During the loading operation inside the bulk cargo hold, the slip barrel should be controlled to move to different positions for keeping the balance of the ship and a suitable shape of the bulk materials. Therefore, there are two main purposes of the ship identification algorithm for automated ship loaders. The first purpose is to locate the position of the bulk cargo holds in the ship, which can assist the ship loader to move its slip barrel into the holds correctly. The second purpose is to identify the edges of the cargo hold when the slip barrel is inside the hold, which can assist the slip barrel to move itself safely inside the hold.

To achieve these two purposes of the ship identification algorithm, there are 4 Laser Measurement Systems (LMS) installed on the platform of the slip barrel. LMS is a type of LiDAR equipment to measure the distances from the LMS to the target in a 180° sector section, as shown in Figure 1. Therefore, a LMS can acquire the cross section 3D point data of the target surface. With the relative movement between the LMS and the target, different cross section 3D point data can be collected. Finally, the whole surface 3D point cloud can be obtained. Based on the 3D point cloud, the bulk cargo holds can be identified. Meanwhile, based on the cross section 3D point data, the edges of the bulk cargo hold can be also identified.



Figure 1. The schematic drawing of LMS scanning.

As shown in

Figure 2, to avoid detection blinds of the ancillary facilities on the slip barrel, the 4 LMS were respectively mounted on the 4 corners of the platform of the slip barrel. Thus, the LMS matrix can scan 4 cross sections at the same time. The ship identification algorithm was implemented based on those cross section 3D point cloud data from the LMS matrix.

Ship Surface Rebuilding Algorithm

As shown in

Figure 3, with the movement of the ship loader, the whole ship can be scanned by the LMS installed on the platform of the

slip barrel. The whole ship surface can be rebuilt by the 3D point data collected by LMS.

The panning speed of the ship loader was V_{Loader} (m/s) and the scanning speed of the LMS was F_{LMS} (cross sections per second). Therefore, the interval $D_{interval}$ between the adjacent cross sections can be obtained by Equation (1).

$$D_{interval} = \frac{V_{Loader}}{F_{LMS}} \quad (1)$$

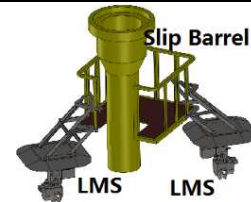


Figure 2. The schematic drawing of LMS installing on the platform of the slip barrel.

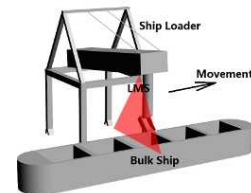


Figure 3. The schematic drawing of LMS Scanning the whole ship.

Next, the 3D point cloud data can be regrouped to represent the whole ship. As shown in Figure 4, the first cross section was put at the origin of the coordinate, and the second one was put right beside the first one with “ $D_{interval}$ ” offset, and so on. The cross sections generated by LMS can all be regrouped into the same coordinate system, and the 3D surface of the ship can be obtained.

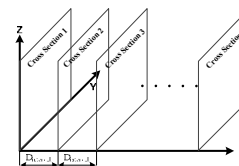


Figure 4. Regroup the 3D point cloud.

However, it was too difficult to process the 3D point cloud directly, because the amount of the data was huge and it may take much time for data processing by a computer, not meeting the requirement for real-time control in automated ship loaders. Therefore, before identification of bulk cargo holds, it was necessary to reduce the amount of point cloud in consideration.

There are two steps to reduce the amount of point cloud.

The first step is to rasterize the point cloud in an acceptable accuracy. To rasterize the point cloud means to overlay the resolution of the point cloud. The resolution of the point cloud determines the ultimate accuracy. When the resolution is higher, the accuracy becomes higher, but the amount of point cloud becomes larger. Meanwhile, a lower resolution would lead to a lower accuracy. Therefore, selecting a suitable resolution is very important. Once the resolution is selected, the rasterizing can be processed. Here, the resolution is defined as “ R_G ”. Then, the axis smallest unit of the coordinate system is redefined equaling to “ R_G ”.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = INT \left(\begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} + \begin{bmatrix} R_G \\ R_G \\ R_G \end{bmatrix} \right) \times \frac{1}{R_G} \quad (2)$$

The rasterizing formula can be represented as Equation (2), where “INT” is a decimal truncation function, X_0, Y_0, Z_0 are the raw points and X, Y, Z are the rasterized points whose dimension becomes “ R_G ”. Figure 5 shows an instance of a rasterized 3D point cloud.

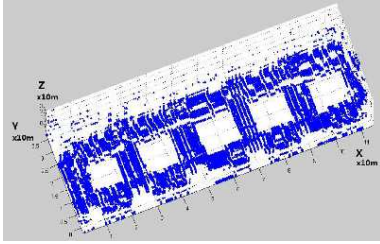


Figure 5. Rasterized 3D point cloud.

The second step is to project the 3D point cloud to the Z-axis plane. Thus, the 3D point cloud can be transformed into a 2D image. Before projection, an image matrix should be built first. Each pixel of the image matrix represents a size of “ $R_G \times R_G$ ” unit in the coordinate system. “ $P_{x,y}$ ” is defined to represent the pixel in the position (X, Y) of the image, which also represents the position ($X \times R_G, Y \times R_G$) in the coordinate system. The value of “ $P_{x,y}$ ” is only equal to 0 or 1. The projection formula can be obtained as Equation (3). Figure 6 shows an

$$Pixel_{x,y} = \begin{cases} 1 & \text{For } \forall Z, \text{ There is at least one point at position}(X, Y, Z) \\ 0 & \text{For } \forall Z, \text{ There is no point at position}(X, Y, Z) \end{cases} \quad (3)$$

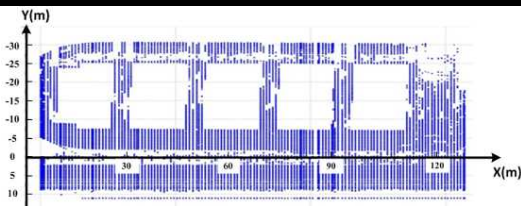


Figure 6. Projected 3D point cloud.

instance of a projected 3D point cloud, where all pixels of value “1” are displayed.

With these two steps, the original 3D point cloud can be compressed into a 2D image, which may accelerate the computing time of bulk cargo holds identification.

Identification Algorithm of Bulk Cargo Holds

To meet the real-time control requirement of automated ship loaders, the 2D image could not be processed with a fine and precise method. Here, a fast bulk cargo holds identification method based on statistics was proposed. For a bulk ship, the shape of the hold is normally rectangular. Therefore, by analyzing the 2D image projected onto different axes, the bulk cargo holds can be quickly identified.

At first, a set (P_x and P_y) of projection should be defined as Equation (4). P_x means all points of the 2D image at the range of $[x, x + D_{interval})$ while P_y means all points of the 2D image at the range of $[y, y + R_G)$. They are the projection units.

$$\begin{aligned} P_x &= \{Pixel_{x,y} \mid x \leq X < x + D_{interval}\} \\ P_y &= \{Pixel_{x,y} \mid y \leq Y < y + R_G\} \end{aligned} \quad (4)$$

To project the 2D image onto the Y axis, a matrix (Project_Y) of projection results is defined as Equation (5), where each element of the matrix is equal to the sum of P_Y and the step length of adjacent projection is equal to $D_{interval}$. “ n ” is the number of sets P_Y in the 2D image.

$$\begin{bmatrix} Project_{Y(0)} \\ Project_{Y(1)} \\ \vdots \\ Project_{Y(n-1)} \\ Project_{Y(n)} \end{bmatrix} = \begin{bmatrix} \sum P_{Y(0)} \\ \sum P_{Y(1)} \\ \vdots \\ \sum P_{Y(n-1)} \\ \sum P_{Y(n)} \end{bmatrix}, \text{ for } \forall k, Y(k) - Y(k-1) = R_G \quad (5)$$

It is similar to project the 2D image onto the X axis, as obtained by Equation (6), where the step length of adjacent projection is equal to R_G . “ n ” is the number of sets P_X in the 2D image.

$$\begin{bmatrix} Project_{X(0)} \\ Project_{X(1)} \\ \vdots \\ Project_{X(n-1)} \\ Project_{X(n)} \end{bmatrix} = \begin{bmatrix} \sum P_{X(0)} \\ \sum P_{X(1)} \\ \vdots \\ \sum P_{X(n-1)} \\ \sum P_{X(n)} \end{bmatrix}, \text{ for } \forall k, X(k) - X(k-1) = D_{interval} \quad (6)$$

Thus, by analysis of the curve of the projections, the bulk cargo holds can be located. As shown in Figure 7, there are 5 notches on the curve. Because the values of the “Project_{X(n)}” are significantly smaller at the positions of the bulk cargo holds, thus, the 5 notches indicate the 5 positions of the bulk cargo holds.

To locate the holds quickly by computer, the curve should be made a binary conversion. The binary conversion uses a threshold “T” to divide the curve in to 2 parts. By Equation (7), The Project_{X(k)} curve can be divided in to 2 parts.

$$ProjectT_{X(k)} = \begin{cases} 1 & (Project_{X(k)} > T) \\ 0 & (Project_{X(k)} \leq T) \end{cases} \quad (7)$$

The threshold “T” is a variable threshold determined by Equation (8), where the “S” is variable parameter. According to the amount of experimental results, 1 is a suitable value of “S”.

$$T = \frac{\sum_{k=0}^n Project_{X(k)}}{n+1} \times S \quad (8)$$

Thus, as shown in

Figure 8, the project curve is transformed into the binary curve and the notches in the curve can be recognized by computer quickly.

It is similar for the 2D image to project itself onto the Y axis, as shown in Figure 9. Likewise, the projection curve can be transformed into a binary curve.

The bulk cargo holds can be located and identified by analysis of the binary curve generated above. There are 3 steps to locate and identify the bulk cargo holds.

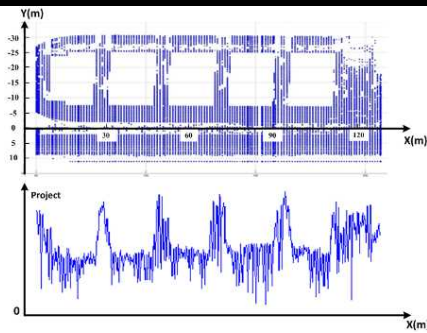


Figure 7. The projection curve in X axis.

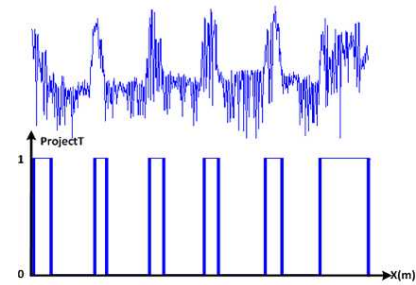


Figure 8. The projection curve in X axis with binary conversion.

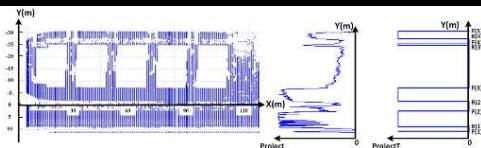


Figure 9. The projection curve in Y axis with binary conversion.

Step 1, mark all rising edges and falling edges of the Project T curve, as shown in Figure 10. Mark the k th rising edge as “R(k)” and Mark k th falling edge as “F(k)”. The value of “R(k)” or “F(k)” corresponds the position of the projection where the edge is located.

Step 2, make the pair of falling edge and rising edge. For each falling edge, its next rising adjacent edge is another one in the pair. If the distance between the pair is too short (less than 5m), the pair is a false pair and should not be considered at Step 3. For an instance, as shown in Figure 10, the “F(1), R(2)” is a pair. And as shown in Figure 9, the “F(1), R(1)” and “F(2), R(2)” are the false pairs, because the distances between them are too short and there are no such small bulk cargo hold in ships.

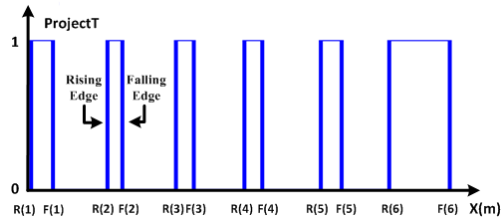


Figure 10. Marked edges on Project T curve at X axis.

Step 3, each pair indicates the cargo hold position in its projecting axis. The falling edge indicates the beginning position of the hold, and the rising edge indicates the end position of the hold. The length of the hold is equal to the distance between the falling edge and the rising edge. Therefore, the position and the length on X axis of the hold can be obtained by Equation (9), where the “F” and “R” are in the same pair. In other words, “R” is the next adjacent edge of “F”, and X_{Begin} is the begin position in x axis of the hold, X_{End} is the end position in x axis of the hold, L_X is the length in x axis of the hold.

$$\begin{aligned} X_{Begin} &= F \times D_{interval} \\ X_{End} &= R \times D_{interval} \\ L_X &= |X_{End} - X_{Begin}| \end{aligned} \quad (9)$$

It is similar for the 3 steps to be repeated to process the project curve on the Y axis, and Y_{Begin} , Y_{End} and L_Y can be obtained by Equation (10).

$$\begin{aligned} Y_{Begin} &= F \times R_G \\ Y_{End} &= R \times R_G \\ L_Y &= |Y_{End} - Y_{Begin}| \end{aligned} \quad (10)$$

Hence, all bulk cargo holds in the ship can be located and identified.

EXPERIMENTAL RESULTS

As shown in Figure 11, an experiment for the ship identification algorithm was performed at the No.2 ship loader in the Coal Terminal of Tianjin Port. There is a LMS installed

on the platform of slip barrel on the ship loader. The algorithm tested two ships in the quayside of the terminal. The moving speed of the ship loader (V_{Loader}) was 1m/s and the scanning speed of LMS (F_{LMS}) was 2 cross sections per second. Therefore, according to the Equation (1), D_{interval} is equal to 0.5 m. And the resolution " R_G " is determined to be equal to 0.5 m. The computer used in the experiment was Advantech PPC-154T with Intel Core i7-2710QE 2.1 GHz CPU and 2GB DDR3 memory.

The transformed images and curves of the first ship are shown in Figure 6, Figure 8, and Figure 9. The transformed images and curves of the second ship are shown in Figure 12 and Figure 13. The experimental results are shown in Table 1 and Table 2. Because it was very difficult to correctly measure the real values of X_{Begin} , X_{End} , Y_{Begin} and Y_{End} of the bulk cargo holds in the quayside, only the errors of the sizes (L_X and L_Y) of holds are calculated in Table 1 and Table 2.



Figure 11. The photo of the field experiment in Coal Terminal of Tianjin Port.

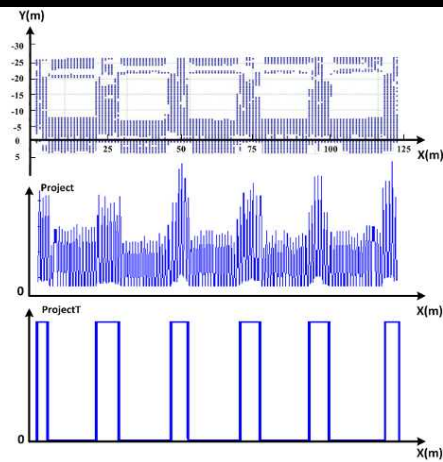


Figure 12. The transformed image and curves of the second ship at X axis.

As shown in Table 1 and Table 2, the computing time for the two ships were all lower than 200 ms, making the algorithm very suitable for real-time operation of automated ship loaders. The maximum error was only 3.23% at the x axis direction while the maximum error was 6.06% at the y axis direction. Because D_{interval} and R_G were both 0.5 m, the minimum resolution of the algorithm computing was 0.5 m, which was the main source of the error. If the moving speed of ship loader was

lower and a smaller R_G value was selected, the accuracy of the algorithm may be better. Meanwhile, the amount of data may be larger and the computing time may be longer.

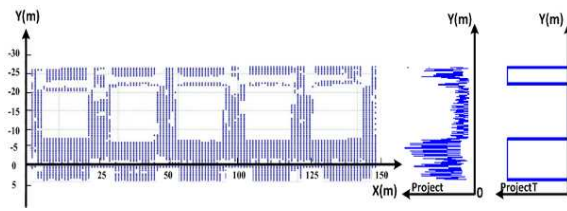


Figure 13. The transformed image and curves of the second ship at Y axis.

Therefore, depending on different applications, there should be an appropriate balance between the accuracy and the computing time. Based on this experiment, the ship identification algorithm may be suitable for the requirement of automated ship loaders.

Table 1. The experimental results of the 1st ships.

The 1 st Ship					
Hold No.	1	2	3	4	5
X_{begin}	10.00	31.00	53.50	73.50	95.00
X_{end}	25.50	46.50	68.50	89.00	110.00
L_X	15.50	15.50	15.00	15.50	15.00
Real Value of L_X	15.50	15.50	15.50	15.50	15.50
Error Rate	0.00%	0.00%	3.23%	0.00%	3.23%
Y_{begin}	-7.50	-7.50	-7.50	-7.50	-7.50
Y_{end}	-25.00	-25.00	-25.00	-25.00	-25.00
L_Y	17.50	17.50	17.50	17.50	17.50
Real Value of L_Y	16.50	17.50	17.50	17.50	17.50
Error Rate	6.06%	0.00%	0.00%	0.00%	0.00%
Computing Time	188 ms				

Table 2. The experimental results of the 2nd ship.

The 2 nd Ship					
Hold No.	1	2	3	4	5
X_{begin}	4.50	29.00	52.00	75.50	100.50
X_{end}	21.00	45.00	68.50	92.00	117.50
L_X	16.50	16.00	16.50	16.50	17.00
Real Value of L_X	16.50	16.50	16.50	16.50	16.50
Error Rate	0.00%	3.03%	0.00%	0.00%	3.03%
Y_{begin}	-6.00	-6.00	-6.00	-6.00	-6.00
Y_{end}	-21.00	-21.00	-21.00	-21.00	-21.00
L_Y	15.00	15.00	15.00	15.00	15.00
Real Value of L_Y	14.50	15.50	15.50	15.50	15.50
Error Rate	3.45%	3.23%	3.23%	3.23%	3.23%
Computing Time	198 ms				

CONCLUSION

This paper formulated a fast ship identification algorithm based on 3D point cloud generated by LMS. Compared to other processing methods of 3D point cloud, the algorithm was more suitable for the real-time control system in bulk ship loaders. With several simple steps, the bulk cargo holds can be identified quickly. First, the cross section data of the ship was generated by the LMS installed on the platform of slip barrel in the ship loader. With the movement of the ship loader, the cross section data of whole ship can be obtained and the 3D surface of the ship can be rebuilt. Then, the rasterizing algorithm of 3D points and the 2D image transforming algorithm were applied to the 3D point cloud, which can hugely reduce the amount of points. At last, the projection algorithm for the 2D image was applied to acquire the identification of the bulk cargo holds. The experimental results showed that the algorithm proposed in this paper was accurate and fast, suitable for applications in automated ship loaders.

ACKNOWLEDGMENTS

This research was supported by the “Young University Teachers' Training Program” of Shanghai Municipal Education Commission, “Local University Capacity Promotion Special Program” of the Science and Technology Commission of Shanghai Municipality (No.13510501800), “Scientific Research Innovation Project” of Shanghai Municipal Education Commission (No.14ZZ140), and the “Ph.D. Innovation Program” of Shanghai Maritime University (No. 2014ycx040).

LITERATURE CITED

- Angeloudis, P. and Bell, M.G.H., 2010. An uncertainty-aware AGV assignment algorithm for automated container terminals. *Transportation Research Part E*, 46(3), 354-366.
- Barrosa, V.H.; Costaa, T.S.; Alexandre, C.M.O., and Lorena, L.A.N., 2011. Model and heuristic for berth allocation in tidal bulk ports with stock level constraints. *Computers & Industrial Engineering*, 60(4), 606-613.
- Chen, K.; Peng, C., and Singhose, W., 2009. Crane control using machine vision and wand following. *Proceedings of IEEE International Conference on Mechatronics* (Nagoya, Japan), pp. 1-6.
- Hyla, P., 2012. The crane control systems: A survey. *Proceedings of 17th International Conference on Methods and Models in Automation and Robotics* (Międzyzdroje, Poland), pp. 505-509.
- Jung, Y.; Jang, I.G.; Kwak, B.M., and Kim, Y.K., 2012. Advanced sensing system of crane spreader motion (for Mobile Harbor). *Proceedings of IEEE International Systems Conference* (Vancouver, BC), pp. 1-5.
- Kawai, H.; Choi, Y., and Kim, Y.B., 2008. Position measurement of container crane spreader using an image sensor system for anti-sway controllers. *Proceedings of International Conference on Control, Automation and Systems* (KINTEX, Korea), pp. 683-686.
- Kim, T.H.; Choi, B.I.; Kim, J.E.; Yang, Y.K., and Song, T.L., 2013. A study of LM-IHPDA algorithm for multi-target tracking in infrared image sequences. *Journal of Institute of Control, Robotics and Systems*, 19(3), pp. 209-218.
- Kirchhof, M.; Jutzi, B., and Stilla, U., 2008. Iterative processing of laser scanning data by full waveform analysis. *ISPRS Journal of Photogrammetry & Remote Sensing* 63, 99-114.
- Lee, L.H.; Huang, P.H., and Shih, Y.C., 2011. Adaptive fuzzy sliding mode control to overhead crane by CCD sensor. *Proceedings of IEEE International Conference on Control Applications* (Dearborn, MI, USA), pp. 474-478.
- Lee, H.S.; Lim, S.S., and Park, D.W., 2011. Application of terrestrial laser scanner and raster operations to change detection of beach. *Journal of coastal research*, 64(2), 1692-1696.
- Mrovlje, J. and Vrancic, D. 2012. Automatic detection of the truck position using stereoscopy. *Proceedings of IEEE International Conference on Industrial Technology* (Seville, Spain), pp. 755-759.
- Natale, D.J.; Tutwiler, R.L., and Baran, M.S., 2010. Using full motion 3D Flash LIDAR video for target detection, segmentation, and tracking. *Proceedings of IEEE Southwest Symposium on Image Analysis & Interpretation* (Austin, TX, USA), pp. 21-24.
- Rong, A.Y. and Grunow, M., 2009. Shift designs for freight handling personnel at air cargo terminals. *Transportation Research Part E: Logistics and Transportation Review*, 725-739.
- Sithole, G. and Vosselman, G., 2004. Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. *ISPRS Journal of Photogrammetry & Remote Sensing*, 59, 85-101.
- Sampath, A. and Shan, J., 2007. Building Boundary Tracing and Regularization from Airborne Lidar Point Clouds. *Photogrammetric Engineering & Remote Sensing*, 805-812.
- Shimoni, M.; Tolt, G.; Perneel, C., and Ahlberg, J., 2011. Detection of vehicles in shadow areas using combined hyperspectral and lidar data. *Proceedings of IEEE International on Geoscience and Remote Sensing Symposium* (Vancouver, Canada), pp. 4427-4430.
- Tang, P.B.; Huber, D., and Akinci, B., 2010. Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. *Automation in Construction*, 19(7), 829-843.
- Woo, H.; Kang, E., and Wang, S.Y., 2002. A new segmentation method for point cloud data. *International Journal of Machine Tools & Manufacture*, 42, 167-178.
- Yi, J.H.; Lee, I.; Shbat, M.S., and Tuzlukov, V., 2011. 24 GHz FMCW radar sensor algorithms for car applications. *Radar Symposium (IRS), 2011 Proceedings International*. pp. 465-470.
- Yoon, H.J.; Hwang, Y.C., and Cha, E.Y., 2010. Real-time container position estimation method using stereo vision for container auto-landing system. *Proceedings of 2010 International Conference on Control Automation and Systems* (Gyeonggi, Korea), pp. 872-876.
- Zhen, L.; Lee, L.H.; Chew, E.P., and Chang, D.F., 2012. A comparative study on two types of automated container terminal systems. *IEEE Transactions on Automation Science and Engineering*, 9(1), 56-69.
- Zhou, H.; Zou, X., and Wu, B.C., 2007. Design and development of port crane crash-preventing system based on FMCW radar. *Journal of Scientific Instrument*, 9, 1689-1694.

Copyright of Journal of Coastal Research is the property of Allen Press Publishing Services Inc. and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.