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패치 전파를 통한 단일 카메라에서의 조명 불변의 도로 탐지 방식

Illumination-Invariant Road Detection for Monocular Camera via Patch Propagation

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2015. 12. 14.

Approved by

Professor Yoon, Sung-eui

[Advisor]

[1]Declaration of Ethical Conduct in Research: I, as a graduate student of KAIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.

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ABSTRACT

Road detection is one of the most crucial problems for advanced driving assistance system. In this paper, we propose an efficient illumination-invariant road area detection method via a vision-based approach using an on-board monocular camera on a vehicle. Accurately identifying road areas is challenging due to the road variability caused by illumination changes. To address this problem, we propose to use PCA based illumination invariant grayscale image computed from an input RGB image. We assume that road areas in the grayscale images have the similar texture appearance, and those areas are connected to each other. Based on these assumptions, we develop an efficient, yet robust patch based techniques for identifying seed road patches and propagating them to find the road area. We have tested our method with the KITTI benchmark, and compared the performance against three state-of-the-art techniques. We found that our method shows higher accuracy in a range of 7% to 23% points over the tested methods. Moreover, our method runs two orders of magnitude faster than other tested methods. These results are mainly achieved thanks to the usage of the illumination invariant grayscale images and our patch based approach, which is efficient and robust to various noise.

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Chapter 1. INTRODUCTION

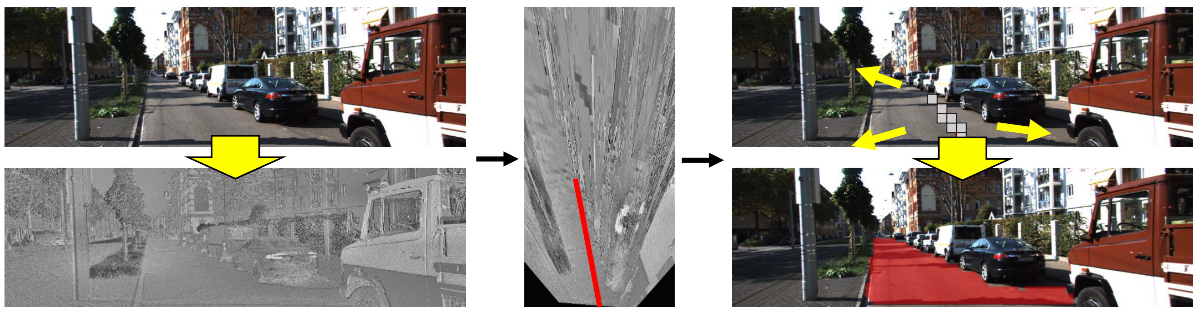
Recent developments of Advanced Driving Assistance System (ADAS) aim to efficiently detect driving environments, and provide various useful supports related to safety and convenience to drivers. One of the most important tasks is to detect road areas ahead of a driving vehicle. Detecting road areas is one of the fundamental steps that are used for other tasks such as vehicle [1], road sign [2] and pedestrian [3] detection.

ADAS can use different types of sensors such as radar, LIDAR, and stereo cameras. In this paper, we focus on vision-based road detection techniques with a monocular camera mounted in front of a vehicle, since this is one of the most cost-effective ways [4], and it is also the easiest ways to install the ADAS to existing old vehicles.

Early work utilizes RGB color features [5], to detect road boundaries on well marked roads [6]. When roads have severe illumination changes, such as shadows, edge based approaches can easily generate false detection. To address this issue, different color spaces such as the HSI space has been used in [7, 8]. Nonetheless, detecting road areas robustly under severe illumination changes remains as the main challenges in the field.

Main contributions. In this paper, we develop an efficient algorithm to detect road areas robust to illumination variation (Figure 1.1). We first propose an PCA algorithm to efficiently find an illumination invariant projection space to remove shadow before road detection (Section 3.1). We found that in our shadow-free grayscale images, patches on road areas have similar texture appearance and are connected to each other. Based on these observations, we adopt a patch based approach, which is very fast and robust to noise, and apply it to two main components of our method: identifying seed patches in the road area (Section 3.2) and propagating them to the other connected road areas (Section 3.3).

To demonstrate benefits of our method, we test our method with the KITTI dataset [9]. We compare our method against three state-of-the-art road detection methods, which are based on deep learning [10], specialized features for road detection [11], optimized segmentation methods [5]. We use a single CPU core for all the tests. Overall, our method achieves higher detection accuracy up to 23% points with more than 300 times faster performance over all the other tested methods. These improvements are achieved mainly thanks to identifying the shadow-free space in a robust way and the fast efficiency of patch-based propagation. We think that our method takes one more step towards designing efficient and accurate road detection methods that can be used for autonomous vehicles.



(a) Shadow free space (b) Seed patch line (c) Patch propagation

Figure 1.1: Overall flow of our road detection method. (a) We first compute a shadow-free grayscale image, (b) followed by identifying a seed line in a road area. (c) Finally, we propagate detected road areas based on the seed patch line.

Chapter 2. RELATED WORK

2.1 Boundary features

Road area detection using boundary features (e.g., road edges) mainly considers low-level information of input images. These techniques commonly extract edges to find boundaries or line paths of roads, and determine road area between detected boundaries.

Chen *et al*. [12] extract path lines and match them with a few candidate line templates. Falola *et al*. [13] use the Sobel operator to extract road edge information and remove salient pixels for segmenting road area. Gao *et al*. [14] use various edge detection methods to recognize road lanes and vehicles. Also, Kuhnl *et al*. [15, 11] use spatial ray features with slow feature analysis. They propose classifiers about road, boundary, and lane models.

These methods are appropriate for structured roads like the highway, which have well-painted lane marks or evident edge boundaries. Unfortunately, they have been identified to be vulnerable to drastic illumination changes such as shadow features [16]. On the other hand, our method considers patches from illumination invariant space to reduce the effect of illumination changes.

2.2 Region features

Road detection approaches with region features utilize raw information such as color or texture of images. Texture based road detection methods use the textural difference of road and non-road regions. Most commonly used texture descriptors are statistical and structural descriptors. For example, average and standard deviation of textures light intensity are statistical descriptors, while contrast, inverse moment, and entropy are structural descriptors [17].

Many vision based road detection methods rely on color-based features. Simple color spaces like RGB, unfortunately, does not represent road features well, because road textures in the RGB space vary significantly as a function of illuminations [18]. Also, features at different distances from the camera vary due to the perspective projection of images. Many existing road detection methods use different color spaces as features. For example, Sotelo *et al*. [7] use hue-saturation-intensity (HSI) color space to find luminance robust features. Additionally, Alvarez *et al*. [18] use shadow removal techniques with entropy minimization methods [19] to construct an illumination invariant color space. We apply this work for our problem.

Some recent approaches use convolutional neural networks. Alvarez *et al*. [20] learn road-texture patterns by color plane fusion and apply neural networks to label transfer. They combine extracted general information and the Naive Bayes framework to classify images. Brust *et al*. [10] present convolutional patch networks with spatial information of the patch. They classify image patches at each pixel position. These methods are used in scene parsing, but they use region texture features for learning. Using convolution neural networks can achieve high detection accuracy, but can require an expensive learning computation cost with a large amount of training images.

We found that most prior road detection techniques are rather sensitive to the variation of illumination, and tend to require high computational costs. In this paper, we propose to use an illumination invariant grayscale image, followed by patch-based approaches for achieving robust, yet efficient road area detection performance. We show benefits of our method by comparing it against the state-of-the-art techniques.

Chapter 3. OUR APPROACH

In this section, we describe three steps of our road area detection method. First, we generate shadow invariant grayscale image using chromaticity plane projection with the minimum variance. Next, we find a seed line from a road area and extract seed patches following the line. Finally, we propagate seed patches to nearby similar patches to cover the entire road area. This work was submitted to ICRA(IEEE International Conference on Robotics and Automation) 2016.

3.1 Illumination invariant space

Road detection techniques can be sensitive to the variation of illumination. Especially, illumination changes such as shadow on roads pose challenging problems. For designing a robust and efficient technique with a monocular camera, we propose an illumination invariant color space generated by PCA.

To remove shadows on images, three assumptions commonly known as PLN-assumptions are used. They assume that an image is captured under *Planckian illumination* and *Lambertian surfaces* obtained by *Narrowband camera sensors*. Under the PLN-assumptions, it is important to remove or reduce the influence of illumination variations (e.g., shadows) using an appropriate chromaticity mapping function, which generates impervious intensity space.

The first step is to reduce dimensionality of RGB color space of input images by removing the effect of illumination changes. We use a recent prior work [18] propose to compute chromaticity for each pixel as the following:

$$r = \log\left(\frac{R}{G}\right),\ \ b = \log\left(\frac{B}{G}\right). \tag{3.1}$$

This function computes log-chromaticity values using the G channel as the normalizing channel. However, it works under the ideal narrowband sensor camera. Certain real camera has broadband sensors, and Finlayson *et al.* [21] suggest geometric mean log color space in that case. Geometric mean mapping function follows:

$$r = \log\left(\frac{R}{(RGB)^{1/3}}\right),\ \ b = \log\left(\frac{B}{(RGB)^{1/3}}\right). \tag{3.2}$$

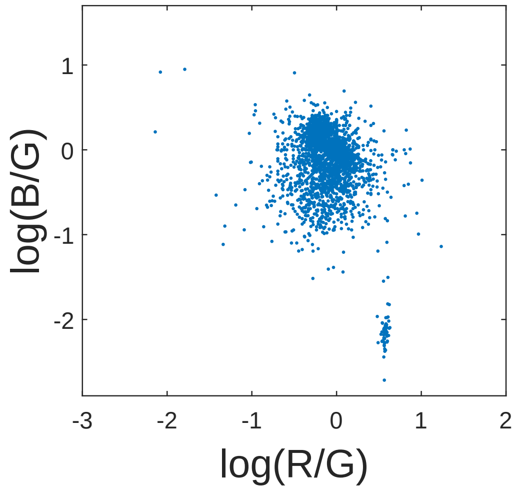
We find that the log mapping function (Equation (3.1)) works well for certain types of camera sensors such as Sony ICX084. We find, however, that other types of sensors such as Sony ICX204 does not work well. For those camera sensors including the recent ICX204, we find that the mapping function based on the geometric mean (Equation (3.2)) works well.

Figure 3.1 shows two different chromaticity mapping results of an input image from the well-known KITTI dataset [9]. In this case, we use the mapping using the geometric mean (Equation (3.2)), resulting in reducing illumination changes more effectively.

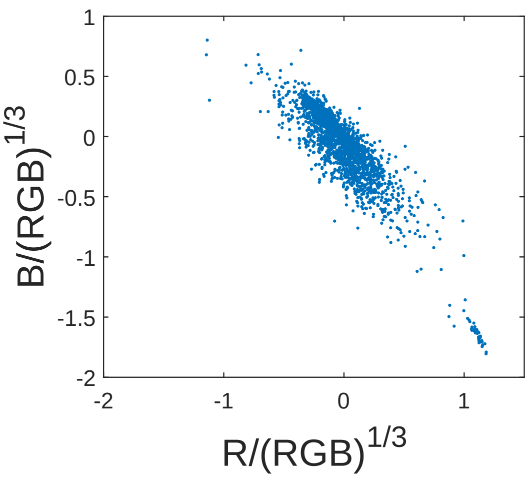
Once we compute the 2-D log-chromaticity space, our next step is to find a projection direction that minimizes the influence of illumination variance. The dotted arrows shown in Figure 3.2 are an example of projection direction. Intuitively speaking, color appearances of a material are mapped along the projection direction. In other words, along the projection direction, we can see the illuminant temperature changes.

Prior methods [22] try out many projection directions and pick the one with the minimum entropy. We find that this method is slow for our purpose and sensitive to outliers in the chosen chromaticity mapping space. We

(a) Original RGB image



(b) Log-chromaticity plane



(c) Geometric chromaticity plane

Figure 3.1: (a) Original RGB image. (b) and (c) show two different mapping planes with log-chromaticity and geometric-chromaticity respectively that we use for the KITTI dataset.

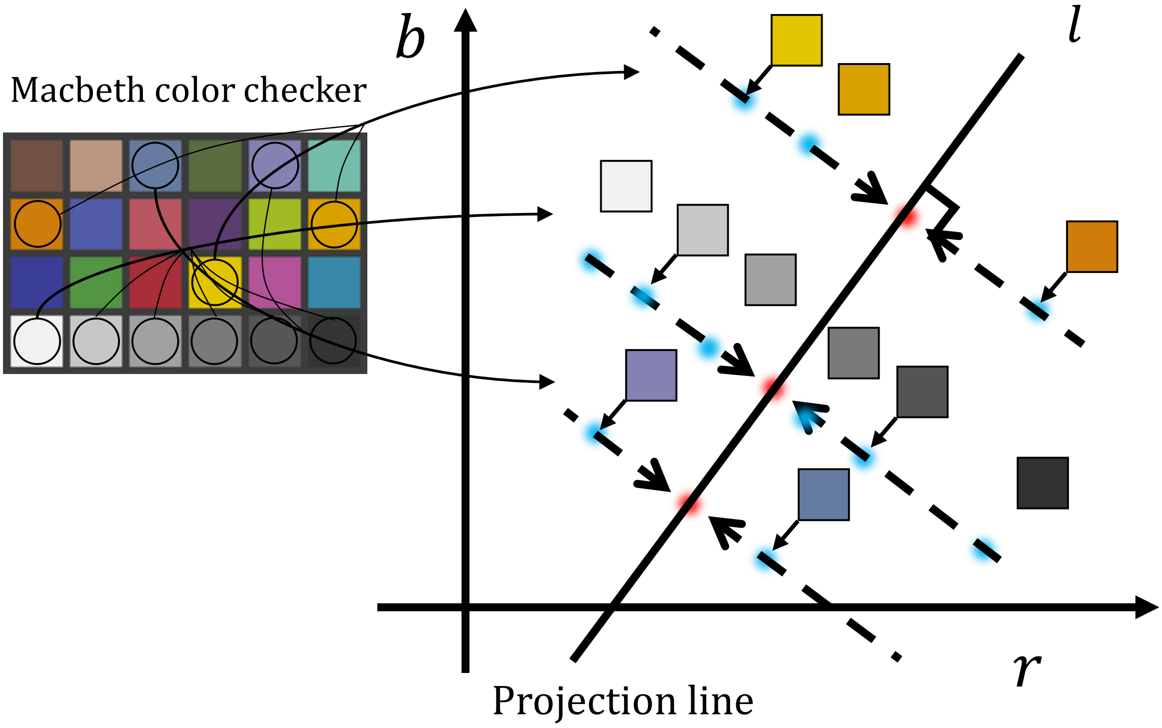


Figure 3.2: This figure shows the ideal log chromaticity plot from the Machbeth color checker. Patches of different chromaticities are mapped on different dotted lines. We achieve an illumination invariant space by projecting patches onto the projected, solid line l.

find that variance measure is more robust than the entropy measure, especially under some noise and outliers. Figure 3.3 shows entropy and variance curves with different projection lines parameterized by a line angle.

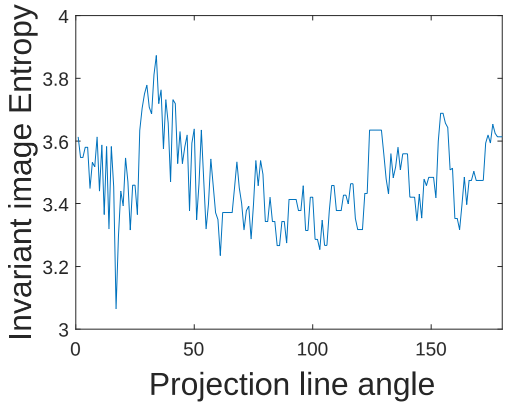
Ideally, we aim to find an optimal projection direction that results in the largest variances along the projection direction, since variances are correlated with illumination changes and canceling them reduces the influence of illumination changes effectively. To achieve our goal, we propose to use PCA (Principal Component Analysis) as a global approach that identifies a semi-major axis with the maximum variance (Figure 3.3).

To apply PCA, we consider the chromaticity mapping values as $2 \times n$ matrix X, where n is a number of sampled pixels. The covariance matrix $C = XX^T$ is decomposed using the singular value decomposition as follows:

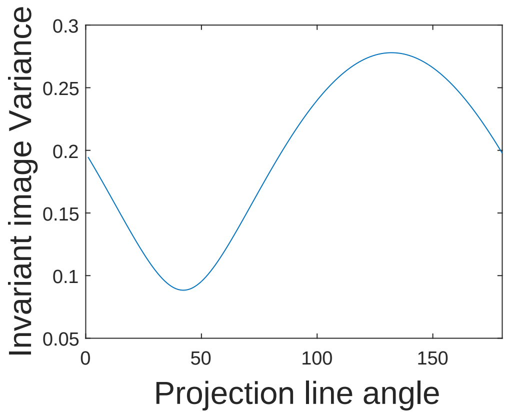
$$C = XX^T = \begin{pmatrix} e_1 & e_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} {e_1}^T \\ {e_2}^T \end{pmatrix}, \tag{3.3}$$

where e_1 and e_2 are the two eigenvectors with their corresponding eigenvalues λ_1 and λ_2, respectively. We choose the largest variance λ_1 and its eigenvector e_1 as the projection direction.

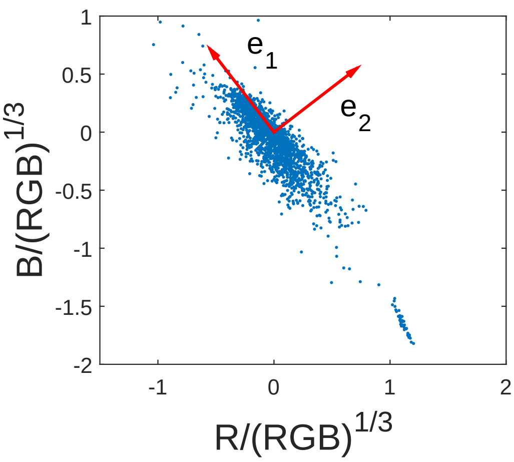
Our PCA based method shows two to three times faster performance with 2% point higher detection accuracy than the prior, entropy based approach. We achieve higher accuracy mainly thanks to the robustness of our method to noise and outliers. The faster running performance is acquired, mainly because our method computes the projection with the maximum direction by accessing the data two times during the PCA computation, while the prior, entropy based approach performs projections many times (e.g., 180 times). More detailed comparisons and analyses in terms of accuracy and runtime performance are in Chapter 4.



(a) Entropy



(b) Variance



(c) PCA

Figure 3.3: (a) and (b) show entropy and variance curves as a function of projection line angle. (c) shows two eigenvectors from PCA. We pick e_1 as the projection for creating the shadow-free image.

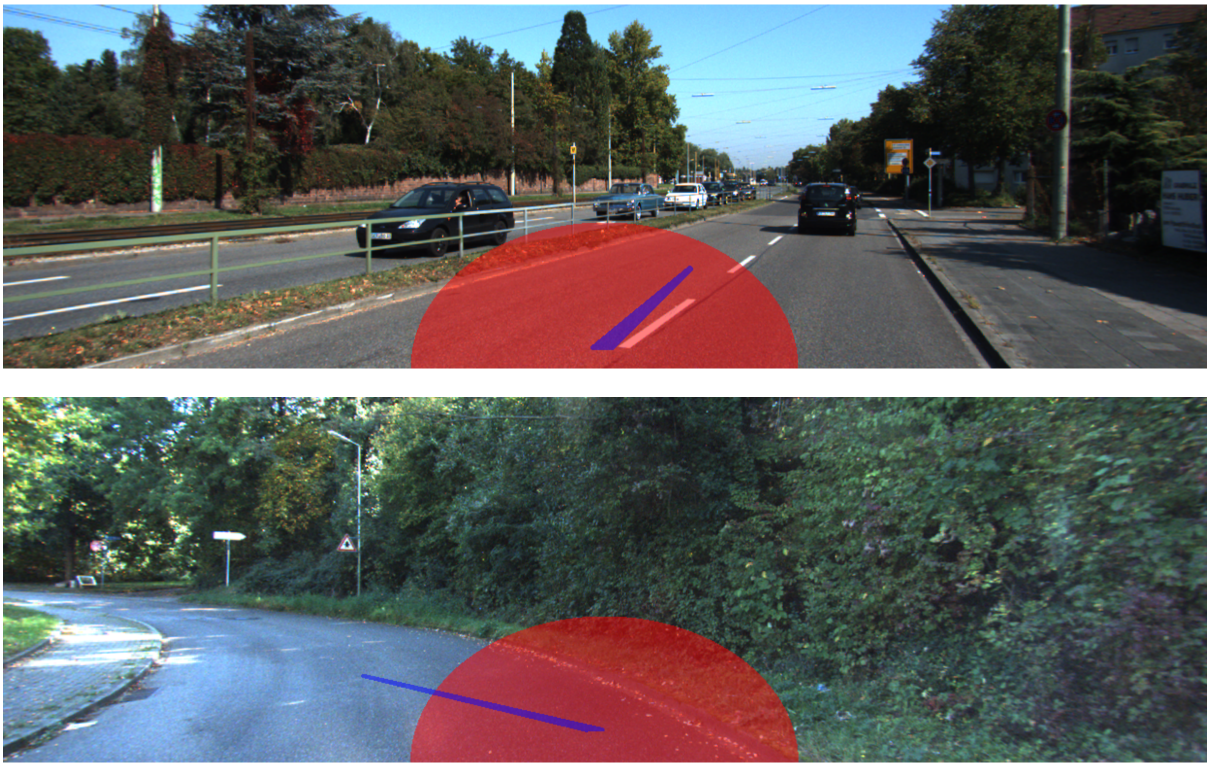


Figure 3.4: These figure shows seed area (red ellipses) of a prior heuristic that assumes road area is located in the bottom middle area of an image. Seed computed by our method are also visualized in blue lines.

3.2 Computing seed patches

Our method identifies road regions by propagating patches from seed road patches for efficient performance. In this approach, it is critical to select the correct seed patches from images. We use the shadow-free grayscale image of an input image to extract seed patches, since it is created in a way to minimize the illumination variances.

Many prior methods including [5] also utilize the idea of using seeds that are in the road region. These methods commonly identify such seed pixels based on a heuristic that the bottom middle areas are usually located in the road. This approach is very simple and reasonable for most roads. The heuristic, however, can fail when some obstacles are located in front of the camera or a road shape is strongly curved like Figure 3.4.

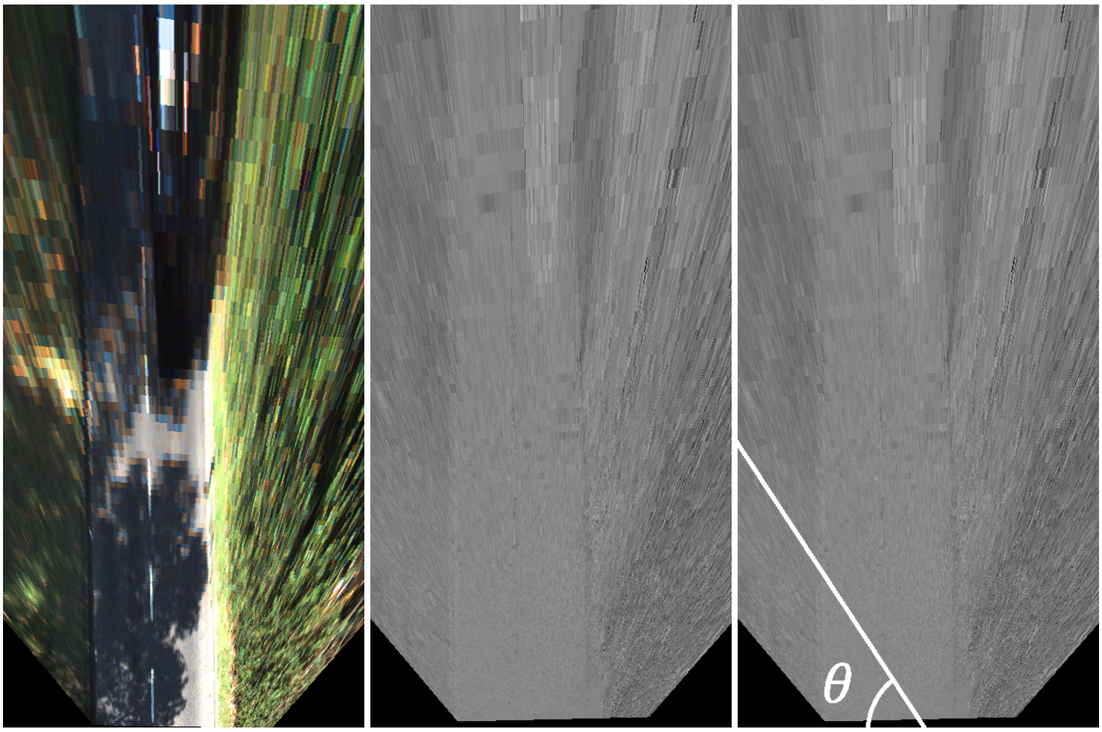
Instead of relying solely on the heuristic, we propose a more robust seed selection method that utilizes the illumination invariant grayscale images. Our method utilizes the idea that the road in an image exhibits similar texture appearances, and considers the variance measure to find similar road textures.

Specifically, after generating the illumination invariant grayscale image, we convert the image to a Birds Eye View (BEV) image (Figure 3.5 (b)). We perform this conversion process, since it can reduce down the noise level on regions located closely to the camera. We then attempt to find the seed line in the BEV image for extracting seed patches. Note that our approach does not use an expensive method to identify lane markers or road boundary. Instead, our method considers different lines, simple proxies of different lane shapes in the BEV image, and treats the line with the minimum variance of pixel values as the seed line.

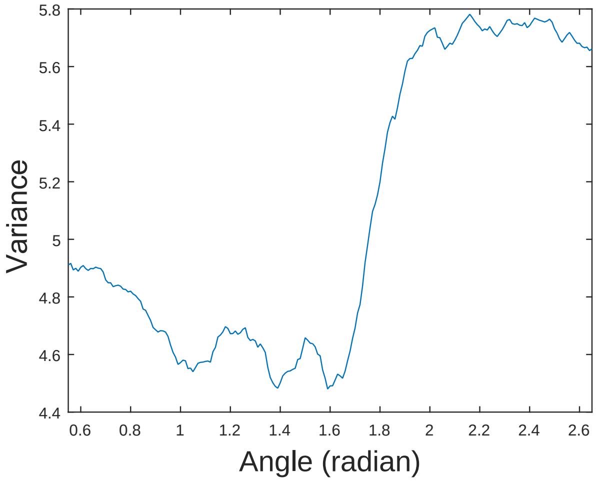
We define lines as a function a line angle, θ, as follows:

$$y = \tan\theta(x - cam.x) + cam.y, \tag{3.4}$$

where $cam.x$ and $cam.y$ are the camera location in the image.



(a) (b) (c)



(d)

Figure 3.5: (a) RGB image in birds eye view (BEV). (b) Graysacle shadow invariant BEV image. (c) The computed seed line. (d) Pixel variances as a function the line angle θ.

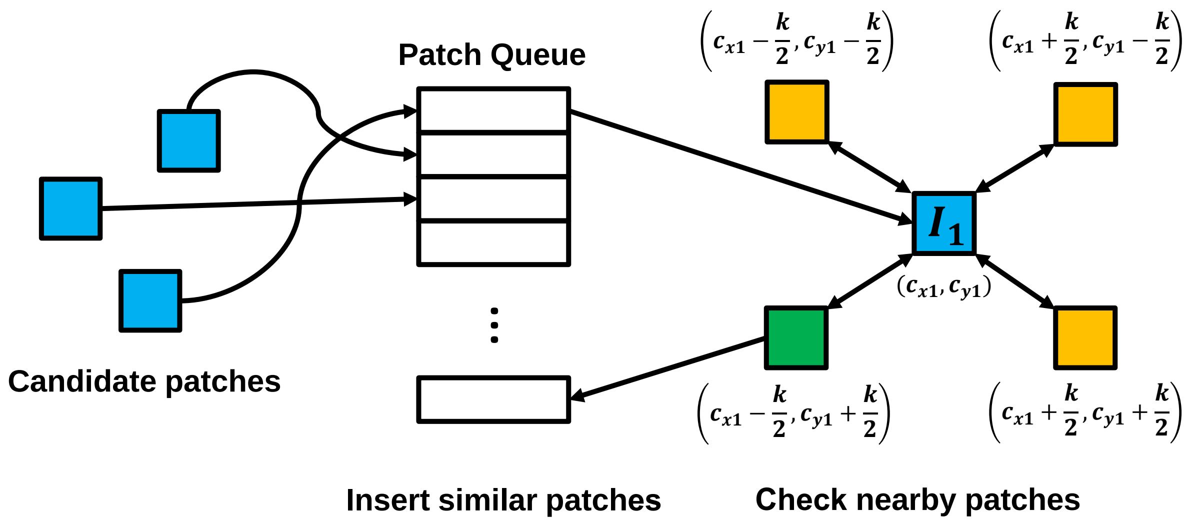


Figure 3.6: This figure shows our patch propagation using a patch queue. Starting from seed patches, we look at nearby patches, and enqueue similar patches for identifying the road area.

Figure 3.7: Original RGB images (top row) with entropy-minimized invariant images (middle row), and our PCA-based variance minimized images (bottom row). Our method removes shadows reasonably well in the visual inspection in addition to road detection evaluations.

For each θ, we access its corresponding line in the BEV image, and evaluate their variance. Figure 3.5 (d) shows a graph of gray level variance as a function of θ. We find the angle with the minimum variance and use it as the seed line. Intuitively speaking, this seed line is considered as finding seeds in the ego lane. We then extract non-overlapping $k \times k$ road patches along the seed line and use them as seed patches for identifying road patches. We find that $k = 20$ strikes a good balance between the accuracy and performance. Fig. 3.4 also shows the computed seed lines based on our method. As illustrated in Figure 3.4, the computed seed lines are located within the road area, regardless the road is straight or curved.

3.3 Patch propagation

Starting from the seed patches extracted from the seed line, we propagate those seed patches by identifying similar, nearby patches. This patch propagation step is also performed in the illumination invariant space. Given the input seed patches, we apply a simple and greedy propagation method to achieve high runtime performance, summarized below:

1. Insert all the seed patches into a patch queue.
2. Dequeue the front patch and compare its similarity with nearby adjacent patches.
3. For similar patches, enqueue them into the patch queue.
4. Repeat step 2) and 3) until the patch queue is empty.

Each patch, I, is defined by $k \times k$ size with its center position $[c_x, c_y]$ in the illumination invariant space. Given the patch I, its adjacent patches are defined in the same size along four diagonal directions from the center position of I (Figure 3.6). For the patch similarity test, we use the L2 distance between two patches, each of which is represented by a k^2 dimensional vector. We measure the average L2 distance, α, between seed patches, and when two nearby patches have a L2 distance less than 1.3α, we treat them similar patches. We use the constant of 1.3 to allow minor patch variations for the similarity test.

Chapter 4. EVALUATION

We evaluate the performance of our method and other tested methods with the KITTI road dataset [9]. This road image data is acquired using an onboard Point Gray Flea video camera based on the Sony ICX204 sensor. The resolution of captured images is 1241 $\times$ 376. The data set contains 289 of images with their ground truth binary labeling, i.e., road or non-road per each pixel. We evaluate our method against those images with the ground truth labelling.

In this paper, we use four different metrics including F-measure and quality measures using True Positive (TP), True Negative (TN), False Positive (FP), and False negative (FN) (Table 4.1). The most important measure metric is F-measure [23].

For further analysis, we compare our method with three state-of-the-art road detection algorithms:

- HRD [5]: It presented a hierarchical grow-cut based segmentation method based on super pixels and GMM (Gaussian Mixture Model). It is based on an optimization approach for identifying similar super pixels using GMM.

- CN24 [10]: It proposed a CNN (Convolutional Neural Net) based road detection method. This network is called convoultional patch network, and contains a spatial layer in addition to common CNN layers.

- SPRAY [11]: They proposed a new SPRAY (spatial ray) feature and integrated it into existing road detection tools such as lane marks, road boundary, and road confidence.

For the CN24 approach, we use C codes implemented by authors, while codes of other prior approaches are not available. We implement our method and others based on matlab and python, while utilizing available library. We run all the methods in the same machine, Intel i7 machine with 3.4 GHz CPU by using a single core.

4.1 Shadow invariant image evaluation

We compare our proposed method, PCA based variance minimization, against the prior entropy based approach. Unfortunately, there are no ground truth results for shadow detection in our tested KITTI dataset. As a second-to-best choice, we compare different methods based on road detection measures and computation time.

Table 4.1: Measures of road detection performance.

Pixel-wise measure	**Definition**
Recall (R)	$R = \frac{TP}{TP+FN}$
Precision (P)	$P = \frac{TP}{TP+FP}$
F-measure (F)	$F = \frac{2PR}{P+R}$
Quality ($\hat{g}$)	$\hat{g} = \frac{TP}{TP+TP+FN}$

Table 4.2: Detection accuracy of two shadow removal methods

Method	R(%)	P(%)	F(%)	$\hat{g}$ (%)	Time (ms)
Entropy based	79.13%	**87.22%**	80.38%	69.61%	43.35
PCA based	**88.15%**	79.59%	**81.52%**	**70.49%**	**17.06**

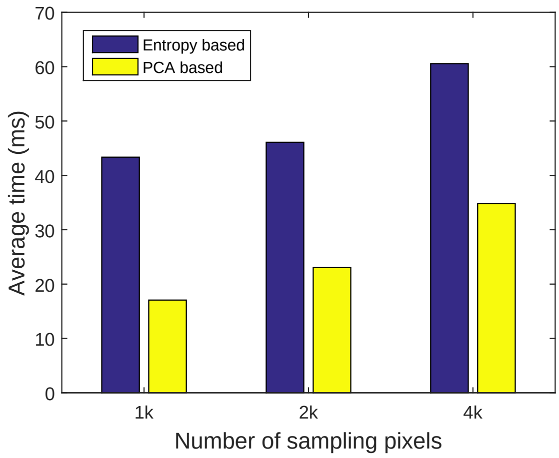


Figure 4.1: Average computation time to calculate shadow free images. Our PCA based method achieves higher performance with the higher accuracy over the entropy-based method.

Overall, our method shows better accuracy than the prior method with three measures out of the tested four different accuracy measure (Table 4.2). In terms of the F-measure, our method achieves 2% point higher accuracy over the prior, entropy based one. Figure 3.7 shows result samples of two tested methods. As can be seen, our PCA based approach achieves visually much better results over the prior entropy based approach.

We also compare computation time of different methods (Figure 4.1). While our PCA based approach shows better accuracy over the prior method, it performs on average 2.09 (up to 2.54) times faster than the prior one. This improvement is achieved mainly because our PCA based method finds the global optimal projection direction without testing many projections. Thanks to the higher accuracy and performance, we choose our PCA based method for computing illumination invariant images and use them for our road detection method.

4.2 Road detection evaluation

We measure accuracy of all the tested methods based on four different road detection measures. Table 4.3 shows detection accuracy of different methods tested with all the images in KITTI dataset [9]. Our method handles shadowed and non-shadowed road images well, and achieves the highest accuracy with all the tested accuracy measures. This is mainly thanks to the accurate estimation of shadow-free images and seed patches.

We focus on illumination invariant road detection, and thus we classify all the available images into shadowed and non-shadowed ones for a deeper analysis. For this process, we manually classify each image into the two sets;

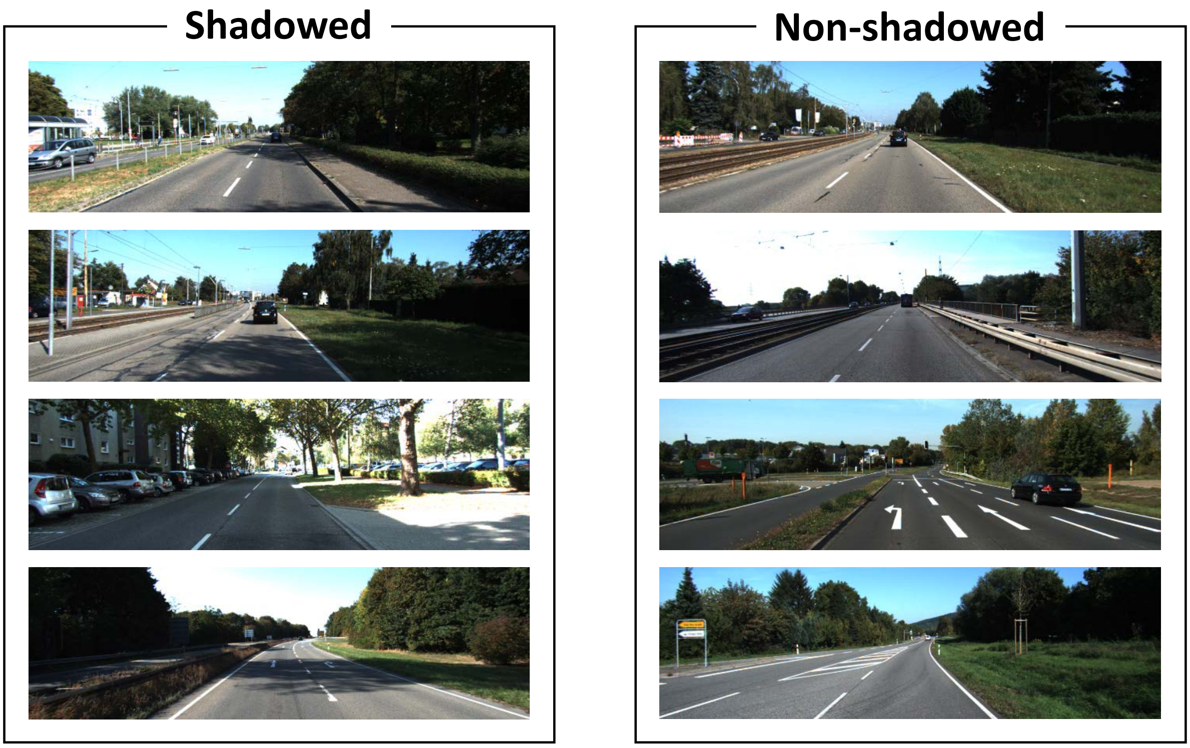


Figure 4.2: Sample images of shadowed and non-shadowed images.

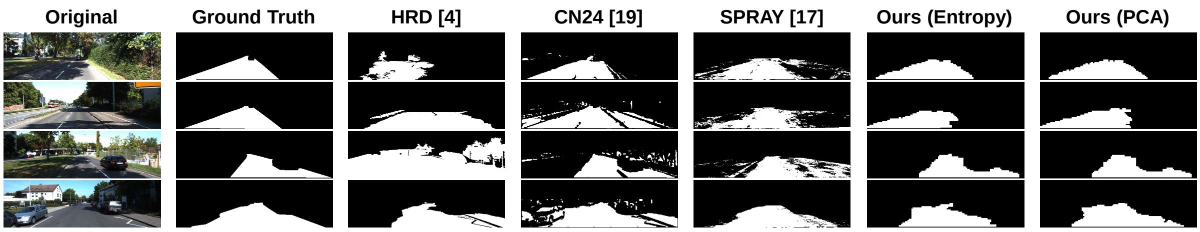


Figure 4.3: Results of different methods. Road and non-road regions in column 2 to 7 are marked with white and black, respectively.

shadowed one, when the image contains a reasonable portion of shadows. Otherwise, we classify them into non-shadowed. Examples in the two categories are shown in Figure 4.2.

Table 4.4 shows accuracy results of all the tested methods in shadowed road images. While all the methods has lower accuracy compared to ones acquired with all the available images including non-shadowed and shadowed images, our method also achieves the highest accuracy across all the tested measures.

Figure 4.3 shows example results of all the tested methods with the ground truth. Our method shows significantly higher accuracy in a range of 7% to 23% points over the tested methods across both shadowed and non-shadowed images. Our patch propagation method benefits from recovering the connectivity of roads by reducing the influence of illumination changes. On the other hand, HRD does not work well in shadowed images, and CN24 detects disconnected sidewalks. SPARY works better than others, but it takes much time to detect road area.

We also measure computation time of different methods. Our method is combined with PCA based minimization shows the highest computational performance to perform road detection with the highest accuracy. Our

Table 4.3: Detection accuracy on the whole benchmark

Method	R(%)	P(%)	F(%)	$\hat{g}$ (%)	Time (s)
HRD [5]	80.96%	61.86%	65.29%	51.59%	82.467
CN24 [10]	83.03%	74.33%	77.00%	64.91%	60.516
SPRAY [11]	80.64%	77.81%	77.81%	64.95%	477.072
Ours	**88.15%**	**79.59%**	**81.52%**	**70.49%**	**2.006**

Table 4.4: Detection accuracy on shadowed road images

Method	R(%)	P(%)	F(%)	$\hat{g}$ (%)	Time (s)
HRD [5]	77.18%	60.81%	63.01%	48.85%	82.467
CN24 [10]	81.33%	75.31%	76.82%	64.90%	60.516
SPRAY [11]	79.50%	76.56%	76.54%	63.12%	477.072
Ours	**88.13%**	**78.37%**	**80.72%**	**69.53%**	**2.006**

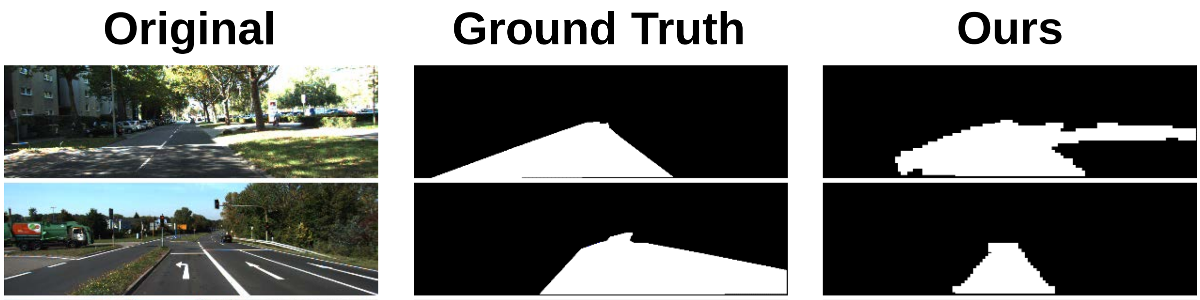


Figure 4.4: Hard cases for our method.

current implementation is based on non-optimized MATLAB codes, but takes on average 241 ms to process one image at the full resolution (1241 $\times$ 376). On average, our method achieves 342 times, 251 times, 1929 times higher performance than HRD, CN24, and SPRAY, respectively. The fast performance of our method is achieved mainly thanks to the PCA based shadow-free space generation method and the efficient patch based approach without relying on complicated optimization process.

We also look at how much improvement each component of our method contributes. We already mentioned that our illumination invariant space results in 2% point higher accuracy over the prior entropy method. While using our illumination invariant space, we also compare our seed selection method over the prior, heuristically generated patches in the bottom middle area of images. Our seed selection achieves 2% point higher accuracy than the prior heuristic selection. Finally, we check accuracy and performance of our patch based method over the pixel based one. Compared to the pixel based one, our patch-based method achieves 4% point higher accuracy and 22 times faster than the pixel-based method. These results demonstrate usefulness of each component of our method.

4.3 Discussions

Our method shows high accuracy and runtime performance with the tested benchmark. We have found, however, that there are hard cases for our method. (Figure 4.4). In some cases, over-saturated and under-saturated areas can be hard to discern in shadow-free images, resulting in overgrowing the road area. Note that this problem occurred and was not fully solved even in many related prior methods. Also, when we have strong road lane marks, they may block our patch propagation. Nonetheless, our method can still identify the ego lane area ahead of the vehicle.

Chapter 5. CONCLUSION & FUTURE WORKS

In this paper, we have proposed an efficient, yet accurate road detection method using a monocular camera. Our method first computes illumination invariant space for removing shadows and other illumination changes on road area from an input RGB image. We then perform efficient patch based techniques for identifying seed patches and propagating them to cover the entire road. Experimental results showed that our method achieves higher accuracy for road detection regardless the presence of shadow compared to three state-of-the-art approaches. Furthermore, our method runs more than two orders of magnitude faster over the tested methods. These results indicate that our method takes one step closer towards real-time road detection with the monocular camera.

As future work, we would like to address hard cases for our method, especially by utilizing other road information such as lane marks and road boundary. This approach can help our method to propagate patches in a more accurate manner by considering these road signs. Finally, we would like to optimize the performance of our algorithm to handle real-time 60 fps video input images.

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Summary

Illumination-Invariant Road Detection for Monocular Camera via Patch Propagation

현존하는 일반 차량과 자율 주행 차량의 징검다리 역할을 할 수 있는 운전보조장치(ADAS, Advanced Drive Assistance System)의 개발은 다가오는 차량의 자율 주행 시대에 대비하여 필수적이다. 운전보조장치는 여러 첨단 센서와 지능형 영상 장비를 통해 전방 충돌회피, 차선이탈경고, 사각지대 감시, 향상된 후방감시 등의 기능을 한다. 이러한 기술 중 전방 충돌회피 및 주행 가능한 도로 영역의 식별은 실제 차량이 주행함에 있어 가장 주요한 문제 중 하나다.

본 논문에서는 차량 전면부에 장착된 카메라를 통해 비전 기술을 사용한 조명 불변의 효과적인 도로 영역 탐지 방식을 제안한다. 정확한 도로 영역을 탐지하는 것은 도로의 이미지상 특징이 주변 환경의 조명에 큰 영향을 받기 때문에 어려운 문제이다. 이 문제를 해결하기 위해, 우리는 입력으로 들어오는 RGB 이미지를 주성분분석(PCA, Principle Component Analysis) 알고리즘을 사용하여 밝기에 무관한 흑백 이미지로 변환한다. 본 연구를 통해 변환된 흑백 이미지에서 도로 영역은 유사한 텍스쳐 특징을 가지고 이 영역들은 서로 연결되어 있다는 점에 착안하여 이에 기반한 강인한 패치 전파 알고리즘의 도로 탐지 방식을 제안한다.

제안한 방식의 타당성을 검증하기 위해, KITTI banchmark 라는 상용 벤치마크 데이터를 사용하여 기존에 사용되고 있는 세가지의 도로 탐지 방식과 비교한다. 패치 전파 알고리즘을 사용한 도로 영역 탐지는 실험한 다른 방식들에 비해 7%   23%의 높은 탐지 정확도를 보이며 매우 빠른 검색 속도를 보인다. 이러한 결과는 조명 불변의 흑백 이미지가 가지는 정보의 간결성과 제안한 패치 전파 알고리즘에 의해 이미지가 가지는 잡음을 다소 처리하게 되어 얻어졌다,

감 사 의 글

석사과정 동안 연구에 집중할 수 있도록 열과 성을 다하여 지도해주시고, 앞으로도 많은 도움을 주실 윤성의 교수님께 가장 큰 감사를 드립니다. 석사 기간 동안 동고동락한 SGLab 연구실 동료 분들에게도 감사의 말을 전합니다. 논문 쓰는 동안 조언을 해주셨던 재필 형, 동혁 형, 연구 아이디어에 많은 도움을 주신 웅직 형, 현철 형, 용선, 명배, 민철 형, 프로젝트를 하며 도움을 주셨던 윤석 형, 수민 누나, 영어 대화에 용기를 준 Pio, 수업을 들으며 도움을 주셨던 정수 형, 병윤, 그리고 논문 작성에 있어 큰 도움을 줬던 재형. 모두에게 감사의 말을 전합니다.

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