Title
Lidar Based Reconstruction framework for Truck Surveillance

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ABSTRACT

Monitoring Commerical Vehicle Activities is very important for developing and maintaining efficient freight transport systems. In the existing Literature this is broadly done through vehicle classification and reidentification problems using various sensing technologies. Lidar is an emerging traffic sensing technology which could potentially serve as a multi functional sensor for transport systems. In out current work we mainly focused on developing and qualitatively assessing a Lidar based Reconstruction framework for Truck surveillance purpose. We proposed a two stage Truck body reconstruction framework and found the results of reconstructed Truck bodies are quite promising for several truck-trailer configurations. For certain types of Truck-Trialer configurations such as containers due to the sparsity of scanned points in lateral direction, the wheel portion of reconstructed body still has noticeable deformations. We would like to address the same in our future work.

Keywords: Truck Body Reconstruction, Roadside Lidar Sensor, Commercial Vehicle Monitoring

1. INTRODUCTION

Road Frieght Transportation systems play vital role in the economy of a region and entail movement of widevariety of commodities with the help of commercial vehicles. Understanding the seasonal, temporal, and spatial patterns of the class based commercial vehicle activities through surveillance is important for the agencies (*1*). The class-based surveillance data is useful in freight forecasting models, air pollution assessment, assessing the health impacts on adjoining communities, road network asset management etc (*2*). Various sensing technologies have been used for monitoring commercial vehicle activities. Determining the body type or class of the commercial vehicle and reidentification of same commercial vehicle in the road network have been two important research problems associated with monitoring the commercial vehicle activities. Moreover, Commercial vehicle classification problem is more closely associated with understanding which types of commodities are carried (*3*).

The sensing technologies used for monitoring commercial vehicles can be classified as intrucive and non-intrusive. Intrusive sensors are installed in the travel lanes and non-intrusive sensors are installed in the vicinity of travel lanes either using overhead-gantries or roadside mounted poles. Asborno, I.M. et al., (*4*) synthesized information about the sensing technologies from FHWA's Traffic Detector Handbook. As per their work even though Intrusive Sensors' such as advanced ILD perform quite accurately, the installation and maintenance costs of these sensors as well as the pavement surface quality in high volume freight corridors are deterring factors for this sensor. Nonetheless ILDs are well accepted and installed sensors. Bernas, M., et al., (*5*) provided a comprehensive review of various Low-cost sensing Technologies for the purpose of road traffic monitoring. Both the studies reviewed the advantages, limitations and applications of Inductive Loops, Cameras, Magneto meter, Weigh in Motion (WIM), Acousitc Sensors, Infrared Radars, Microwave Radars, GPS systems, Cellphone, Bluetooth, RFID. GPS and Cellphone based systems are majorly sensors present within the commercial vehicles and the data is collected throught sampling design. Won, M (*6*) also has provided a state of the art comprehensive review of Intelligent Traffic Monitoring Sytems for the Vehicle Classsification problem.

While most of the sensors mentioned above can classify vehicles based on length, Inductive loops, WIM, Microwave Radars, Active Infrared Radars, and cameras can be used for axle-based classification. Hernandez, S.V., et al., (*1*) showed that more than 50 body types can be classified using ILD signature data. The performance of ILD is highly dependent on pavement conditions and involves difficult maintenance process. Video Detection based methods under perform during inclement weather and light conditions.

Lidar based infrastructure mounted traffic sensing is an emerging technology. Lidar sensors are not affected by variations in light and their efficiency during inclement weather needs to be investigated. Sun, Yuan et al., (*7*) ; Zhang, J et al., (*8*) developed methodologies for tracking vehicles using Roadside Lidar Sensors. Asborno, M et al., (*4*); Wu, J et al., (*9*); Ho, Lee (*10*); Olcay, Sahin et al., (*2*) tried to use Lidar Sensor for vehicle classification problem. Their works differ in the configuration of Lidar sensor being used, the above works did not try to reconstruct a comprehensive truck body for vehicle classification problem and hance may be non-adaptable when there is occlusion issue.

The objective of this working paper is to utilize the all the scans of a truck while it is passing through the detection zone of a roadside mounted 32 beam Lidar sensor rotating 180 degrees in Horizontal field of view. For this purpose, we formulated a two stage Truck body reconstruction framework using all the road side Lidar scans of truck while it was in the detection zone.during the first stage a pairwise Lidar point cloud registration is performed and in the second stage all the pointclouds are transformed to a Global Coordinate framework using SLAM based optimization. Rest of the paper is organized as described here. Section 2 presents the existing literature for addressing our problem. Section

3 presents the framework used for reconstructing the Truck bodies which can further be used for vehicle classification purpose. Section 4 presents qualitative and visual results for various types of reconstructed trucks.

2. LITERATURE REVIEW

Lidar sensor captures the 3D points of the target along with corresponding intensity values in its scanning zone. Point Cloud Registration is aligning two such scans of a target and mainly draws its motivation from range image registration. Point cloud registration is an important and challenging problem in the domains such as computer vision, medical image processing, robotics, self driving/intelligent vehicle applications (*11*); photogrammetry, remote sensing, environmental monitoring, etc. In medical imaging multiple images by computer tomography or magnetic resonance imaging are fused using feature-based registration. In remote sensing the Lidar based registration is mainly used for forest parameter estimation, land cover classification, solar energy potential estimation, natural disaster monitoring, water surveys etc(*12*). In computer vision, registration is used for localization and mapping purposes as well as indoor scene reconstruction which is useful for Virtual reality and Augmented Reality based applications.

Initial formulation of point cloud registration is proposed by Besl and McKay (*13*) and the problem is described as aligning the 3D data of an object scanned in sensor coordinate system to a model shape (3D data) represented in model coordinate system by iteratively estimating optimal rotation and translation parameters which minimizes the point-to-point distance between both datasets (*14*). This is called the iterative closest point algorithm and widely used for lidar point cloud registration. ICP algorithm has six stages and needs an initial set of parameters. Original ICP algorithm is sensitive to the initialization of parameters and requires good overlap between the scan and model object to obtain tight alignment. To overcome this several variants of ICp have been proposed as discussed in (*15*).

Other widely adopted strategy for the pointcloud registration is coarse-to-fine registration strategy. In coarse registration, initial registration parameters for the two-point clouds are estimated using some derived features of the point clouds. Generally, point based, or line based, or surface-based features are derived for coarse registration purpose. In fine registration maximum overlap between both point clouds is achieved using either iterative approximation method or normal distribution transformation method. The general point based features extracted are point feature histograms, fast point feature histograms, heat kernel signature, mesh-difference-of-gaussians etc (*12*). Salvi, J et al., (*16*) analysed and provided a comprehensive review of both coarse and fine registration methods. As per their findings, RANSAC based coarse registration yielded better results and they also showcased the local minima problems present in the original formulation of ICP by Besl and Mckay. The coarse-to-fine registration strategy is well suited when we only need to do registration for a couple of point clouds.

For several applications such as indoor scene reconstruction multiple point clouds might need to be aligned together to confirm to a global coordinate system. Zhu, H et al., (*11*) provided a detailed review of both pairwise as well as Groupwise registration methods. They conducted experiments on 10 represntative pairwise as well as groupwise registration algorithms. Their work found a probability based Coherent Point Drift (CPD) method is found to perform better for pairwise registration.

While the literature found wide variety of algorithms for registrstion purpose, in our work we tested the multiway registration framework presented in Open3D (*17*). The results from this are qualitatively assessed and presented in section 5.

3. METHODOLOGY

In the current framework a two-stage truck body reconstruction framework is proposed to obtain a comprehensive scanned body of a truck passing through the sidefire Lidar Detection Zone (LDZ). In the first stage, a sequential pairwise rigid transformation matrix is estimated using a coarse-to-fine registration strategy. In the second stage, global optimization is performed on a posegraph constructed using the sequential pairwise transformation matrices from the first stage to construct the mrged point cloud. The proposed framework is shown in Figure 1 below.

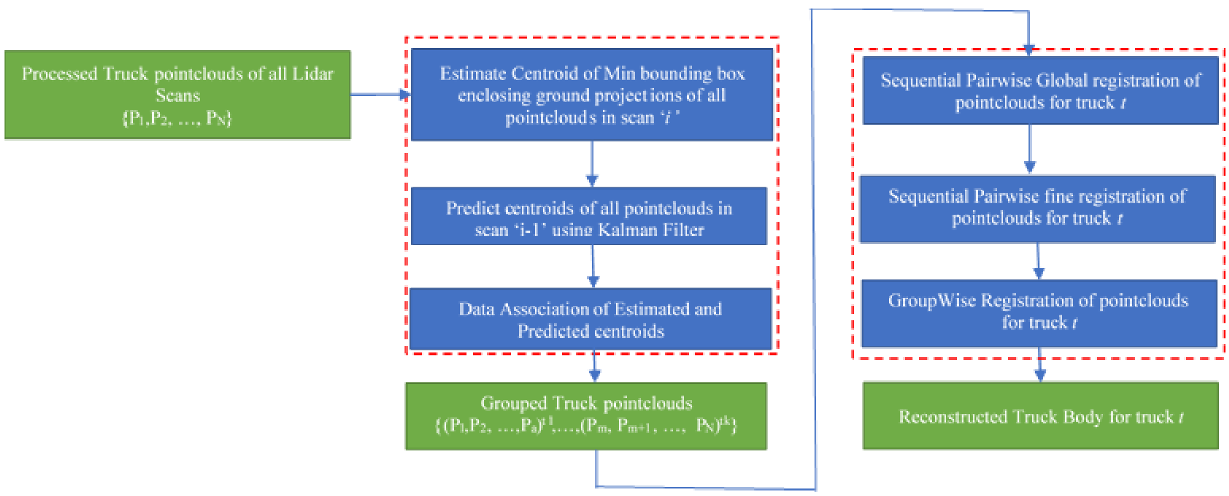

Figure 1. Proposed 2-stage Truck body reconstruction framework

3.1. Experimental Setup and Data Collection

A 32 beam Velodyne Lidar is setup adjascent to Sounth bound I-5 right of way at a Truck Scale facility near SanOnofre, California. Lidar's scanning is restricted to 180 degrees horizontal field of view and scans at a frequency of 10 HZ. Data has been collected for a duration of approximately 134 hours for 12 days.

The raw point clouds obtained from the Lidar are processed to remove background using DBScan and statistical outliers as proposed in (*7*). Each scan of the side-fire Lidar sensor captures all the truck bodies present in its Detection Zone (LDZ) partially. The scan will have rich information of the front portion of the truck when it is entering the LDZ, side of the truck when it is in the midsection part of the LDZ and rear portion of the vehicle when it is leaving the LDZ. A more detailed truck body can be reconstructed by aggregating all its pointclouds captured while traversing the LDZ. The same is illustrated in Figure 1.

3.2. Object Tracking and Data Association

For creating the aggregated and comprehensive truck body it is necessary to track and map the scans corresponding to the same truck from all the scans while the truck is present in LDZ. Processed truck object scans in successive frames would be tracked using the Simple Online Realitime Tracking (SORT) as proposed by Wozke, N et al., (*18*). Centroid of the minimum oriented bounding box of 2D ground projection of the truck is used as state variable for tracking purpose using a constand velocity based Kalman Filter. The same is shown in Figure 3 below. The predictions from previous scan and estimations from current scan of the state variables are mapped to each other using Hungarian Algorithm. The current Framework can track a missed detection upto 5 consecutive scans. There are several Multi Object Tracking algorithms developed in literature, but the current framework is chosen as it performs quitewell in a realtime tracking context.

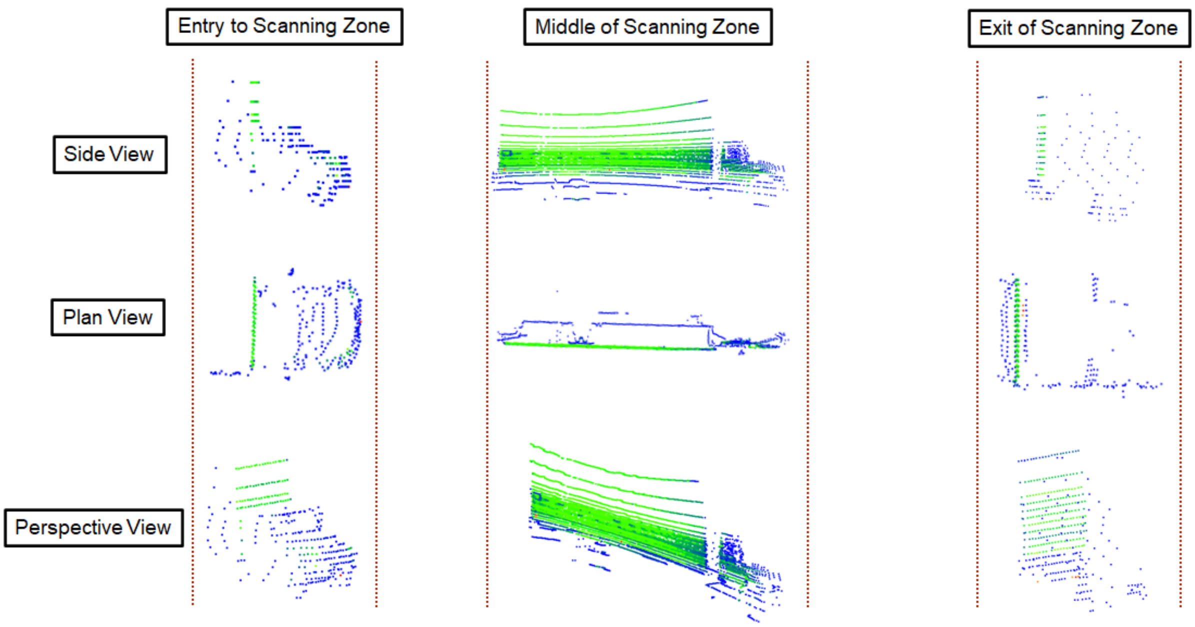

Figure 2. Truck Scans at differen parts of LDZ

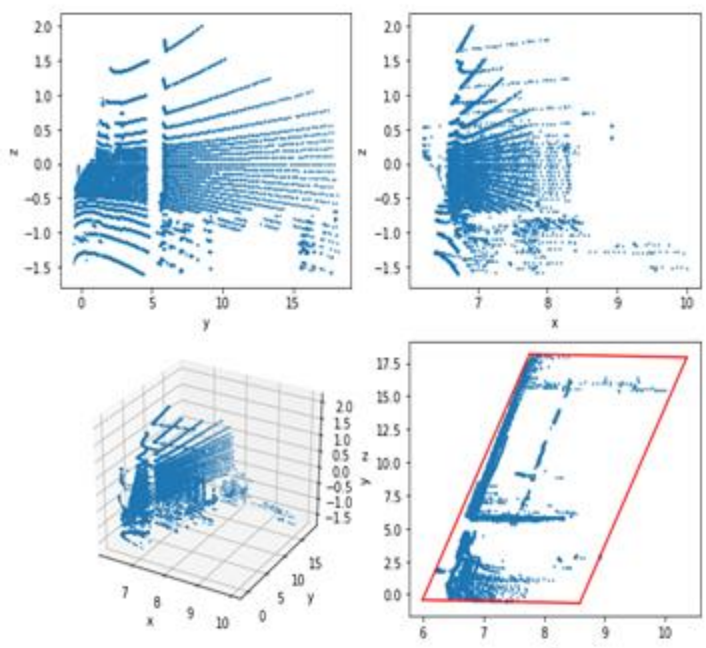

Figure 3. Minimum Oriented Bounding box for Gorund projected Truck Scan

3.3. Sequential Pairwise Registration

A coarse-to-fine registration strategy is adopted in our framework to obtain the sequential pairwise rigid transformation matrices for each pair of truck pointclouds. An initial estimate of the rigid transformation matrix is estimated using fast point feature histograms and RANSAC algorithm. The output from

RANSAC is used as initialization for the standard ICP algorithm and finetuned for tighter alignment. This is illustrated in Figure 4 below.

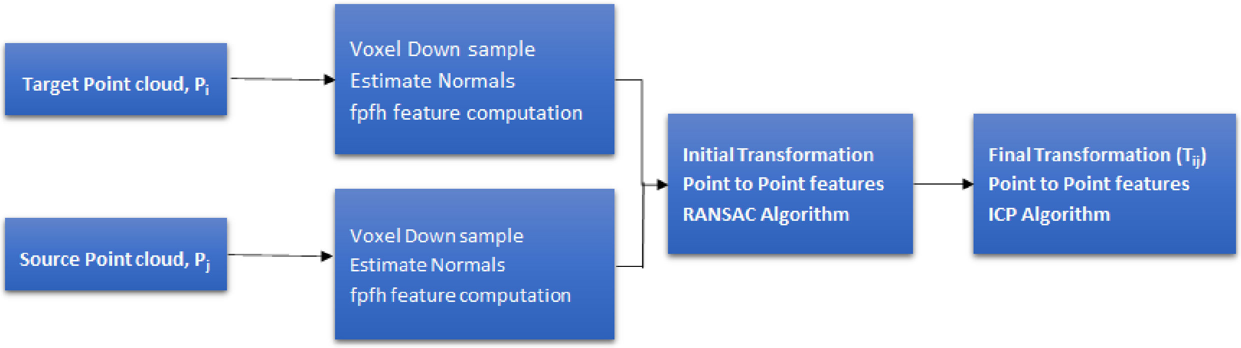

Figure 4. Sequential Pairwise Corase-to-fine registration framework

3.4. Truck Body reconstruction using Posegraph Optimization

The sequential pairwise transformation matrices along with the corresponding pointclouds are used to construct a pose graph. This pose graph is optimized to align all the pointclouds globally and merge with a reference point cloud of truck while it is in the mid section of the LDZ. The SLAM based optimization framework proposed in Choi et al., (*19*) is used in our framework. Construction of posegraph and the merged pointcloud are schematically shown in Figure 5.

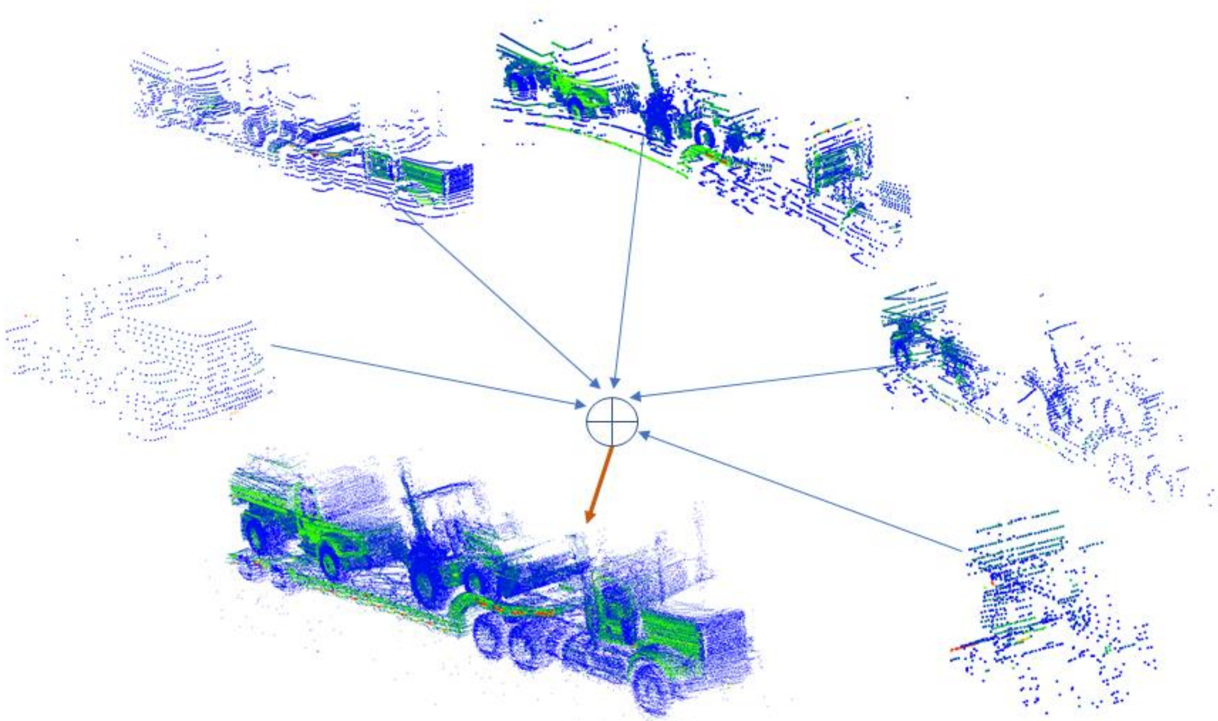

Figure 5. Schmatic Representation of Posegraph based Truckbody reconstruction

4. RESULTS and DISCUSSION

Qualitative results from the Truck body reconstruction results for 9 types of Truck-Trailer combinations are presented in this section. The results are reasonably similar for other additional truck-trailer configurations identified in (*1*). Those results are als verified visually but not presented here for brevity purpose.

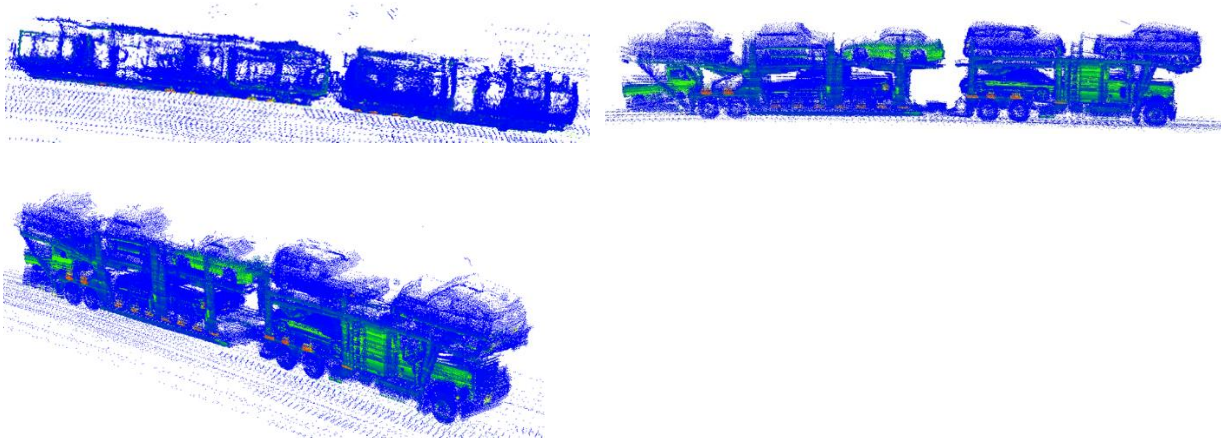

Fig 6.a. Auto Transport

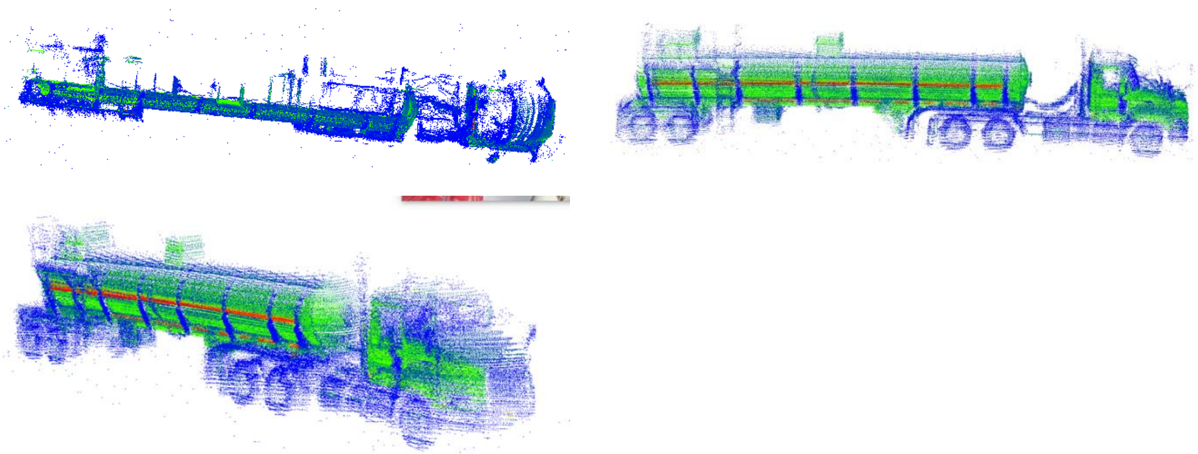

Fig 6.b. Tank Trailer

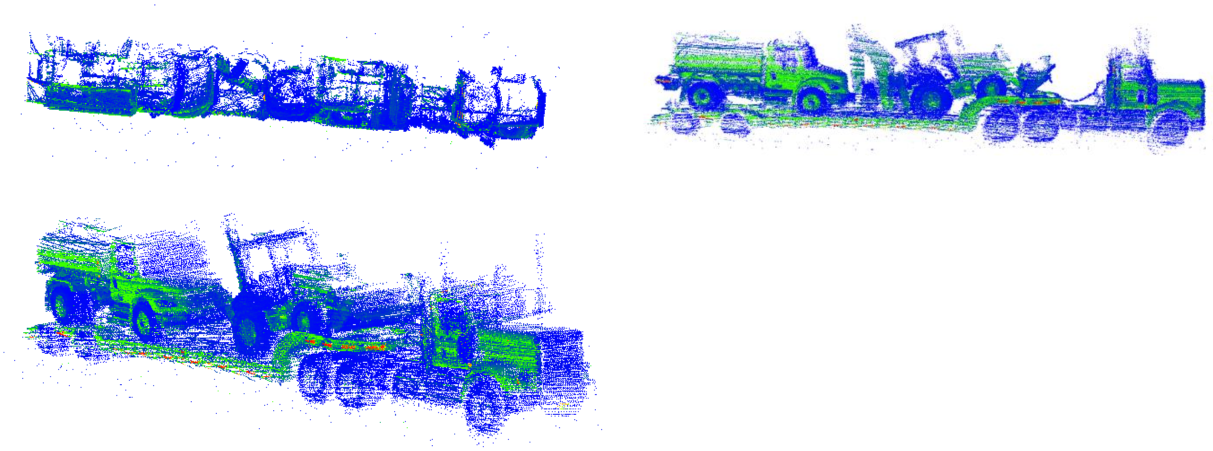

Fig 6.c. Low Boy Trailer

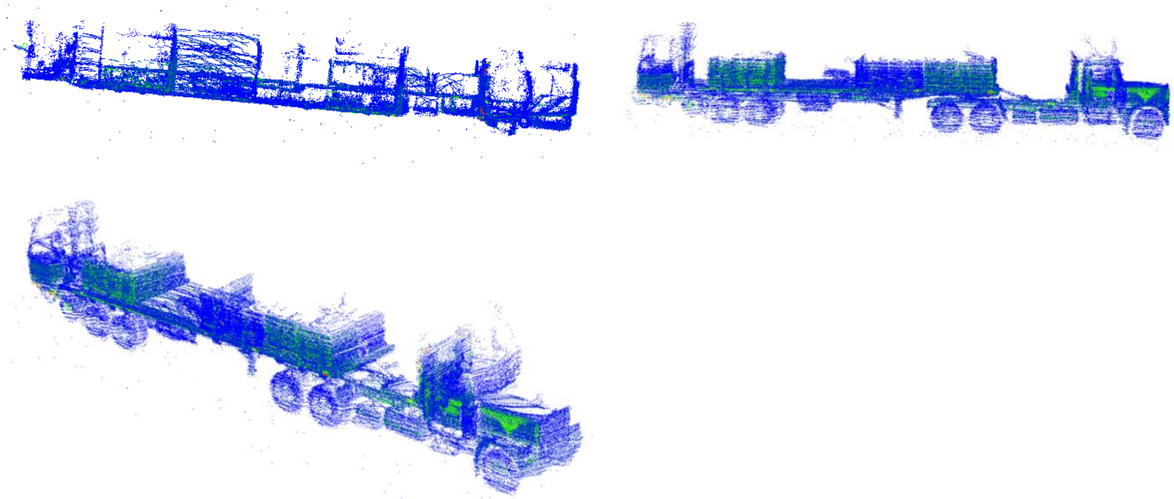

Fig 6.d. Basic Platform Trailer

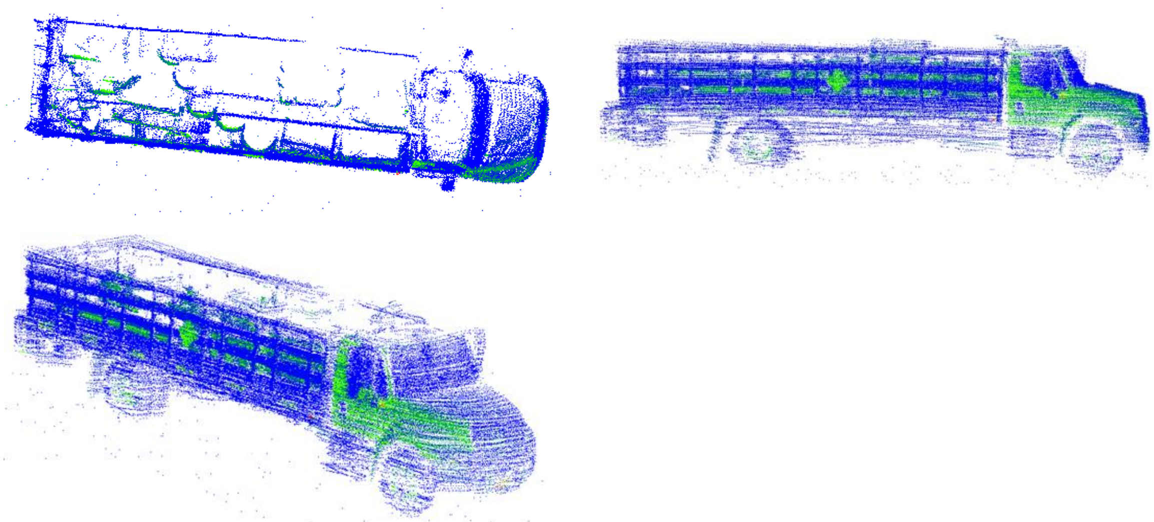

Fig 6.e. Stake Body Truck

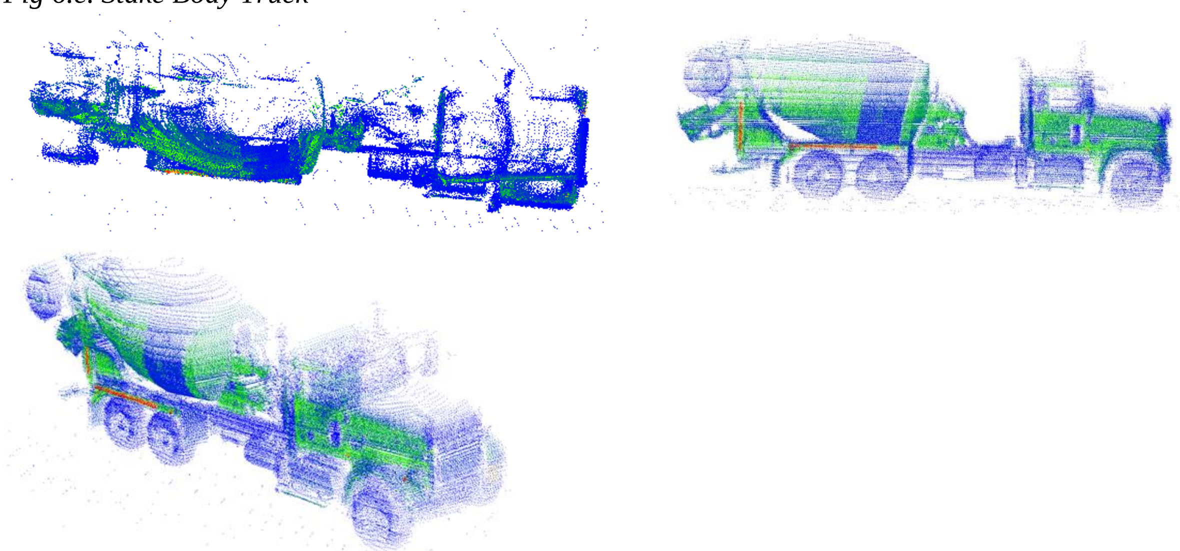

Fig 6.f. Concrete Mixer Truck

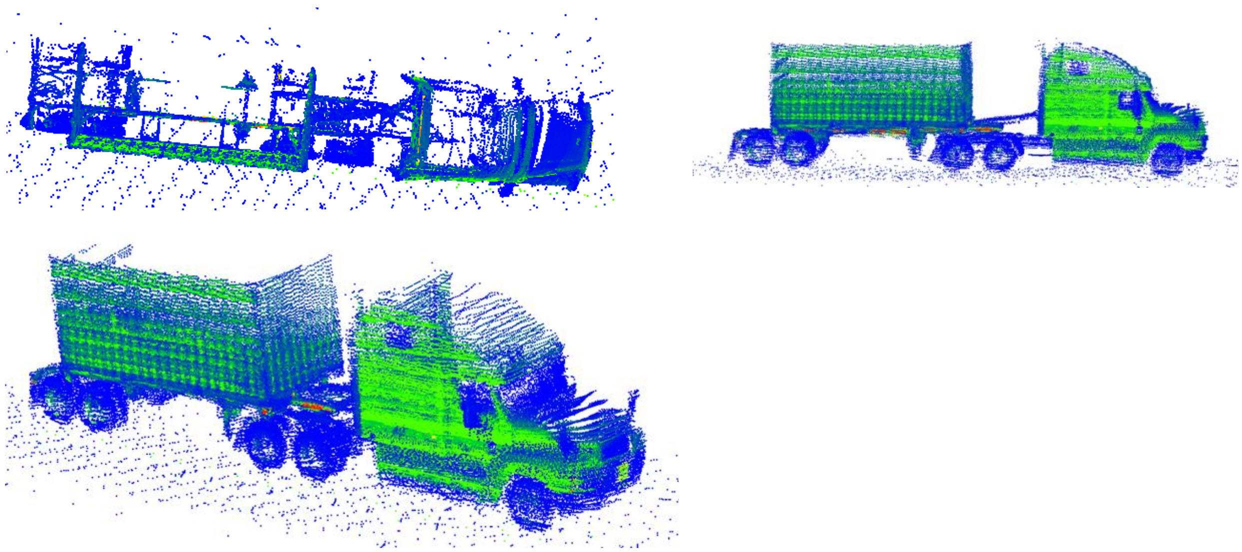

Fig 6.g. 20 ft Intermoddal Container

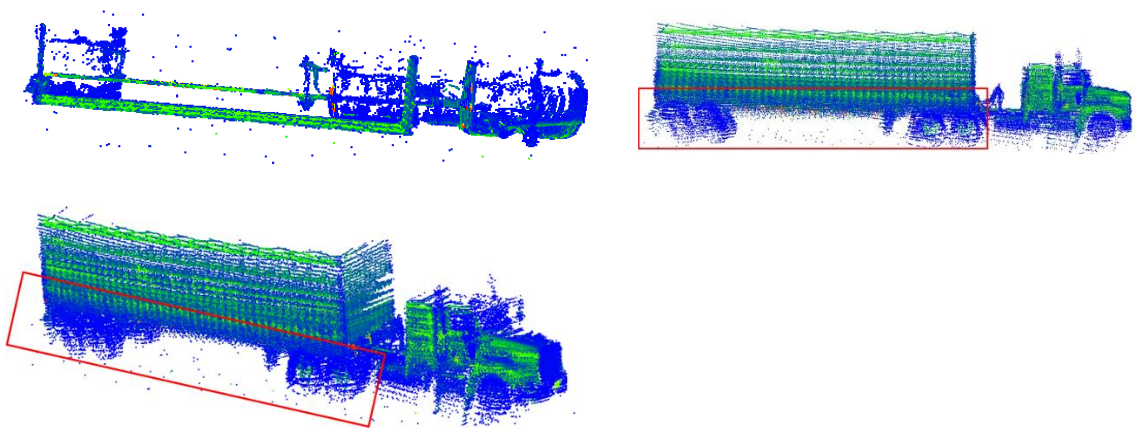

Fig 6.h. 40 ft Container Trailer

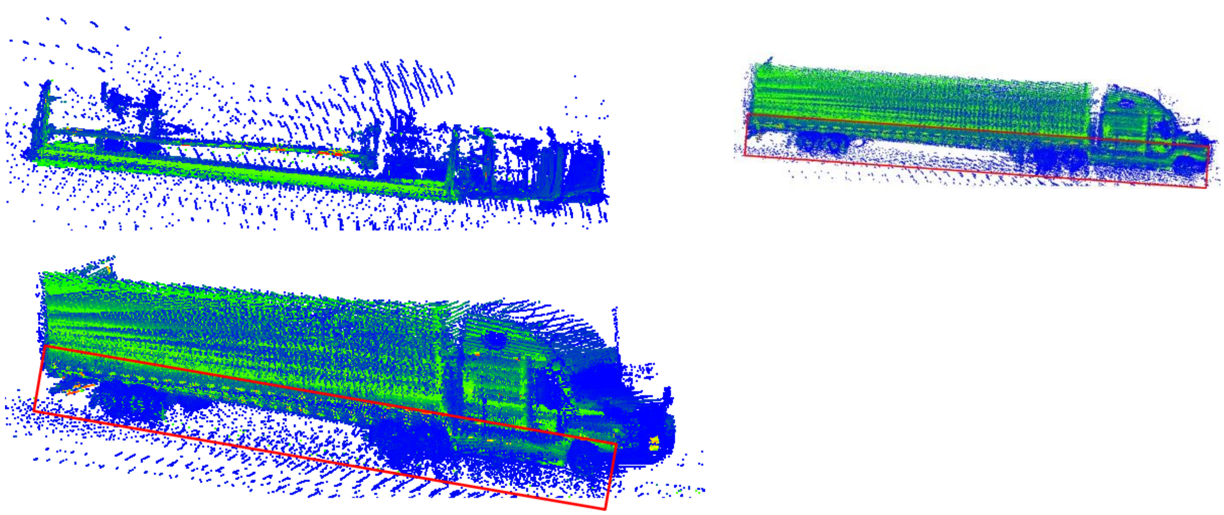

Fig 6.i. 53 ft Container

For the 9 types of Truck-Trailer configurations provided except for the 40 ft and 53 ft container trailers, the reconstructed truck bodies look quite intact. For the 40 ft and 53 ft trailers, qualitative assessment reveals that the sparse presence of points in the lateral direction could be causing the reconstructed body to be slightly misaligned at the wheels. This is being investigated and we would like to address this issue in our future work.

5. CONCLUSION and FUTURE SCOPE

We presented a Lidar based Reconstruction framework for Truck Surviellance purpose. The reconstructed Truck bodies could play vital role in developing commercial vehicle activity monitoring applications such as body classification, axle-based classification, network level commercial vehicle tracking, etc. The presented framework consists of two stages where in the first stage the lidar scans corresponding to the same truck are grouped together using Kalman Filter and Hungarian Algorithm. During the second stage a combination of sequaential pairwise coarse-to-fine registration and pose graph-based optimization are used to build the reconstructed bodies of Trucks passing through the lidar Detection Zone. This framework potentially can remove the occlusion and missed detection issues for a short interval of sensing duration. In the current framework, we did not contrain the reconstruction to be on the ground plane. In our future work we would like to constrain the reconstruction to Road Surface and, we would like to explore the groupwise registration strategies for a potential one stage reconstruction framework.

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