SURVEY ON FEATURE EXTRACTION AND 3D VISION WITH RESPECT TO ADAS

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***Abstract*—** The accurate positioning of vehicles plays an important role in autonomous vehicle. Advanced Driver Assistance Systems (ADAS) are recently becoming a popular topic in development and research, aiming at increasing the safety of vehicles. In survey of previous research on landmark-based positioning, poles were extracted both from online data from sensor and reference data, which were later compared and matched to improve the positioning accuracy of the vehicles. 3D feature points are the one which are proper alternatives to be used as landmarks. To compare the LiDAR online data to another LiDAR derived reference dataset, the extraction of 3D feature points is an essential step. In this paper, the problem related to 3D feature point extraction from LiDAR datasets is discussed. Instead of hand-crafting a 3D feature point extractor, as they propose to train it using a neural network. In this method, set of candidates for the 3D feature points is initially detected by the Shi-Tomasi corner detector on the range images of the LiDAR point cloud. The artificial neural network is able of predicting feature points from these corner candidates Using that back propagation algorithm for the training. Training considers not only the shape of each corner candidates on 2D range images, but also their 3D features like the curvature value and surface normal value in z axis, which are calculated directly based on the LiDAR point cloud. Then the extracted feature points on the 2D range images are retrieved in the 3D space. The 3D feature points extracted by this method are usually distinctive in the 3D space. Their test showcase that the proposed method is capable of providing a sufficient number of repeatable 3D feature points for the matching task. The feature points extracted by this method have great potential to be used as landmarks for a better localization of vehicles. As this paper gives the basic information about how 3D feature points are extracted to assist the driver by providing road information.

***IndexTerms*— ADAS, LiDAR, Feature points, 3D Extraction.**

I. Introduction

ADAS (Advanced Driver Assistance Systems) are nowadays a most popular topic in development and research, aiming at increasing the safety of vehicles. For a safer driving the precise localization of vehicles is essential . The standard GNSS (Global Navigation Satellite System) can't achieve a sufficient accuracy and availability in many circumstances, e.g., lots of high buildings and tall trees in cities, because of the multi-path effect of the GNSS, or in tunnels where no GNSS signal can be received.

While currently, mostly self-driving cars are equipped with LiDAR sensors, it is expected that the LiDAR will be the standard component of future ADAS systems, used for obstacle detection and environment sensing. The main use of this type of sensors in ADAS will also help to improve the localization of vehicles. By measuring the distances to some known landmarks Vehicles can localize themselves in a known environment. In Brenner, the poles were extracted from the dense 3D point cloud measured by a mobile mapping LiDAR system. A map of landmarks was generated as reference data Using these extracted poles, and stored in a GIS. The vehicle data was provided with the help of four SICK laser scanners, mounted in pairs of two on rotary units on vehicle roof. By matching the poles detected in vehicle data with the reference data the localization accuracy of the vehicle was significantly improved. The vehicle data was measured by an automotive multilayer laser scanner mounted on the front of a vehicle. The poles extracted from the vehicle data were later matched with the reference data, which consists of the landmarks derived from a dense mobile mapping LiDAR point cloud. By this approach the localization accuracy is also improved.

But sometimes there are limited number of poles in the environment. If the poles are replaced by the generic 3D feature points as the landmarks, this will greatly enhance the ability to localize vehicles in general environments. To estimate this goal, automatic 3D feature point extraction and matching methods between LiDAR datasets are necessary.

The main goal of this paper is to find the proper solution for extracting the 3D feature points from LiDAR data point clouds. The extracted feature points should be distinctive and repeatable in both datasets. Distinctiveness describes that how suitable these points are which is mainly used for the effective description and the matching between scans. Repeatable means the points should be robust against noise and changes in viewpoint (Tombari, 2013). These 2 criteria are used later for the evaluation of this approach. Afterwards this approach is also compared to other existing methods of feature point extraction and description, and the influence on registration tasks is analyzed.

II. RELATED WORK

The matching between LiDAR datasets using 3D feature points can be simplified as a key point-based registration problem. A widely used approach for registration is the Iterative Closest Point (ICP) algorithm. It assigns to the closest points and estimates least squares transformation between two scans. Then, the closest point sets are predetermined and the procedure is iterated until the minimum error is achieved. The key to a successful registration with the help of ICP is a good initial guess of relative transformation, otherwise it will likely converge to a local minimum.

A key-point based registration can reduce the search complexity greatly and provide the required initial transformation. For the feature point extraction methods for 3D point clouds, there are generally two groups of approaches. One extracts feature points directly based on their local neighborhood in 3D space, such as Intrinsic Shape Signature (ISS) (Zhong, 2009), Key Point Quality which usually use the Principal Component Analysis (PCA) of the neighborhood in 3D space and use a set of criteria to identify feature points. With the relative large area and thus many points for dense point cloud data , the method which iterates over each data point may be the very time consuming.

The other group of approaches extracts feature points on a 2D representation of the 3D point clouds e.g. range image, intensity image and retrieves 3D coordinates based on their related range information. The standard 2D feature detection and description methods, such as SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features) and ORB (Oriented FAST and Rotated BRIEF) were used for registration between terrestrial laser scan. They extract the large number of feature points but with less distinctiveness and repeatability. Even though RANSAC can be used to remove wrong assignments, the large number of mismatched points would still have negative effects on the registration. A major objective is therefore to get a low number of feature points with a high quality.

To handle this non-linear classification problem with a large number of features, they chose a neural network using back propagation as classifier. As stated in LeCun et al. (1989), the artificial neural network using back propagation has shown a great success in handwritten zip code recognition, which inspires to exact feature points also with this method. With the generalization ability of this neural network classifier, more distinctive feature points are expected to be extracted.

In their approach for 3D feature point extraction from LiDAR data consists of five major steps: (i) generating range images, (ii) corner detection on range images, (iii) derivation of training examples, (iv) neural network training using back propagation and (v) prediction for the 3D feature points.

Generating Range Images

Before generating range images from the LiDAR point cloud, we firstly removed the points on the ground, because these points usually have less distinctiveness in the 3D scene. Then, the range image was generated based on the 3D observation point and heading angle. With given horizontal and vertical opening angles, a raster with a certain resolution was computed. The resolution used in this experiments was 0.06° both in horizontal and vertical direction. Afterwards, we calculated the distance between the observation point and all the data points in the point cloud. These distance values were then inserted into each corresponding cell on the raster according to their angular relationship to the observation point. If several data points were found in the same cell, the point nearest to the observation point was chosen.

The mobile mapping system recorded the trajectories of vehicle using a GNSS and an IMU (Inertial Measurement Unit). With these trajectories, a sequence of range images was generated along the driving direction as shown in Figure 1.

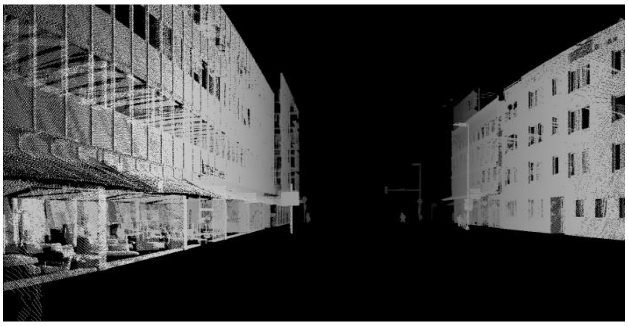

Figure 1 Generated range image

Corner Detection

Based on the idea introduced above, they are building a supervised learning algorithm. For the range images, it is impractical and also time consuming to take all the pixels on the images into account for the training. To reduce complexity of the training data, a better solution is that to detect as many candidates as possible on the image and then carry out the training only on these candidates. The candidates should be representative in the local areas and possess a dense coverage on the range images.

In this case, corner detectors on 2D images are good choices to detect feature point candidates. The Shi-Tomasi corner detector (Shi and Tomasi, 1994), a modification of the Harris corner detector (Harris and Stephens, 1988), shows a good result with representative and dense coverage of the stable corner points in the 2D images. The points are extracted only using eigen value decomposition, which makes it fast and robust.

The LIDAR data has the same resolution in general but the range images generated from the observation points on the streets have finer resolution in the near range and coarser resolution in the far range. Thus, there are so many small holes as well as the noisy points to be found in the near range area on the range images. Small holes were removed using morphological closing in image space, and a median filter was applied to reduce noisy points.

The Derivation of Training Examples

Some of the corner points which are extracted in the range images after morphological closing and median blurring cannot be retrieved directly in the original point cloud. This is because these two operations changed the edge of the objects significantly. To avoid this situation from happening, a table was set up when range images were generated from the 3D point cloud. The table records the correspondence between each pixel in the range image and its corresponding 3D coordinates. When detected corner point has the no value for pixels on original range image, then kd-tree search is used to find the nearest neighbor pixel with value in the local 2D space. If a point with range value is found in the neighborhood, it replaces the old point. If there is no nearest point can be found in the local area, this point is discarded. After that, the corresponding 3D point for each 2D feature point can be found with the correspondence table generated beforehand by a simple lookup.

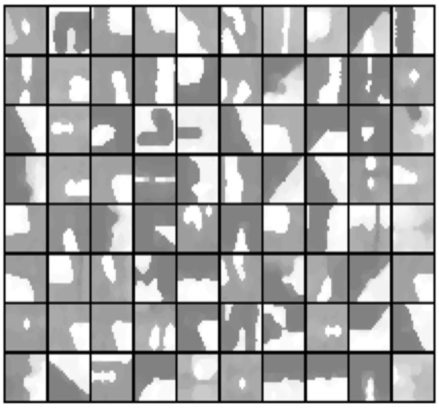

Figure 2 The templates in 32×32 window.

With the candidates which are retrievable as they are detected by the "Shi-Tomasi" corner detector, as described in the above, a 32×32 window was centered at the each candidate to extract the templates, which were then used as the training data for the neural network. Figure 3 shows some of the template examples and their grey values at each template indicate the distances to the current observation point.

Then, all the templates were marked as feature or non-feature. Generally, there are some rules for the selection of feature points. As above mentioned, the corners of buildings, traffic lights, poles and the windows are assumed to be as good feature points. The templates with significant rectangle or corner structures were marked with feature points. Others were marked as non-feature points.

Neural network training using Back Propagation

The neural network using back propagation is generally a supervised learning method. It tries to imitate how the neurons exchange information with each other in the brain in a simple way. Each of the connected nodes in the neural network constitute of the simplest representations of the connected neurons in the brain.

In LeCun et al. (1989), an artificial neural network using the back propagation algorithm was applied to recognize handwritten zip code. It presented the good results on recognizing the numbers written in the form of grey value pixels. Inspired by this application, we want to learn "good" landmark points among the ones detected by the Shi-Tomasi corner detector, based on our local feature vector. The algorithm of the neural network consists of the two parts. One part is the forward propagation, which is used for prediction, and the other part is the back propagation which is used for training.

We implemented the neural network algorithm according to Bishop {2006}. To minimize the cost function in the back propagation part, we used a nonlinear conjugate gradient algorithm provided by Scipy (2013).

Prediction for the 3D feature points

After the training process as described in Section 4.4, the weight parameters between each two neighboring layers were estimated as two matrixes. With these parameters, the forward propagation algorithm can be used to predict all unlabelled examples only by matrix multiplication and application of the activation function, which makes this approach efficient. With the candidates predicted as feature points in 2D space, their 3D coordinates can then be retrieved using the correspondence table.

By this method after completing there experiment they got the results which is shown :

Data

The LiDAR data for our experiments were collected by a Riegl VMX-250 Mobile Mapping System (as shown in Figure 5) in the city centre of Hannover, Germany. The system includes the two Riegl VQ-250 laser scanners, which is able to measure 600.000 points per second (Riegl, 2012). Position and orientation of the system were measured by a GNSS receiver, an IMU and an external Distance Measurement Instrument (DMI). All the data were post-processed using the RIEGL software packages and the different additional software for GNSS/IMU processing to generate the geo-referenced LiDAR point clouds.

Figure 3 Riegl VMX-250

The result got in Reegl VMX-250 experiment [5]

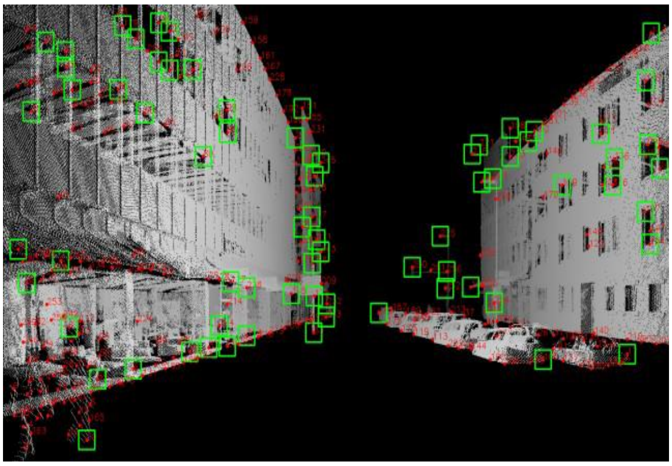

Figure 4 Feature points extracted by our approach on the range image (Candidates detected by Shi-Tomasi corner detector as red points, the selected feature points in green windows)

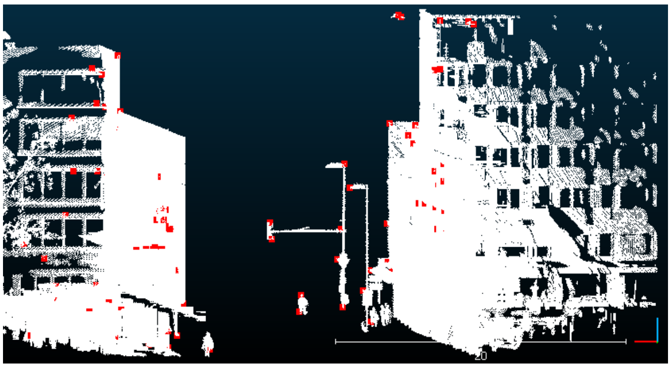

Figure 5 The extracted feature points, shown in the 3D point cloud

The results above indicate that the 3D feature points extracted by Y. Feng and et. al. approach are generally distinctive. The feature points are located at the desired positions, like the corners of buildings and traffic lights.

III. CONCLUSION

In this paper, we proposed survey on a 3D feature point extraction method from range images. From [1] firstly generated the range images from LiDAR point clouds by projection of the points. Then the Shi-Tomasi corner detector on these images to extract 3D feature point candidates. In [2] Using the trained neuronal network, they are able to predict 3D feature points for other datasets measured in similar scenarios. According to evaluation, this approach produces a less number of feature points, which have the higher quality in terms of repeatability and RMS error, compared to SIFT and SURF features. Then from this survey we conclude that the LiDAR is used for the feature extraction which assist the driver by providing 3D vision of front image of the vehicle.

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