Path Planning for Unmanned Vehicle Motion based on Road Detection using Online Road Map and Satellite Image

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Abstract. This article presents a new methodology for detecting road network and planning the path for vehicle motion using road map and satellite/aerial images. The method estimates road regions from based on network models, which are created from road maps and satellite images on the basis of using image-processing techniques such color filters, difference of Gaussian, and Radon transform. In the case of using the road map images, this method can estimate not only a shape but also a direction of road network, which would not be estimated by the use of the satellite images. However, there are some road segments that branch from the main road are not annotated in road map services. Therefore, it is necessary to detect roads on the satellite image, which is utilized to construct a full path for motion. The scheme of method includes several stages. First, a road network is detected using the road map images, which are collected from online maps services. Second, the detected road network is used to learn a model for road detection in the satellite images. The road network using the satellite images is estimated based on filter models and geometry road structures. Third, the road regions are converted into a Mercator coordinate system and a heuristic based on Dijkstra technique is used to provide the shortest path for vehicle motion. This methodology is tested on the large scene of outdoor areas and the results are documented.

1 Introduction

Nowadays, automatic navigation systems have been developed and applied in many research areas on robotics, autonomous vehicle, intelligent transportation systems, and other industry applications. Motion path planning, localization, and mapping become important research areas in various applications of autonomous navigation. There have been several groups of researchers focusing on autonomous vehicle/robot, especially intelligent transportation in outdoor environments, such as in [1–3]. In automatic navigation of mobile systems, first, they require to provide a global path network for robot/vehicle motion. Therefore, path planning is an important part in every autonomous vehicle system.

Recently, path planning methods have been achieved widespread successes in several industries as well in academic disciplines, which include unmanned ground mobile robot/vehicle, and aerospace applications. The rapid advance in recent years indicates that the more autonomous applications maybe on the horizon. There are many studies on the planning algorithms and implementations [4]. So far, there have been proposed methods for the path detection and planning [5, 6]. In general, there are several approaches to solve the problem of the path planning, but they are usually separated into the global and the local path planning approaches. The global path planning is concerned with the high-level of paths, which is a topological structure and the whole path for motion from the source to the destination of a travel itinerary. It deals with the navigation around the global regions. The local path planning is related to the low-level of paths in detail. It is only a segment of the global path, for obstacle avoidance, dealing with local motion navigation, e.g., the angles of turn, appropriate velocities.

The objective of this paper is to develop a complete, relevant, and efficient application for constructing the shortest path, which provides a real trajectory for autonomous vehicle motion in outdoor environments. In general, user can buy data of the paths for vehicle motion from commercial services. There are several business services, which support a constructed path on real traffic scene of transportation systems. However, in that case, they are expensive and the system becomes dependent on quality, and limitation of the services. This paper focuses on planning the global path, which is self-constructed based on road map and satellite images. The proposed method consists of several steps as follows. First, a road network is estimated by using the road map images, which are retrieved from online map services. Second, road regions on the satellite images are detected. This task is used to solve the problem of road segments, which are not annotated in the road map images. The corresponding road regions, which are detected at the first stage, are used to learn a road color model for detecting the rest of road segments in the satellite images. The road regions are estimated based on color filter, difference of Gaussian (DOG), and Radon transform techniques. The color model of the road is used to filter candidate of road regions. The DOG filter is also used to enhance candidate road borders and roadbeds. The dominant values of the Radon transform are used to detect road regions. The result of road detection is refined based on road joint structure. Third, the shortest path for motion is estimated by using path planning algorithms, e.g., Dijkstra, best-first graph search algorithm (BFS), Rapidly-exploring Randomized Tree (RRT). In this stage, a road network in image pixel coordinates is converted into the Global coordinates, which provides suitable information for the task of online vehicle navigation.

2 Related work

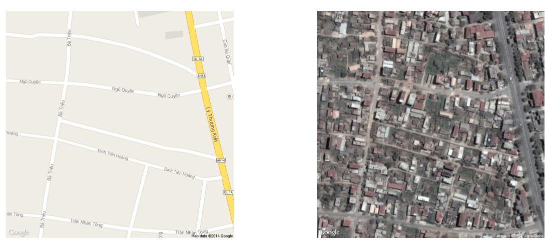
In recent years, some of the most convincing experimental results have been obtained using promising methods for motion planning [7–12]. A global path planning method based on the modification of rapidly exploring random tree algorithm was presented in [13]. The method was constructed for providing effective partial motion and achieving the global objective. Another group of researchers in [14] presented a motion planning method using guided cluster sampling. That paper developed a point-based Partially-Observable Markov Decision Process (POMDP) approach, which takes into account all the motion errors, sensing errors, and imperfect environment map for robots active sensing capabilities. The experimental results show that the approach contributes an efficient method to balancing sensing and acting to accomplish the given tasks in various uncertain conditions. However, the method requires high computational cost to find an optimal solution [15]. To adapt to changing and uncertain conditions, Toit and Burdick [16] presented a method for motion planning based on integral individual components of dynamic and uncertain environments in planning, prediction, and estimation. In outdoor environments, traffic law guiders are used to estimate the expected behaviors of the dynamic interaction system to predict their future trajectory, and constrain the future location of moving objects in more uncertain environments. In the case of the global path planning for motion under certain maps, computational cost of that method becomes high cost when it is applied for high-level motion planning. Furthermore, authors in [17] focused on developing an interpolation method for optimal cost-path-motion function based on well-known Dijkstra and A^* algorithms. Taking advantages of each of these algorithms, authors exploited to provide an effective method, which estimates the shortest path based on respondent information. The computational cost is significantly reduced by implementing an A^*-like heuristic.

In the field of outdoor path planning, there are several groups of researchers [5, 6, 18, 19], who have been focused on road detection and planning a trajectory for vehicle motion by using satellite/aerial images. Typically, the authors in [6] used a neural network to detect roads on high-resolution aerial images. In that paper, the authors analyzed to learn roads using a road surface context for reducing misdetection, e.g. roofs of buildings are similar to road surfaces without context of surrounding scenes. Chai *et al.* [5] presented a method to estimate a road network based on the Monte Carlo mechanism using sampling junction-points input images. The network extraction method is focused on investigating shape and extracting structures from nature textures. However, those methods could not overcome the problem of roads fully obscured by high buildings, tunnels, trees.

On the contrary, in this paper, instead of focusing on path detection using only the satellite images, the proposed method interests in both high-level of the road map and the satellite images for detecting a road network to plan the shortest path in outdoor environments. The road map and the satellite images are provided free of charge by online services, such as Google Maps, OpenStreetMap, Bing Maps. The proposed method takes advantages of prior knowledge of the road map images, which provided by map developers, to simplify road detection with high accuracy and low computational cost. This approach does not only construct the path network but also estimate a directed road network. For simplicity, this method believes the prior knowledge of the maps service. Some road segments are not annotated in the road map services, they would be supplemented by detection in the satellite images.

3 Problem formulation

Regarding the autonomous of robot/vehicle navigation in outdoor environments, global path planning plays an important role in the optimal motion planning applications. Although there are, at present, several different specialized commercial services, which provide complete real-world traffic applications, they are expensive and applied into just several limited applications. Further online road networks are insufficiently and not frequently updated or users should pay extra charge for map updates, as well the required precision and correctness of the trajectory cannot be assured users. In the case of open source projects, free and editable bitmap map layers are provided (satellite, road, boundaries, elevation, etc.). In both cases, the main problem of road map is that they are not fully annotated, especially in areas such as countryside, towns, as depicted in Fig. 1. On the other hand, the problems of road detection based on satellite images are low-resolution, having variations in spectral properties of road surfaces, e.g., vehicle presence and occlusion by buildings, tunnels, overpass, trees, as depicted in Fig. 2. Therefore, in order to address the challenges of global path planning, the authors present a method based on the advantages of multilayer for both road detection and the shortest path estimation applying to autonomous navigation.



(a) (b)

Fig. 1: Some road segments are not annotated by map service, (a) road map image, (b) corresponding satellite image

(a) (b)

Fig. 2: Road segments are occluded by trees: (a) Road markers are appeared in the road map image, (b) Road segments are fully obscured by trees in satellite image.

For appropriately detected road using road map and satellite images, the characteristics of road can be described as follows:

• Road surfaces can be paved or unpaved. In the first case, the most common type of material are asphalt, concrete, brick. In the second type, roads are designed using gravel or stones materials. Therefore, spectral characteristic of roads are not uniform, particularly in the case of unpaved road. This characteristic is the cause required learns the color model in local region area detection in surroundings areas of the detected road regions based on result of road map.

• Due to the material of road surfaces, roads can be confused with building roofs, grounds, especially in low quality of images. This problem can cause high rate of false detection based on spectrum filter. Therefore, road network structure is useful for reducing false detection.

• The width of road is almost constant. The ratio of length/width of road is usually larger than that of building roofs. Roads are incorporated constructing a road network. It is different to building roof, which is isolated with other parts.

• The detection results of road regions are sometime discontinuous in short distance due to the environment occlusion.

4 Road network detection

Recently, there have been several methods for road detection using satellite images were developed [5, 6, 18]. In contrast to the former methods, this article presents a simple and efficient method to detect roads using both of the satellite and road map images. The scheme of road network detection consists of several following steps.

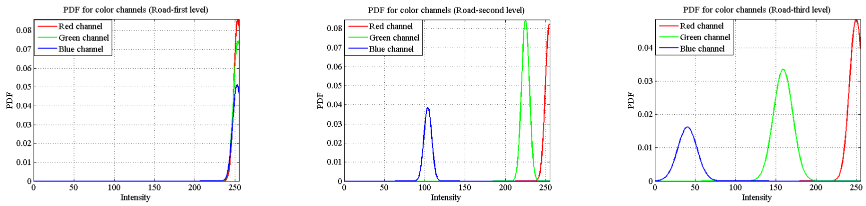
4.1 Map images based road network detection

As prior knowledge, this work believes in annotation of road map services. In order to filter out road regions, the statistic of color channels is used. The representative colors of road annotation in map images are separated into several classes with regard to the number of hierarchy of road maps. The representative colors have specific color characteristics. To investigate the color features, we built our own database for training, which gives the following probability density functions (PDF) of the red, green, and blue channels in Fig. 3. The road candidate regions are estimated by using Gaussian probabilities based on color channels by the following formulation:

$$P(r|x) = \prod_{ch \in C} P(r|x_{ch}) \tag{1}$$

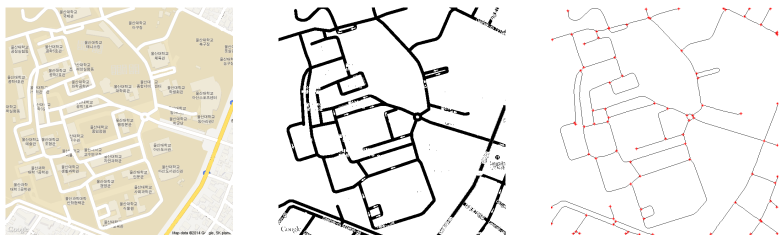
where x is pixel image, C is color channels (red, green, blue), and r is road candidate.

To highlight differences with previous methods [5, 6], the road map images are retrieved from the map service with low-resolution image in this paper. The road candidates are disconnected as result of noise and other annotations of the



(a) (b) (c)

Fig. 3: Probability distribution color channels of road regions, (a) PDF of the first level of road, (b) PDF of the second level of road, (c) PDF of the third level of road.



(a) (b) (c)

Fig. 4: Path network detection using the road map image, a) road map image is retrieved from Google Maps, (b) road candidates are estimated by color filter and segmentation, and (c) post process to connect the discontinuous road regions and extract the path network.

road map, see also Fig. 4. It should be noted that some world maps do not allow for removing the annotations in some locations in the maps because of several special purposes related to the map services. To deal with this problem, a rolling ball method is used for connection the discontinuous roads.

Taking advantage of the map images, the road direction is estimated based on arrow signals, as depicted in Fig. **??**). The final road network is presented by the directed graph.

4.2 Satellite images based road detection

In the case of some road segments, which are not annotated by map services, they are detected based on the satellite images. The road regions resulting from previous subsection are used to construct a training dataset from the corresponding regions of the satellite images. Let I_M be a road map image and I_S be a corresponding satellite image. All detected road pixels on I_M are mapped into I_S to construct a dataset for learning spectrum color model, as depicted in Fig. 5 (a). The probability density functions (PDF) of the red, green, and blue channels of road colors are shown in Fig. 5 (b). This color model is also used to

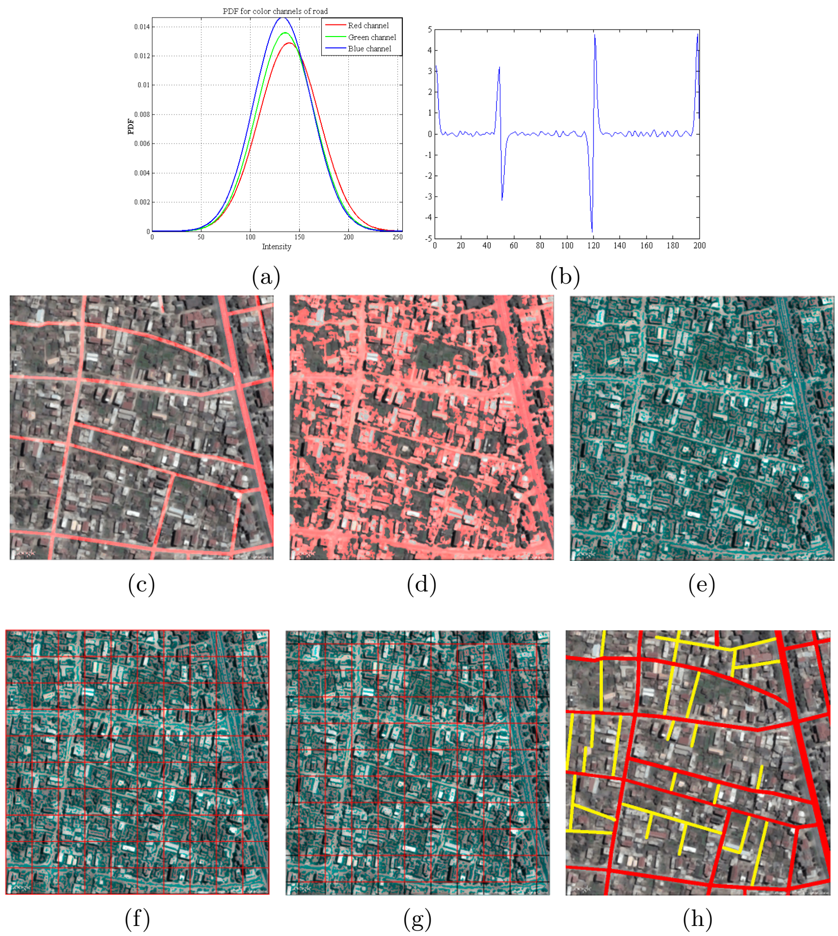


Fig. 5: Road detection process using satellite: (a) PDF of color channels of road regions, (b) DOG filter is used to emphasize object borders, (c) Road regions in satellite image corresponds to road detection results from map image (light- pink) is used for training color model, (d) candidate road regions (light- pink) using color model filter, (e) candidate road borders (dark-cyan) and roadbeds inside of long-edges, (f-g) two grid sub-regions of DOG image are used for computing the Radon transform to detect local candidate road segments, (h) road detection result based on combine of road map image (red) and satellite image (yellow).

filter out road regions in the satellite images by (1). The result of candidate road regions is shown in Fig. 5 (c). In this step, there are many false negative and false positive results due to some properties of roads aforementioned in section 3.

The DOG filter is used to enhance the boundaries of roads. The filter image results are obtained by convolving the grayscale satellite image with difference of two kernels of Gaussian with standard deviations σ_1 and σ_2.

$$F(I, \sigma_1, \sigma_2) = I \otimes \left(\frac{1}{2\pi\sigma_1} e^{-(x^2+y^2)/(2\sigma_1)} - \frac{1}{2\pi\sigma_2} e^{-(x^2+y^2)/(2\sigma_2)} \right) \tag{2}$$

Image filter using DOG preserves spatial information that lies between the ranges of frequencies that are preserved in the two smoothed images by Gaussian filters. It also removes high-frequency noise while emphasizing edges between regions of different intensity of gray, see also Fig. 5 (d) for example. By setting the threshold, border of regions are obtained to construct a binary image, called I_{DOG}. The result is superimposed on the original satellite image in Fig. 5 (e).

The roadbeds and road borders are filtered by using Radon transform combining with candidate road regions, which are estimated by color filter in the previous section. The I_{DOG} is divided into grid subregions, as depicted in Fig. 5 (f, g), and then the Radon transform is applied for each sub-region to estimate road segments. Two-dimension Radon transform $R(x', \theta)$ of an image $f(x, y)$, is defined in [19] as follows:

$$R(x', \theta) = \iint_D f(x, y)\delta(x \cos\theta + y \sin\theta - x')dxdy \tag{3}$$

where D is image domain, $f(x, y)$ is binary DOG filter image, $\delta(.)$ is the Dirac function, $\theta \in [0, \pi)$ is a rotation angle from x-axis to the normal direction of x'.

The Radon transform values of the binary DOG filter image are shown in Fig. 6 (b). Each triple of adjacent local extreme values is used to predict the candidate road segments, as depicted in Fig. 6 (c-d). Each part of x' is a candidate road segments if three sequence extreme values are alternating lay out two sides of Ths_{up} and Ths_{low}, and the width b is limited by w_m value (the maximal width of roads). The results of candidate road segments from sub-regions of two grids are projected on whole image to discard the road candidates in short distance and only maintain that of long distance. The result is integrated with the result of the color filter to discard the false detections, e.g., rivers, roof of buildings. Finally, the geometry of road structure in [5] is used to post-process for improving the accuracy of road detection. The result is shown in Fig. 5 (h).

5 Estimation the shortest path for motion

To make online vehicle navigation more convenient, the road network result in pixel image is converted to the global coordinates (Mercator coordinate system). The details method for converting from pixel image into global coordinate is referred to [20, 21] for details. Generally, global image services, e.g. Google Maps, Bing Maps, use similar organization of the world map. The world map can be represented by two-dimensional map, which likes a rectangle of 360 degrees wide

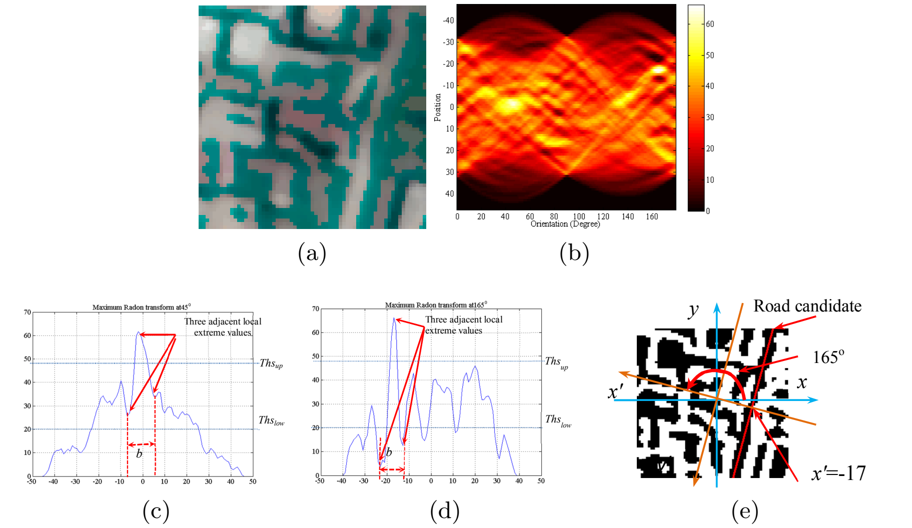


Fig. 6: Radon transform for road detection: (a) Binary image of DOG filter result is superimposed on the satellite image, (b) Radon transform results, (c) three adjacent local extreme Radon transform values indicate the non-candidate road region, (d) three adjacent local extreme Radon transform values indicate the candidate road region, (e) Radon transform for detection road borders and roadbeds.

and 180 degrees high. The world map is represented by a pyramid of tiles. The origin of a tile is located at the Northwest corner. The top level (zoom level =0) has 256×256 points, next level 512×512 points. For each next level of the tile pyramid, the point space is expanded by doubling of size in both directions x and y. Therefore, the image pixel at zoom level ξ is converted into the Mercator coordinate by follows:

$$Y = Y_0 - \left(y - \frac{h}{2}\right) \times \frac{\tau}{2^{\xi}} \tag{4}$$

$$X = X_0 + \left(x - \frac{w}{2}\right) \times \frac{\tau}{2^{\xi}} \tag{5}$$

where (w, h) is the size of image, (x, y) is a location of the point in image, (X_0, Y_0) is the located center of image in the Mercator coordinate. The initial resolution of tile size τ is $156, 543.034m$ (the circumference of the Earth in meters 40,075,016.679m divide 256 points). The part of equation $(y - h/2) \times (\tau/2^{\xi})$ is used to convert image pixel to meter unit in the global coordinate.

A point at the location (x, y) in the Mercator coordinate is converted into the GWS84 coordinate system by following equation [21], with ϕ and λ are latitude and longitude in the GWS84 coordinate, σ is the radius of the Earth.

$$\lambda = \frac{360}{2\pi}\frac{X}{\sigma} \tag{6}$$

$$\phi = \frac{180}{\pi}\left[2\tan^{-1}(\mathrm{e}^{\mathrm{Y}/\sigma}) - \frac{\pi}{2}\right] \tag{7}$$

This section presents a method to estimate a path for vehicle motion with the minimum cost of feasible trajectory based on the road network configuration. There are many methods for estimating the optimal path [4], e.g. Dijkstra, BFS, RRT. The shortest path problem in this paper is considered in two-dimensional Euclidean spaces. We construct a discrete directed graph $G(V, E)$. The set of vertex $V = \{v_i, i = i..n\}$ is defined as the set of intersections and ending points of the road network. The set of edges $E = \{e_i, i = 1...m\}$ is defined as the set of road segments between pairs of adjacent intersections or the ending points. A road segment, which connects intersection point to adjacent another one or the ending point, is represented by two edges in opposite direction. In the case of one-way road, it is represented by single directed edge. The Euclidean distance is used to compute the cost of each edge. Given the source position s and the destination position d, the path planning problem is estimation of a feasible trajectory T with the lowest cost for vehicle motion. The cost-function of trajectory is a non-negative cost, which is defined by $c : V \to R_{\geq 0}$.

The objective of this task is finding the shortest path from the source location to the destination location under assumption that there is no obstacle (the problem of obstacle avoidance will be dealt with in partial motion planning). This paper uses Dijkstra algorithm combining with heuristic based on greedy BFS for fairly flexible and potential searching in a huge area of the map. It is particularly desirable when applying heuristic search techniques in large graphs, which are typically required by a robot operation in outdoor environments, to restrict the point-to-point searching to examine only relevant areas of the input graph [22].

6 Experiment

This section presents evaluated results of the proposed method for automatic extracting the shortest path for vehicle motion in outdoor environments and comparison our method with state of the art methods. The dataset for road network detecting in road map images is manually collected based on annotations of road regions. In general, there are three kinds of color patterns for representing road regions in the road map images. The training dataset for road detecting in satellite images is automatically extracted using road results in the road map images. The color channel distributions are presented in Fig. 5 (b). This method is proposed for real application while other methods based on only aerial/satellite image are limited to special conditions. They can not deal with the case of roads fully obscured by high buildings, trees, tunnels in the satellite images, see Fig. 3. In contrast, detection method based on the road map images is dependent on prior knowledge of road marking, for example some road segments are not annotated in the road map services, see Fig. 1. Advantage of the road map images based method is that it does not require high-resolution

Table 1: Comparison of methods using the road map image and the aerial image

	Road map	Satellite image
Require high-resolution images	No	Yes
Overcome occlusion confident	Yes	No
Depend on update of aerial images	No	Yes
Depend on prior knowledge of road annotation	Yes	No
Computational time (second)	< 10	> 100
Accuracy (%)	> 95.0	< 67.5

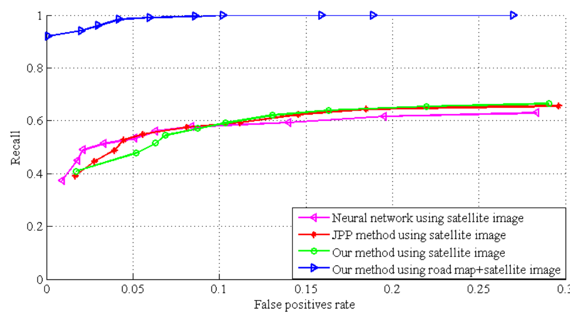


Fig. 7: Comparison results of our proposed method with previous methods on low-resolution satellite image and road map image

images, consume low computational time for detection roads due to a simple algorithm. It is suitable to implement the road detection in real applications for autonomous vehicle. The summary of comparison is presented in Table 1. In this experiment, we evaluated our proposed method on road map and satellite images, and compare with the method [5] (denoted by JPP method) and [6] (denoted by neural network method). All most methods result in low accuracy when apply into low-resolution satellite images. Our method result is slightly better than other methods because it is learned the model based on local spectral color, which accommodates the color model with variety road spectra (source from variety material of road surfaces). Our method is successful when supplement with the result of road detection using road map images.

The image dataset for experiment was automatically retrieved from the Google Maps service. The input parameters of the center location of regions are manually located on map service. In the case of towns and villages, there are many road segments, especially branch roads (byroad), were not frequently updated, while in the cities, almost all road parts were annotated by map services. The experiments were evaluated under configuration of 640×640-pixel resolution images and the zoom level of 15, 16, 17, and 18. The images at the zoom level of 15, 16, 17, and 18 cover areas of about $1,222.99 \times 1,222.99m^2, 611.49 \times 611.49m^2, 305.75 \times 305.75m^2, 152.88 \times 152.88m^2$ respectively. Fig. 7 presents the

(a)

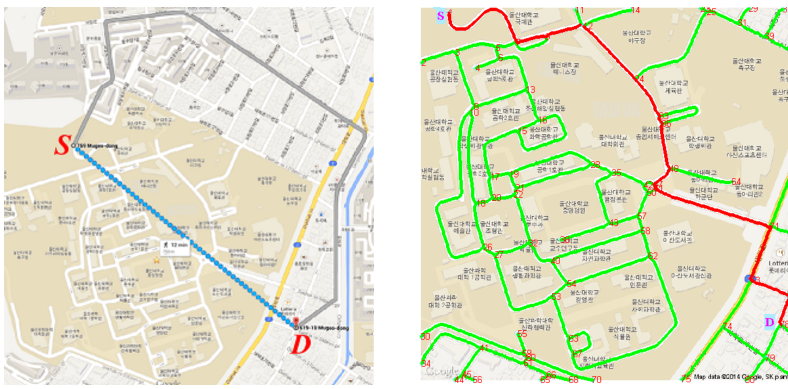
(b)

(c)

Fig. 8: Typical road detection: (a) Satellite images,(b) road map images,(c) road network estimation results with many additional detected road segments by our proposed method.

Table 2: Comparison of methods using the road map image and the aerial image

Region	Zoom level	Road segments		Intersections		Consuming time
		TPR	Precision	TPR	Precision	
Downtown rotary	15	0.989	0.989	0.997	0.984	5.07
	16	0.995	0.980	100%	0.974	4.55
	17	100%	100%	100%	100%	3.90
	18	100%	100%	100%	100%	3.65
University campus	15	0.994	0.991	0.994	0.988	5.09
	16	100%	100%	100%	100%	3.92
	17	100%	100%	100%	100%	3.47
Small town	16	100%	100%	0.987	100%	4.50
	17	100%	100%	100%	100%	3.78



(a) (b)

Fig. 9: The path planning for motion: (a) The resulted path from Google service with two option gray and turquoise path,(b) Our detected road network (green) and the shortest path for motion (red)

comparison results of our method with other methods. Our method was evaluated on both situations of only using satellite image and using road map and satellite image. Fig. 8 shows typical results of images and trajectories of path detection based on our method using both road map and satellite images. The intersection and ending points of roads are ordinally numbered. The experimental results are demonstrated that our method can detect many additional road segments, which do not available in road maps, as shown in two first columns of Fig. 8(b,c).

The evaluation results are shows in Table 2. The markers on road map service and additionally manual annotation by authors are considered as ground truth data for evaluation and comparison. The sensitivity and precision criteria are used for evaluation of the method. The sensitivity (Recall, True positive rate-

TPR) is computed by #TPR = #True positive/ (#True positive + #False negative). False positive rate (FPR) is computed by #FPR = #False positive/ (#False positive + #True negative). The precision is computed by #Precision = #True positive/ (#True positive + #False positive). The experimental results show that the road detection result at the higher the zoom level is more precision and vice versa. The road detection is perfect at the zoom level 17 and higher.

The path planning results are presented in Fig. 9. Google service results incorrect path for travel in local areas or the case of unpopular regions, as shown in Fig. 9(a). This problem is solve by our proposed method, as presented in Fig. 9(b). In this experiment, the algorithm (1) is applied to estimate the shortest path for vehicle motion using the images at zoom level 16. The trajectory in red color represents for the shortest path from the source location s to the destination location d with the cost of motion is 1,364 meters.

7 Conclusion

This paper presents the method to enhance the efficiency in constructing the path using both road map and satellite images for autonomous vehicle motion in outdoor environments. The method focuses on estimation of paths in the global coordinate for motion without using expensive commercial services. It consists of several parts. First, a road network is estimated using the road map images, which are retrieved from online free charge map services. Second, a road network is also estimated using the satellite images based on prior knowledge of the first stage for learning the color model and using image processing techniques such color filters, difference of Gaussian, and Radon transform for detection road segments. The final road network is constructed and refined based on the geometry structures of road system. Third, the shortest path is estimated using the path planning Dijkstra algorithm combining with heuristic based on BFS technique. The trajectory result of the path network is processed in the global coordinate for convenience in online vehicle navigation when combines with the GPS. By the use of road map images, it takes advantages of maps annotation to provide high confidence of the shortest path for vehicle navigation. One disadvantage of using the road map is that it depends on the update of road information. To compensate this problem, the satellite images are used to detect the lack of annotated road segments for constructing full road network. The experimental results demonstrate the effectiveness of this method under the large scene of the outdoor environments.

Acknowledgement. This work was supported by the National Research Foundation of Korea (NRF) Grant funded by the Korean Government (MOE) (2013R1A1A2009984).

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