I-008

Road Crack Detection for Making Complex Road Surface Drivable Functions

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***Abstract*— This paper presents an image processing based automatic road crack detection method to develop complex road surface drivable functions for vehicles. First, the road areas which include cracks are extracted as crack images regarding the pixel variance of the road image. Then cracks are extracted from crack images by introducing a method on discriminant analysis. According to experiments using different road images, the new proposal is effective in detecting road cracks.**

Keywords*— *complex road surface; crack detection; image sample variance; discriminant analysis

I. Introduction

The vehicle technology has been invented several decades ago and extremely fast development has been achieved. Car industries and some Universities in the world have developed vehicles focusing different directions such as environment friendly vehicles and easy drivable vehicles. For example, it is common to see hybrid vehicles(HV) on the roads in many countries. The fuel usage of some counties is getting decreased due to the significant popularity of HV. As a parallel technology, electric vehicles(EV) are also getting popular little by little and more development can be expected within several years.

On the other hand, intelligent transportation systems(ITS) have also been proposed to reduces the traffic problems such as accidents and traffic jams. Most of ITS have been designed by applying information technology (IT) which have also been achieving significant developments in last few decades. ITS technologies can roughly be divided into two main categories as driver assistant systems and autonomous vehicles. Driver is supported detecting internal and external information by vehicle in the driver assistant systems, and all the decisions regarding to driving is made by vehicle detecting the same information in the autonomous driving. Many studies have widely been conducted to that information detection and most studies detect internal and external information of the vehicle installing the sensors and cameras on the vehicle. Some examples of ITS can be introduced as: car navigation, traffic light and traffic sign recognition[1], obstacle detection[2], pedestrian detection[3], vehicle to vehicle communication[4], infrastructure to vehicle communication[5], and so on. Many driver assistant systems have already been applied in the modern vehicles. However, autonomous vehicles are not commercially available in the market yet. Anyhow, with the reliable and durable ITS developments, autonomous vehicles can be expected to available in the market to buy in the near future. But, well smoothed smart roads would also be necessary to drive an autonomous vehicle, it would not be driven under the complex road conditions.

The above mentioned all the technologies have been developed assuming that the vehicle is driven under smoothed road conditions. When we look at the world road development situation deeply, bumpy roads can be seen in many developing regions. The reason is that those countries are not economically rich enough to spend money on road developments. The expenses of road constructions are also very high. But, to develop those regions, transportation is very important factor and vehicles those are possible to drive under complex road conditions are also necessary.

Even the roads are well constructed, roads deform easily due to the natural disasters such as earth quake, flood and typhoon. After or during a natural disaster, transportation is extremely important to rescue people, and send necessary good for the people at the disaster areas. But, the vehicles around us cannot be used for these purposes if the roads are damaged. For a recent example, the earthquake occurred at the northern Japan in year 2011, the rescue process was seriously delayed due to the road damaging since rescue teams could not reach to earthquake and tsunami hit areas smoothly.

We conduct studies to develop functions for vehicle to make it easy to drive under complex road surface conditions. Here, cracks and obstacles in the road surface are detected by installing cameras and sensors on the vehicle, and vehicle movement is controlled following that information. In this paper, we focus the crack detection problem and propose a method for detecting them by processing the images from on-vehicle cameras.

Crack detection is an interesting computer vision problem and some studies can be seen in the literature [6][7]. In those studies, the basic differentiation of normal road surface and road crack is conducted using the discriminant analysis (DA). But, the threshold given by DA, depended on the road surface color, size of the image and road texture, as a result, robust differentiation cannot be conducted. Thus, in this paper, a new robust method for detecting road cracks, regardless of them is presented by applying image sample variance and discriminant analysis together. Here, first image areas belong to normal road surface and crack road surface are roughly distinguished by using the image sample variance. Then, cracks are extracted further processing the image area belongs to crack road surface. The new proposal was tested capturing the images by an on-vehicle camera. According to the tests, the new proposal is effective for the desired crack detection.

This paper is consisted of five sections to present the entire project work. Section 2 mainly describes about the structure of the vehicle functions which make it easy to drive under complex road conditions. The proposed road crack detection method for developing above mentioned functions are presented in the section 3 and the experimental results of the proposal can be found in the section 4. Finally, the section 5 concludes the paper introducing some future works as well.

II. Complex Road Surface Drivable Functions

We develop functions for vehicles which make it easy to drive under complex road conditions. At the beginning, those functions are tested using small robot type vehicles. We focus two types of functions as vehicle speed controlling functions and vehicle flying functions. Figure. 1 illustrates the basic structure of the above mentioned both functions.

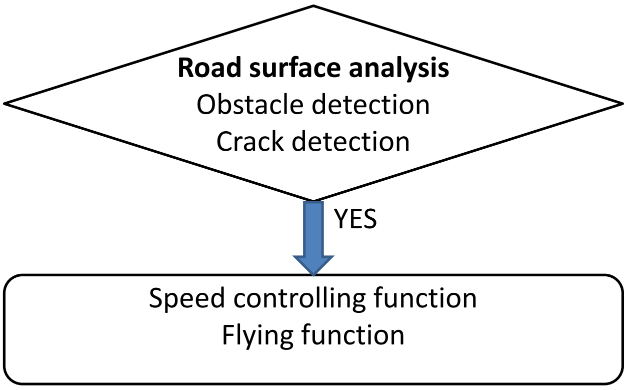

Fig. 1. Basic structure of speed controlling and vehicle flying functions.

A. Speed Controlling Function

As Fig. 1 illustrates, vehicle speed is controlled to avoid or move over obstacles and road cracks. If the vehicle cannot avoid obstacles and cracks, then vehicle is automatically stopped. This speed controlling can be used as a driver assistant system and they can also be applied in autonomous driving vehicles. At the basic step, we develop this function by using small robot type vehicles.

B. Flying Functions

In the speed controlling function, if the obstacles or road cracks are too larger vehicle automatically stop moving. We focus to avoid stopping by adding some flying functions to vehicle. This kind of vehicle is called as autonomous flying vehicle(AFV). Here, at the beginning steps, we plan to develop a small type robot which includes moving and flying functions.

To develop above mentioned functions, road surface analysis is very important. Here, this analysis is conducted to detect the obstacles and road cracks. Many studies have been conducted for obstacle detection problem. However, not so many studies are in the literature for crack detection problem. Thus, this paper mainly focuses on crack detection problem.

III. Road Crack Detection

There are some studies can be seen in the literature for road crack detection[6][7]. In these methods, basic differentiation of normal road surface and road crack is conducted using discriminant analysis. As mentioned above, only applying discriminant analysis does not work well in some situations. Thus, in this paper, a new robust method for detecting road cracks is presented applying image sample variance and discriminant analysis together.

Figure 2 illustrates the main processing flow of new proposal. First, road image is smoothed and then gray scaling process is also conducted. The gray scaled imaged is processed to extract the road crack areas. In this paper, the image area that includes cracks is called as crack image. By processing the crack image (I_c), the road cracks are detected. Each processing step is detailed in the next sub-sections.

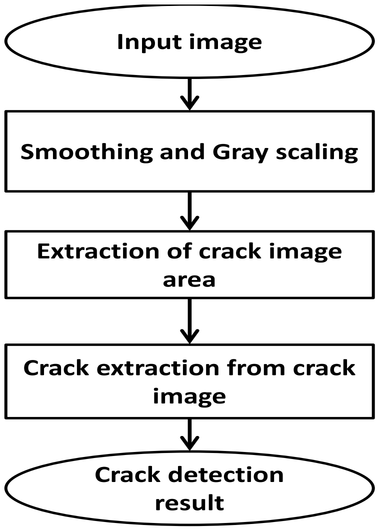

Fig. 2. Main processing flow.

A. Smoothing and Gray Scalings

At the beginning step, road image is smoothed using bilateral filter and medium filter. Bilateral filter is able to strengthen up the crack edges while removing the noises.

(a) (b)

Fig. 3. Smoothing and gray scaling, (a) An example of road image inclucding cracks, (b)Results of smooting and gray scaling.

After applying the bilateral filter, again road image is smoothed by applying the medium filter. With the medium filter, crack edges can be smoothed while removing the noises. The main reasons for smoothing by applying above mentioned both filters are to remove noises as much as possible preserving the crack edges. In the next processing step, crack image area is extracted by image sample variance. Noises cause errors in that crack image extracting. After smoothing processes, gray scaling process is conducted. Figure 3(a) illustrates an example of road image including some cracks and Fig. 3(b) illustrates the results of smoothing and gray scaling processes.

B. *Extraction of Crack Image Areas*(I_c)

After gaining the gray image, the crack regions are extracted by calculating the sample variance of the image. Road surface has almost a constant color, but color differences appear in the case of that cracks are in the road. Thus, the pixel variance of the normal road surface differ from one includes cracks. The image area which includes cracks is extracted from the road image on this feature. Figure 4(a) and (b) illustrate the examples of smoothed gray-scaled crack and non-crack images respectively, and their variance calculation for each pixel is illustrated in the Fig. 4(c) and (d) respectively. Here, lowest variance is indicated by black and highest variance is indicated by white and in between them variance is indicated by gray scale levels. The sample size for each pixel is 15×15pixels and reference pixel is set as midpoint of the sample. This is commonly used image sample variance calculation, the variance for each pixel is calculated.

However, calculating sample variance for each pixel is time consuming. In this paper, we calculate the sample variance for each sample, not for each pixel. In the other words, separated image sample variance calculation is conducted. Equation 1 illustrates the common equation for calculating the variance of certain number of data. Here, n and $\bar{x}$ indicate the number of data and average value of the data respectively. Equation 2 illustrates the conversion of Equation 1 to achieve variance of separated image sample ($\sigma_s{}^2$) calculation.

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad (1)$$

$$\sigma_s{}^2 = \frac{1}{s_w \times s_h - 1}\sum_{i=1}^{s_w \times s_h}(X_i - \bar{X})^2 \qquad (2)$$

Let, width and height of the sample be s_w and s_h respectively in pixel unit, therefore, number of pixels inside a sample $= s_w \times s_h$ (see the Equation 2). $\bar{X}$ means the average of pixel values of a separated sample. Figure 4(e) and (f) illustrate the calculated image sample variance for separated samples of the images illustrated in the Fig. 4(a) and (b) respectively. Here, lowest variance is indicated by black and highest variance is indicated by white color and in between them variance is indicated by gray scale levels. As Fig. 4(e) illustrates, crack image areas take high variance values and non-crack image areas takes low values. The crack image areas are extracted from road images following this feature. Figure 5 illustrates those sample values on a graph.

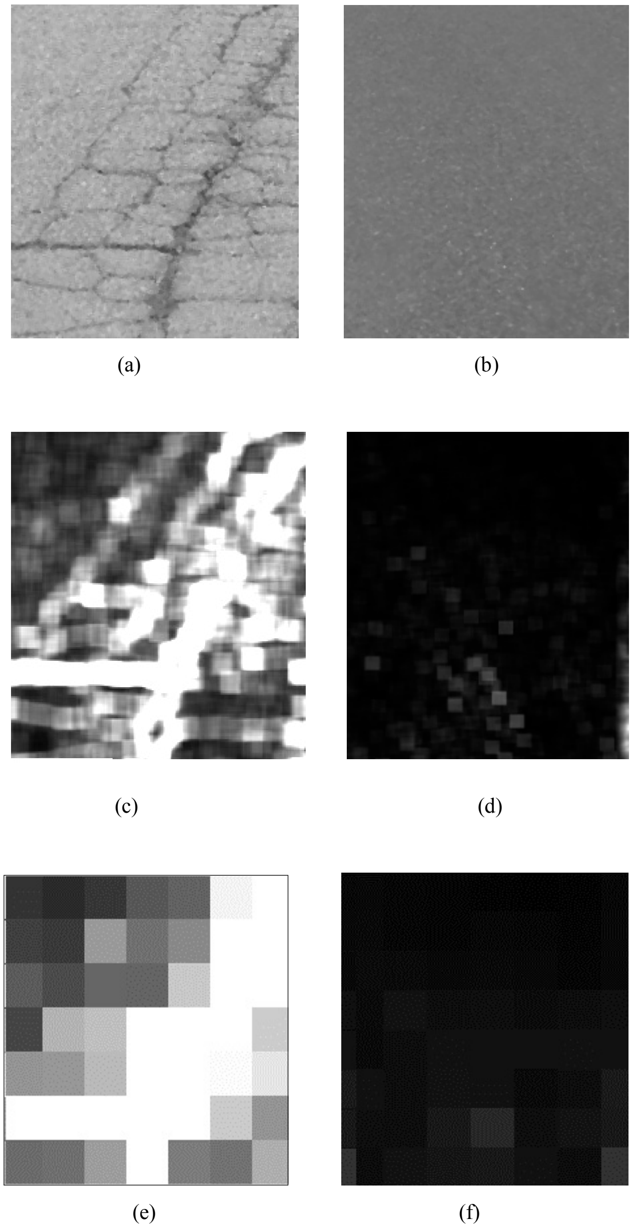

Fig. 4. Calculation of image sample variance, (a) An example of gray-scaled and smoothed crack image, (b) An example of gray-scaled and smoothed non-crack image, (c) Sample variance calculation of (a) for each pixel, (d) Sample variance calculation of (b) for each pixel, (e) Sample variance calculation of (a) for each samples, (f) Sample variance calculation of (b) for separed samples.

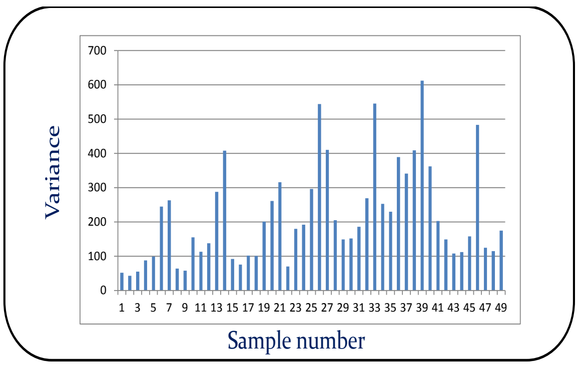

Fig. 5. Sample variance distribution.

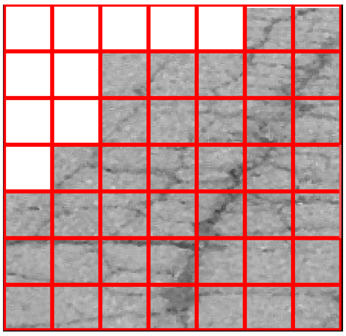

Fig. 6. Crack image are extraction(Non-crack area is indicated dy white color).

A threshold (th) is needed to distinguish the samples those include cracks (I_c) and those do not. In this paper, this threshold is decided considering the mode ($M(o)$) of the sample variance values. Here, maximum sample variance value (V_{max}) and minimum value (V_{min}) values determined. To calculate $M(o)$, C number of classes is defined in between V_{max} and V_{min} following the equation 3.

$$\frac{V_{max}-V_{min}}{C_w} = C \tag{3}$$

C_w: width of a class.

The th is decided following the equation 4.

$$th = M(o)_u + C_w/2 \tag{4}$$

$M(o)_u$: Upper limit of $M(o)$

Figure 6 illustrates the approximate crack image area (I_c) extraction results of the image illustrated in the Fig. 4(a). Here, white samples are regarded to road surface without cracks and other samples are regarded to cracks.

However, road image parts those include road lines, road characters and arrow road signs can also be detected as I_c with this idea. We, first recognize those objects on the road using conventional studies. Then, crack detection is conducted. In this paper, crack detection problem is only presented.

C. Crack Extraction

After extracting a crack image area from a road image, cracks are extracted by further processing crack image area. Here, all the images samples (sampled for image variance calculation) those include cracks are used for processing. Cracks are extracted from each sample by applying the discriminant analysis which is same as Otsu's binarization method [8].

In the discriminant analysis, first image sample is divided into two classes and then calculate variance within two classes (σ_W^2) or the variance between two classes (σ_B^2) following the Equation 5 and 6 respectively.

$$\sigma_W^2 = \omega_1\sigma_1^2 + \omega_2\sigma_2^2 \tag{5}$$

$$\begin{aligned}\sigma_B^2 &= \sigma^2 - \sigma_W^2 \\ &= \omega_1(\mu_1-\mu)^2 + \omega_2(\mu_2-\mu)^2 \\ &= \omega_1\omega_2(\mu_1-\mu_2)^2 \end{aligned} \tag{6}$$

where $\mu = \omega_1\mu_1 + \omega_2\mu_2$

The weights (ω_{1_i} and ω_{2_i} , i = 1~256) are the probabilities of the two classes separated by t_i, i = 0 ~ 255). The threshold (t) for extracting cracks can automatically be determined when σ_B^2 takes maximum value or σ_W^2 takes minimum value. But, in the implementation, calculation of σ_B^2 is quicker, since it only includes calculation of probabilities and average values. For this reason, σ_B^2 is used to gain the threshold. Following the threshold, the cracks are indicated by black pixels and other area is indicated by white pixels. To smooth the detected cracks, morphology operation is applied, here, image is eroded once and then dilated once

IV. Experiments

The new crack detection proposal was tested cpaturing the appropriate images to confirm the its' effectiveness. The experimental environment and results are presented in the next sub sections.

A. Experimental Environment

The road images those include cracks were taken at different road surfaces. To confirm the false positive rate, the road images without cracks were also taken. The images were taken by using an on-vehicle camera driving the vehicle in the day time. The 150 road images those include cracks and 150 road images without crack were prepared for the experiments.

All the experiments were conducted on a computer having configuration of Intel(R) CoreTM i7, 3.00Hz and 8.00GB RAM.

B. Results

Figure 7 illustrates some examples of crack detection results. Here, the left images are original images and right images are crack detection results. The cracks on the different kinds of road surfaces could be detected effectively. However, some of very tiny cracks cannot be detected effectively. In the fourth example (from the top) of the Fig. 7, some tiny cracks were not detected effectively, since they are very tiny and are not clearly appeared due to installing angle of the on-vehicle camera. This problem would be able solve by conducting the projective transformation. The detection rate is 94% according the experiments conducted using 150 crack images, including total of 177cracks on them. The false positive rate is 5%. We conducted experiments to calculate the false positive rate using 150 road mages without cracks. Some false positives were also shown in crack detection using crack images as well. The cracks on the different roads having multiple surface colors can be detected with the new proposal.

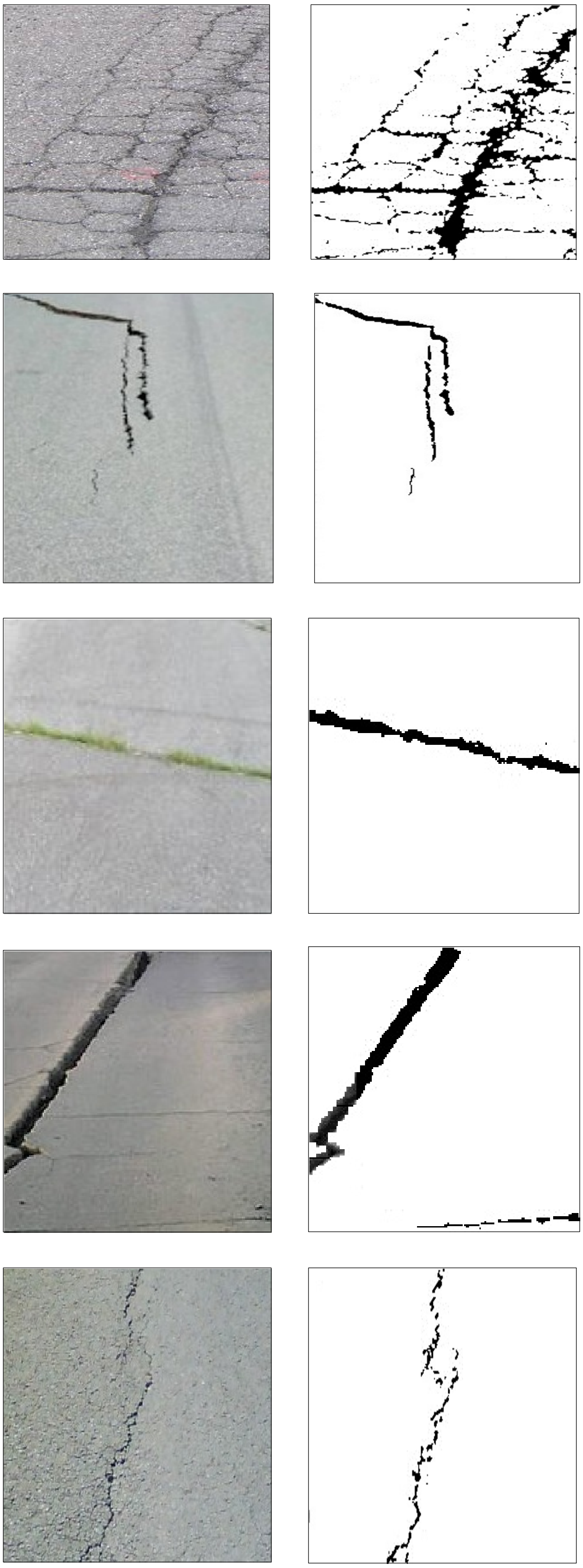

Fig. 7. Exprimental results *(Left:original images, Right: Crack detection)*

Figure 8 illustrates an example of crack detection of the top left image in the Fig. 7 using a conventional method [6]. Here, first image is smoothed by Anisotropic Diffusion and cracked are detected by discriminant analysis. That method is not effective when so many cracks are in the image. However, new proposal is very effective in the case of that so many cracks are in the road.

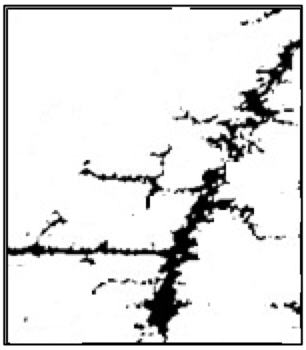

Fig. 8. Crack detection result of the image illustrated in the Fig. 3(a) by conventional method.

Development of functions for driving under the complex road surfaces using the proposed crack detection method will be the main future work of this study.

V. CONCLUSIONS

This paper proposes a road crack detection method to develop vehicle functions for driving under the complex road surfaces. First, the road areas which include cracks are extracted as crack images regarding the pixel variance of the road image. Then cracks are extracted from crack images by introducing a method on discriminant analysis. According to experiments, new proposal showed high detection rate, confirming its' effectiveness.

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