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Street-side vehicle detection, classification and change detection using mobile laser scanning data

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ABSTRACT

Statistics on street-side car parks, e.g. occupancy rates, parked vehicle types, parking durations, are of great importance for urban planning and policy making. Related studies, e.g. vehicle detection and classification, mostly focus on static images or video. Whereas mobile laser scanning (MLS) systems are increasingly utilized for urban street environment perception due to their direct 3D information acquisition, high accuracy and movability. In this paper, we design a complete system for car park monitoring, including vehicle recognition, localization, classification and change detection, from laser scanning point clouds. The experimental data are acquired by an MLS system using high frequency laser scanner which scans the streets vertically along the system's moving trajectory. The point clouds are firstly classified as ground, building façade, and street objects which are then segmented using state-of-the-art methods. Each segment is treated as an object hypothesis, and its geometric features are extracted. Moreover, a deformable vehicle model is fitted to each object. By fitting an explicit model to the vehicle points, detailed information, such as precise position and orientation, can be obtained. The model parameters are also treated as vehicle features. Together with the geometric features, they are applied to a supervised learning procedure for vehicle or non-vehicle recognition. The classes of detected vehicles are also investigated. Whether vehicles have changed across two datasets acquired at different times is detected to estimate the durations. Here, vehicles are trained pair-wisely. Two same or different vehicles are paired up as training samples. As a result, the vehicle recognition, classification and change detection accuracies are 95.9%, 86.0% and 98.7%, respectively. Vehicle modelling improves not only the recognition rate, but also the localization precision compared to bounding boxes.

1. Introduction

In many populous cities, on-street parking places have strict parking regulations which need to be controlled and monitored regularly. Types of vehicles using certain parking lots are important for street parking design and management. For instance, the time span and type of vehicles parked on commercial streets are interesting to street managers and street-side shops. Ordinary vehicles are not supposed to park on reserved spots, e.g. disabled or delivery. Vehicles that do not belong to a residential area are not encouraged to park there for a long time. Vehicles are supposed to park inside the parking spots (within the parking line) and not on the pavements. Utility vehicles and passenger vehicles usually have different parking rules, e.g. fees and durations. Many cities implement the alternate side parking rule: only one side of the street can be parked on, on a given day. In France, vehicles are only allowed to park at the same spot for maximum seven consecutive days. In Paris, it is even illegal to park on the same spot for more than two hours in certain areas. These regulations are normally controlled by investigators. The process is tedious, time consuming and unproductive.

To facilitate the automation of on-street parking monitoring, we aim to accurately detect vehicles, including vehicle recognition and precise localization. Also, vehicle categories are important information for parking regulations. Furthermore, due to a demand of local public authorities to estimate the parking durations, we need to detect whether two vehicles parked at identical locations at different times are the same or not.

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Current technologies, e.g. video surveillance using static cameras, are able to detect vehicles in parking lots hence generating the occupancy rate. However, it is obviously difficult to install cameras on all the streets of all the cities. Mobile mapping systems (MMSs) can be a promising alternative. They are moving vehicles equipped with cameras and/or laser scanners that are georeferenced by a georeferencing unit so that the acquired data are in a geographical coordinate system and can be used directly for localization (Paparoditis et al., 2012). 3D vision using images acquired from MMSs have been used for large scale applications, e.g. street scene understanding (Zia et al., 2015), city level change detection (Taneja et al., 2013). Since the 3D information from images are generated indirectly, precise geometry extraction, localization and 3D modelling still remain challenging tasks. Moreover, optical cameras are sensitive to light conditions, such that they might not work during night time. On the contrary, laser scanners measure the surroundings actively and directly in 3D with a high level of precision (a few centimeters). They open the potential to precisely detect and model vehicles which can be used for more detailed investigations, such as whether a vehicle has parked properly in one parking spot or whether two same colored vehicles are really the same.

There are studies focusing on one or two aspects of this practical problem, such as vehicle detection. But precise localization, fine-grained classification and change detection of vehicles using laser scanning (also referred to as lidar) point clouds have not been investigated yet. Not to mention a complete system of all the tasks for car park monitoring.

Vehicle oriented object detection using laser scanning data can only be found in few studies (Toth et al., 2003; Yao et al., 2008; Börcs and Benedek, 2012). Most studies deal with a generic classification problem, i.e. classifying all objects in the data rather than a specific one (Serna and Marcotegui, 2014; Weinmann et al., 2015). One common procedure is to remove points belonging to the ground and building façades, and then cluster the remaining points into segments. Then features are extracted from the segments. Some categorize the features as at point or segment level, others extract features in different dimensions, mostly in both 2D and 3D. In addition to geometric features, other features, e.g. RGB and intensity are also utilized if available. Then the dataset is classified using supervised classification methods. Detected vehicles can be roughly localized by a bounding-box using their 3D coordinates. However, lidar data are typically incomplete because vehicles are only scanned from one side. Hence a bounding-box cannot recover the whole shape of a vehicle and is mostly not accurate enough for fine detailed applications.

Vehicle shapes are universalized due to the pursuing of high-profile outlook and aerodynamic designs. Some vehicles lie between two categories in terms of size and shape, e.g. crossovers, making the classification a difficult task. To identify whether vehicles have changed in between the different epochs, one straight forward method is to find out the corresponding vehicles in two datasets, then compare their geometries. Normally a threshold is set to identify whether the difference is significant enough to be a change. The challenge is that vehicle comparison can be affected by many factors, e.g. registration error, scanning perspective, point density, anisotropic sampling, occlusion. Then the threshold of the difference can be hard to set.

In this paper, a complete system for detailed on-street parked vehicle information extraction is proposed, including vehicle recognition, localization, classification and change detection, for the purpose of parking monitoring. A deformable vehicle model is proposed to fit vehicle hypotheses for precise localization, and its parameters are used as features for supervised learning. Furthermore, it can be used for visualization purposes.

2. Related work

2.1. Vehicle detection

Image-based vehicle detection has been intensively studied for the purposes of scene understanding (Bileschi et al., 2004; Arróspide et al., 2012; Zia et al., 2015), traffic monitoring (Gupte et al., 2002; Huang and Liao, 2004), intelligent vehicles (Betke et al., 2000; Jazayeri et al., 2011; Caraffi et al., 2012), etc.

Bileschi et al. (2004) detect vehicles using the part-based method (Agarwal et al., 2004). Keypoints are extracted from the test images, then vehicles are detected by comparing the keypoints against a vocabulary of vehicle-specific keypoints learned from the training set. Instead of using keypoints, Arróspide et al. (2012) utilize gradient-based descriptor, which is the simplified histogram of gradients (HOG) (Felzenszwalb et al., 2010), for efficient vehicle detection. Tuermer et al. (2013) detect vehicles from airborne images using also HoG features and disparity maps. Bensrhair et al. (2002) detect vehicles in 3D based on features extracted from stereo vision.

Apart from terrestrial, aerial and spaceborne optical images (Leitloff et al., 2010), other types of sensors, e.g. thermal infrared (Hinz and Stilla, 2006; Yao et al., 2009), and synthetic aperture radar (SAR) (Maksymiuk et al., 2012, 2013), are also used for vehicle detection. Moreover, in recent years, vehicles have been increasingly studied using both airborne laser scanning (ALS) and MLS point clouds in 3D.

Toth et al. (2003) extract vehicles utilizing ALS data by thresholding height histograms, and then classify them into several main categories using rule-based and machine learning classifiers. Yao et al. (2011) also detect vehicles with ALS data using support vector machines (SVMs) after segmentation. Velocities are also estimated for the purpose of traffic monitoring and analysis. Börcs and Benedek (2012) add intensity values and number of echoes as features for vehicle detection using ALS data.

Himmelsbach et al. (2008) use an MLS system for object detection, then classify the detected objects as vehicle and non-vehicle using SVMs. Keat et al. (2005) extract vehicles from MLS data using Bayesian programming and finally map a whole parking lot. Golovinskiy et al. (2009) analyze point clouds generated from combined ALS and MLS. They first segment compact objects, then describe them with shape and context features and classify them into different urban object classes, including vehicles and traffic signs. Velizhev et al. (2012) improve the vehicle and pole object detection results using the same data by incorporating the implicit shape model (ISM) framework. To recognize an object, random keypoint descriptors are matched with a pre-generated dictionary of *geometric words* and then the potential object center is assigned by weighted votes. Serna and Marcotegui (2014) develop a full pipeline of segmentation and classification of urban objects using MLS data. Segmented objects are classified using SVMs with different sets of features. The method is applied to three datasets, one of which is focused on vehicles. High precision and recall are reported.

Supervised learning for vehicle detection or classification are popular for laser scanning data. Different types of features at point or object/segment level are explored: geometric features, contextual features and intensity/color features. In many computer vision studies, detailed models are used to facilitate object detection and classification in images or video. However, object modelling towards scene understanding, including object detection and classification, using laser scanning data still remains a challenge.

2.2. Vehicle modelling

Detailed 3D object representations facilitate scene understanding (Zia et al., 2015). Geometrically accurate models help to improve