Application of Automatic Image Recognition in Pavement Distress for Improving Pavement Inspection

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Abstract

High-frequency road inspection is the key to maintain all levels of road quality and to avoid casualties caused by bad road in Taiwan, inspections depend on open contract manufacturers, and they provide high-frequency road inspections and inspections of ancillary facilities, the inspection frequency is from one day to one week, according to the requirements of different agencies. However, the inspection equipment of the manufacturers and the inspection data lacks follow-up applications or numerical conversions, such as PCI, and cannot be applied to big data to enhance the long-term conservation of roads. This study uses existing road inspection methods and existing equipment to develop a back-end image recognition inspection software, hoping to improve the inspection efficiency by adding automatically identify damage, import it into the PCI values of ASTM D6433-16, and export the road quality in numeric. This study uses a traffic recorder and an imaging device as the main hardware, using the relationship between the image from the film and the speed of the car to obtain the image of the complete road, using SLIC Superpixels algorithm, which with two stages of image grouping, the pavement damage in the image will be selected. Using damage classification to define patches, potholes, longitudinal cracking, and crocodile cracking, then import into PCI for calculation. The results of this research has good conformity characteristics with semi-automated pavement inspection software, by adjusting the relationship between image capture frequency and car speed, it can develop a comprehensive pavement inspection, although the effectiveness must be reduced due to the depth measurement limit of 2D images, and less meticulous than traditional manual inspections, it is closer to the manual detection than the current semi-automation, the labor and time costs can be reduced for PCI measurement. The future hopes to deepen the development of imaging devices and artificial intelligence learning, to enhance the effectiveness of this software.

Pavement Distress Image Recognization Superpixel

1 Introduction

The Construction and Planning Agency Ministry of the Interior of Taiwan planned to use the pavement condition index (PCI) regulated by ASTM D6433-11(Miraliakbari) as the major index for monitoring the pavement condition (Construction and planning agency ministry of the interior, 2003). However, PCI inspection is very time consuming and laborious and it is hard to execute and promote the current method. The current inspection method relies on the contractor inspections, they record pavement distress type in PCI numerical format. But the result is very rough, which makes it hard to apply their inspection data to calculate the PCI value or to make a long-term pavement maintenance plan. Therefore it is very necessary to improve the current pavement inspection method(Futao Zhu, 2014). The objectives of this study are as the followings: improve the road inspection method by using superpixels automatic distress recognition method, develop a pavement distress recognition software based on superpixels method, using clustering to extract distress from an image, develop an automatic road inspection software which can capture and analyze sufficient images to cover the complete pavement, and compare the cost and efficiency with traditional manual pavement inspection, semi-automatic inspection method, and automatic inspection method. The current road inspection method is using a semi-automatic method developed by National Central University, by selecting the distress with visual inspection, it relies on the captured images of which the capturing spacing is 25 m, and a training engineer input the captured images then select the severity of the distress, then the software calculates the distress quantity and the PCI value every 100 meters, this method could process the grayscale of image pixels and set the thresholding value from average grayscale of every pixel or segments in the image and extracts the distress, (Hui Wei, 2017), however, it needs other image processing techniques to extract the distress from traffic marking, shadow, and corrupted image. The disadvantage of this method is that it ignores other information from the original image and only process the grayscales after applying the thresholding filter(Miraliakbari; Gavilán, 2011). It is hard to remain the distress and remove the corrupted at the same time, especially when the pavement image is very similar, this method needs to try many different filtering to extract better distress image, therefore, it is hard to make an automatic inspection through this method(P. Bibiloni, 2017).

2 Pavement Image Recognition

This research aims to improve the quality of contractor's road inspection method, the method contractors using is very simple and lacks the modern technology to upgrade, the equipment for road inspection includes inspection vehicle, driving recorder and GPS vehicle trajectory recorder. This study focuses on developing automatic pavement distress identification software that automatically identifies the distress from captured road images. To achieve the goal, there are two concepts necessary to be conquered: one is to capture the image from the road then process it, and the other is how to analyze the captured image. There are three main objects for developing the image capturing system: image processing and camera calibration, setting the image capturing system and image pixel calibration turning the pixel size into real parameter size. SLIC superpixels algorithm is the main analysis method in this study and there are three objects in this concept: lab pixel analysis, k-means pixels clustering and distress distinguish. Compared to the traditional image binary thresholding method, superpixels analysis method identifies the pavement distress more efficiently. The flowchart is shown in Fig.1.

2.1 Equipment and Database Collecting

There are three cameras used in this study, two of them are inexpensive dash cam and the other is a higher level sports camera. RadiQ R32 and ONPRO GT-Z01 are the dash cam models used to develop the automatic image analysis program, RadQ R32 has better performance in image sensing and resolution, while it lacks the GPS system which is equipped by the ONPRO GT-Z01. To develop the software, this study collects data from four kinds of roads, the freeway with the highest speed limit and no motorcycle allowed has the best quality, the freeway allowed heavy motorcycle has the second best, the Provincial Road is similar to the City Road but the speed limit is higher has the third best quality, the City Road has the worst road condition in the collected data. With the advantage of modern camera technology, video recording resolution is also highly improved. To inspect the road completely, this research first records the pavement condition, the video is displayed in consecutive images which are called frames, and the appearance frequency of frames is expressed in frames per second. The human visual system can process 10 to 12 images per second and perceive them individually, while higher rates are perceived as motion, it is very common to see 30 fps to 240 fps in modern camera and the dash cam usually takes the video at 30 fps to 60 fps. Under the same fps, the driving speed would affect the distance between each image. Fig.shows the distance between the images at the different speed and fps, for instance, at the speed of 80 km/h and recording frequency at 15 fps, the space between images is 1.5 meters. To inspecting the whole road and save the calculation time, it is important to find out the least number of pictures that the system needs to run in every second to cover the

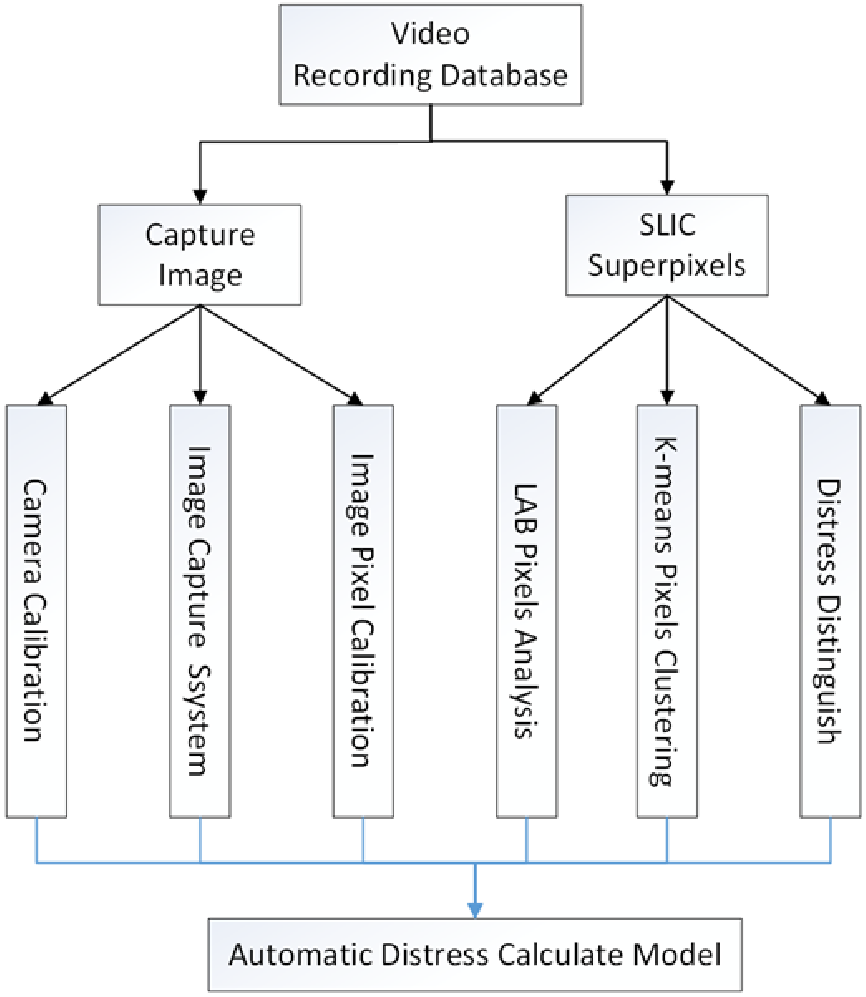

Figure 1: Flow Chart

entire road, for instance, it needs 6 images to calculate at 80 km/h and 4 images to calculate at 40km/h. In this study, it is assumed that the speed limit in National Freeway is 90 km/h, the speed limit in the urban road is 50 km/h and the width of the selection area is 4 meters, to inspect the pavement completely and make the software works efficiently, the software calculates 6 images per second for the National Freeway and 4 images per second for the urban road.

2.2 Pavement Condition Inspection Application

This study has manually inspected Taiwan National Freeway No.3 section from 83 km to 89 km and some sections in the urban road, to get the true quantity and distress in the inspected part. Manual pavement condition inspection is the most accurate method but is time-consuming and laborious, therefore, traditional PCI inspection could only be conducted by taking samples of the road and take the PCI value to represent the road condition(C. Harriet Linda, 2011). Although manual inspection is not very convenient, the engineer can get 19 kinds of distress details including length and depth from manual inspection. National Central University has developed a semi-automatic pavement condition inspection method which an encoder is triggered every 20 m using a camera to capture the road image, and a system gets the image with GPS information. With the information and the image from the inspection vehicle, an engineer would distinguish the distress including the types, severity and the scope but excludes the depth from the image, the software then calculates the PCI based on the scope of the distress. This study compared the performance of manual, semi-automatic, and automatic pavement condition inspection method.

2.3 Automatic Image Recognition Developing and Image Preprocessing

The objective of this study is to develop an automatic pavement condition inspection software by using common equipment to improve the road inspection nowadays, a dash cam would be the most practical, but the captured images include many unnecessary parts for distress analysis, therefore, the images need to be preprocessed in the first place, which includes the camera calibration, analysis range selection, and image pixel calibration. To calculate accurate pavement condition index, getting the precise distress data of road is the key point, including the distress type, distress area and severity, therefore, the images captured from the video have to be calibrated according to the photography angles, photography altitude and the distortion of the image as shown in Fig.2 and Fig.3, once the image is calibrated, pixels of the image could represent the true distress area of the pavement.

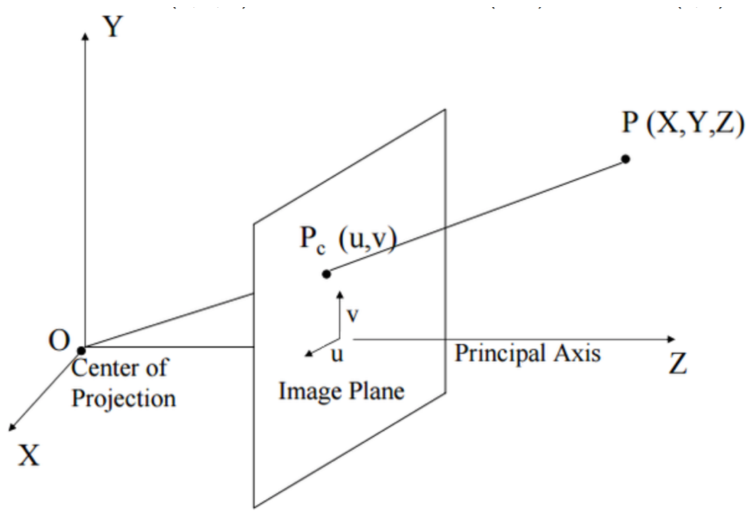

Figure 2: Camera Calibration Theories

$$\begin{pmatrix} u \\ v \\ w \end{pmatrix} = \begin{pmatrix} f & 0 & t_u \\ 0 & f & t_v \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

Figure 3: Calibration Matrixes

Set the coordinate system $\Omega_1(X, Y, Z) \in R^3$ in the center of the camera focus O, and Z-axis perpendicular to the object surface Π_1. The rays coming from the circle Γ_1 formed a skewed cone on the surface Π_1, whose boundary curve C can be expressed as follows:

$$(X - \alpha Z)^2 + (Y - \beta Z)^2 = \gamma^2 Z^2$$

Parameters α and β specify the skewness of the cone in X and Y directions and the parameter γ specifies the sharpness of the cone. Thus, if the distance from the camera focus to the object surface is denoted by d, the circle equation becomes $(X - \alpha d)^2 + (Y - \beta d)^2 = (\gamma d)^2$.

The camera coordinate system $\Omega_2(X, Y, Z) \in R^3$ is also centered in the camera focus, but its Z-axis is orthogonal to the image plane Π_2, and its x- and y-axes are parallel to the image axes u and v. Thus, the transformation from Ω_2 to Ω_1 is expressed by using the following rotation:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

where the vectors $[a_{11}, a_{21}, a_{31}]^T$, $[a_{12}, a_{22}, a_{32}]^T$, and $[a_{13}, a_{23}, a_{33}]^T$ form an orthonormal basis. Now, we can express in camera coordinates:

$$\left[(a_{11} - \alpha a_{31})\, x + (a_{12} - \alpha a_{32})\, y + (a_{13} - \alpha a_{33})\, z\right]^2 + \left[(a_{21} - \alpha a_{31})\, x + (a_{22} - \alpha a_{32})\, y + (a_{23} - \alpha a_{33})\, z\right]^2$$
$$= \gamma^2 \left(a_{31}x + a_{32}y + a_{33}z\right)^2$$

Let us denote the focal length, i.e. the orthogonal distance between O and Π_2, by f. Then, the intersection Γ_2 of C and Π_2 is expressed as:

$$\left(n^2 + k^2 - r^2\right) x^2 \ + \ 2\left(kl + np - rs\right) xy \ + \ \left(l^2 + p^2 - s^2\right) y^2 \ \ +2\left(km + nq - rt\right) x \ +$$
$$2\left(lm + pq - st\right) + m^2 + q^2 - t^2 = 0$$

where

$$\begin{array}{ccc} k = a_{11} - ta_{31} & n = a_{21} - sa_{31} & r = \gamma a_{31} \\ la_{12} - ta_{32} & p = a_{22} - sa_{32} & s = \gamma a_{32} \\ m = (a_{13} - ta_{33})f & q = (a_{23} - sa_{33})f & t = \gamma a_{33} f \end{array}$$

We notice from equation that the projection is a quadratic curve and its geometrical interpretation can be a circle, hyperbola, parabola, or ellipse. In practice, due to the limited field of view the projection will be a circle or ellipse. From this equation the center of the ellipse (u_c, v_c) can be expressed as:

$$u_c = \frac{(kp-nl)(lq-pm)-(ks-lr)(tl-ms)-(ns-pr)(wp-qs)}{(kp-nl)^2-(ks-lr)^2-(ns-pr)^2}$$
$$v_c = \frac{(kp-nl)(mn-kq)-(ks-lr)(mr-kt)-(ns-pr)(qr-nt)}{(kp-nl)^2-(ks-lr)^2-(ns-pr)^2}$$

In order to find out what is the projection of the circle center, let us consider a situation where the radius of the circle is zero, i.e. $y = 0$. Consequently, r; s, and t become zero, and we obtain the position of the projected point that is due to the symmetry of the circle also the projection of the circle center (u_c, v_c):

$$u_0 = \frac{(lq-pm)}{(kp-nl)}$$
$$v_0 = \frac{(mn-kq)}{(kp-nl)}$$

For non-zero radius ($\gamma > 0$) there are only some special case, e.g. the rotation is performed around the Z-axis ($a_{31} = a_{32} = 0$). Generally, we can state that the ellipse center and projected circle center are not the same for circular features with non-zero radius.

This study tried to develop an object-oriented programming software designed for different vehicles and different cameras. Therefore, finding a method to transform the pixel value to the reality parameter is the key to develop an object-oriented programing software. To transfer the parameter from pixel to reality parameter, it is necessary to build the image scale from objects with known length. Generally, the road facility especially the pavement is lacking such objects to transfer the scale. Therefore, the existing PCI software usually measure the angle, altitude and the pixel scale beforehand. Traffic signs, markings, and lights have been strictly regulated. Therefore, traffic marking could be the objects to get the image scale. There are two axes in the image necessary to adjust, the X-axis and Y-axis. The length of the traffic marking is 4 meters, and the width of the traffic lane marking is designed to fulfill the speed limit, e.g. the marking width of the lane of the national freeway is 3.75 meter. Using the length and width of known objects, this study derived the following formula to transform the image without the influences of the camera filming angle and filming height. The original image is showing the parallel lane marking which is influenced by the filming angle that extends would have an intersect point, therefore, the formula1 transforms the x-axis of the image into disjoint parallel lines. X-axis transform:

$$F\left(x\right) = x \cdot \left(1 + \frac{(x_0 - x_1)}{Y_0}\right) \cdot y$$

x: The location of the pixel in x axis, x_0: The bottom x-axis location of the lanes marking, x_1: The top x-axis location of the lanes marking. Y axis transform:Using two sets of the label if l_0 = Unreformed pixel length, L1 = the first label length, L2 = the bottom of the second label y axis location.

$$L1 = l_0 \cdot N - \int_0^{L1} d_y$$
$$L2 = l_0 \cdot N - \int_L 2^{L3} d_y$$
$$L1 = L2 = Markinglength$$
$$Findl_0$$

Next is the assignment step, each pixel i is associated with the nearest cluster centers, as shown in Fig.4. This is the key to speed up the algorithm, limiting the size of searching region reduces the calculation time, while conventional k-means clustering would compare all cluster centers for every pixel. The searching region of this study is done in a region 2S × 2S around the superpixel center, as the CIELAB image shown, the image pixels would be assigned by the clustering cover, and once the clustering is finished, the following step is to adjust the cluster centers with the mean [L A B X Y] vector of the pixels belongs to the cluster, the cluster region could be considered as a new segment of the image. In conclusion, the software usually would cluster the image into 200 segments, then use the new segments image to execute 2nd phase K -means clustering, that would cluster the image into 3 groups and show in different colors. In the end, the software would recognize one of the colors as the distress, which depends on the area or the shape of the color. The above is the software computation process, and the new SLIC segment is utilized in the followings steps.

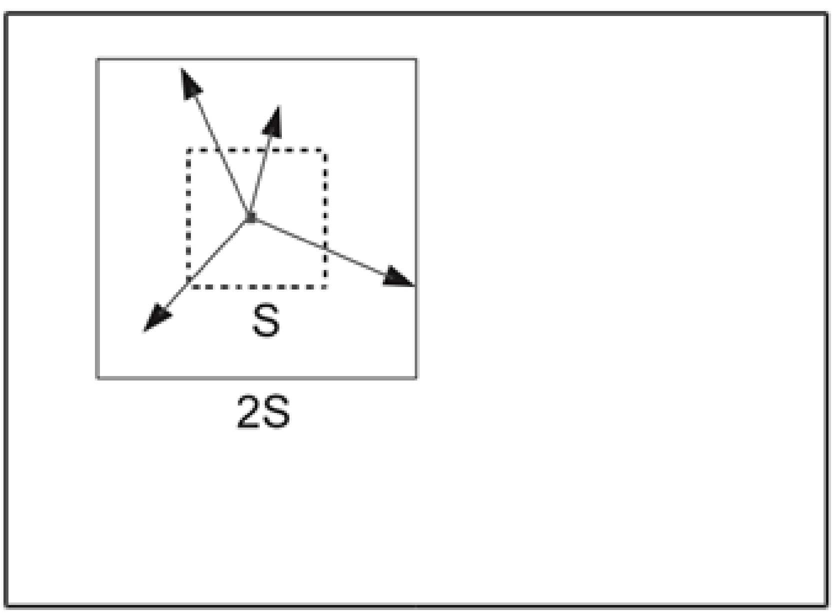

Figure 4: Searching Region

First of all, to speed up the computation time the distress image filter is necessary. The purpose of the image distress filter is to reduce number of images need to run through the following distress analysis parts and only calculate images with highly distress chance. As reference, the distress image filter is taking the RGB Standard Deviation (S.D.) of the image segments as the filter standard. According to the Sensitivity analysis for image database, taking the filter value as 20 as the summation value of the red color S.D., green color S.D. and the blue color S.D. could be efficient picking up the distress images from the database. Therefore, all images would go through the 20 S.D. filters, if the value is higher than 20 that would be taken as images with highly distress chance and then run through the following distress analysis; if the S.D. value is under 20 the software would take is as good condition pavement. Once images S.D. value bigger than two, the images would be clustered again. In this second-time K-means clustering the basic unit of the image would be the segments clustered by the first-time K-means clustering. The clustering would be according to the mean LAB color value of every segments and the N2 value that we want to cluster into. Generally, the N2 value would be 2 or 3 since the pavement is quite simple. Therefore, the purpose of the clustering is differentiating the distress parts and the good condition part of the road. The conclusion of this chapter is using the camera calibration to remove the distortion, image scale transferring from length known marking and selecting the analysis region to remove unnecessary parts of the image. These steps are the procedure from video to the analysis region image. Then the region would proceed the superpixels-automatic recognition method to extract the distress.

2.4 Distress Types Classify

Once the distress has been extract from the image, this study classifies them into Patching, Potholes, Alligator Cracking and Manhole detection. This would measure the distance, length, region of the distress and input the data into PCI. After selecting the distress parts through the software, the distress could be initially separate into large area distress e.g. patching and the cracking distress (Ying and Salari, 2010). To classify more kinds of the distress, the distress parts need to be further calculate. The Algorithm differentiates the distress through the ratio of the vertical distress segments and the horizontal segments. The crack connectivity checks will them follow the following steps: Scan the Status Matrix, block by block, and find the crack block giving it corresponding id number, add the length of the crack to the Length Table of the current branch, and check its eight neighboring blocks. If only one neighbor is a crack block, add the crack length into the corresponding items in the Length Table, move to the neighboring block, and continue the process. If there is more than one neighboring block as the crack block, and select one of them as the extension direction of the current branch and continue the extension check. Then save all the others into the Branch Candidate Table. If there is no crack block in the neighboring blocks, it would be taken as the end of the branch extension. If the branch length is shorter than threshold, then the branch would be ignored. Find the next branch candidate from the branch candidate table, and continue the extension check until the table is empty. The length of a crack is the sum of the length of all the branches contributing to that crack. Finally, if the length of the crack is shorter than a threshold, it is not considered to be a real crack. The threshold for crack and branch length would be changed by the window size. From the references, the threshold T_C is calculated as:

$$T_c = 1.8s$$

S is the size of the window. Cracks are classified into three types: longitudinal cracking, transverse cracking and alligator cracking. The type of a crack is determined by its angle with the horizontal axis (Ω) and the number of branches in the crack. Note that the angle is calculated according to the start and end points of each crack. If there are branches, no matter what angle it is, the crack will be considered a block type.

3 Result Analysis and Discussion

3.1 Pavement Inspection Recording Database

The data collection includes four kinds of the major roads in Taiwan. Since the objective of this study is to develop an automatic analysis of the road recording video without the equipment limitation such as specific camera type and the inspect vehicle type, the collected data were from different kinds of vehicle and Dash Cams. The normalization of the collected is relying on the image processing method and then analysis those normalized data.

3.2 Superpixels Reliability

The reliability of the superpixels application on the pavement detection comes out with the comparison with the semi-automatic image detection method. The semi-automatic way would select the distress region by human eye which is the current inspection method in Taiwan PCI inspection method since that comparing the semi-automatic distress region with the distress region from superpixels represents whether the automatic way could have the same performance with the current method. Fig.5(a) is an asphalt patching image which would be analysis through the semi-automatic distress inspection method and the superpixels method. First of all, selecting the patching area through human eye selection to be the real distress region and calculating the numbers of pixels in the region. The pixel number is 5557948 in the Fig.5(b) and the distress ratio is 39.26%. Fig.5(c) is showing the result of the superpixels analysis and the number of the distress is 14155776 and the distress ratio is 39.15%. The variables in the superpixels are the initial clustering number N1 and the second clustering number N2. The Table 1 is showing the accuracy in different N1 as the table show taking high clustering number would not have better accuracy since the noise would be also bigger and generally the accuracy is $\pm 2\%$ to the true value and the performance is better when the N1 is 800 and N2 is 2. But since the resolution performance in Dash Cam would be lower than the close shooting, therefore the N1 would take 100. From the comparison with the superpixels-automatic method and the semi-automatic method,

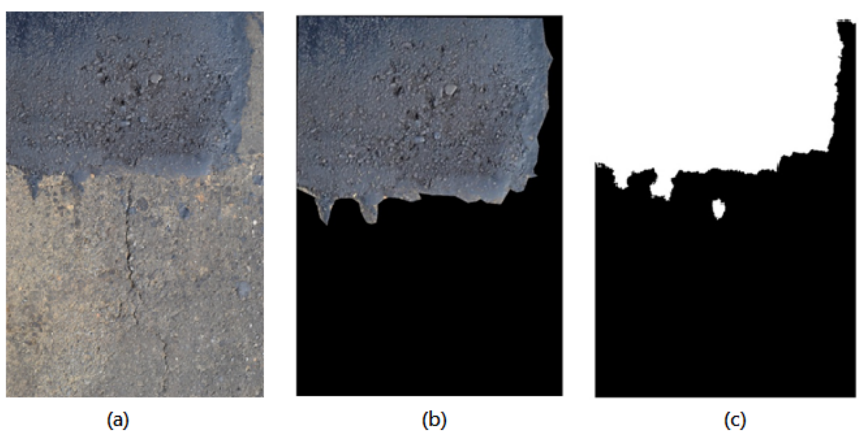

Figure 5: Distress Extracts from Superpixels

the results shows the N1 value has better performance and faster speed when the N1 value is smaller than 500 and in this study we would take 200 as N1 value.

3.3 SuperPixels Comparison

From the collecting-database, National Freeway No.3 Guanxi Section 83km to 89km which inspect through the manual inspection, semi-automatic inspection and automatic inspection. In this study, the objective

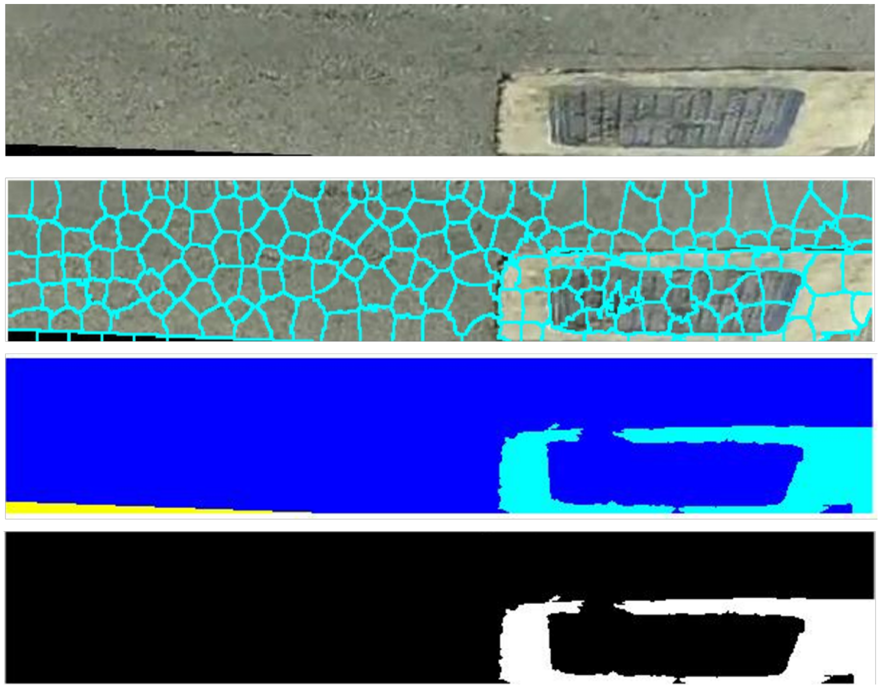

Figure 6: Superpixels Automatic Recognition Image

Pieces	Distress pixel number	Total pixel number	Distress pixel rate	Accuracy
300	4721480	14155776	0.34	98.97%
400	4836756	14155776	0.34	99.72%
500	5240733	14155776	0.37	98.81%
800	5139003	14155776	0.36	99.24%
1000	4951139	14155776	0.35	100.24%
1200	5076777	14155776	0.36	100.22%
1500	5179682	14155776	0.37	102.33%

Table 1: Reliability in Superpixels

is advancing the current road inspection method since that the first thing is making sure the image could completely show the condition of the road. The FPS of the film is 60 which mean the recorder could capture 60 images in one second and the spacing is 0.5 meter in the 100km/h driving speed. The length of the selecting area is 4m so it should analyze 15 images in one second. And the number of images would be 250 in one kilometer. The NCU Semi-Automatic Inspection Image Capturing spacing is 25 meters and the number of images would be 40. The quantity of the distress would be measured for all inspection methods. The following Table 2 would compare the quantity of distress and PCI values from different inspection methods. The result is better than the semi-automatic method since the software could get comprehensive road images and extract distress from them. From analyzing the 2nd Taiwan Provincial Rd. in Keelung, the distress detection numbers are different in different inspection methods. In this study, the distress number from manual inspection would be taken as the real quantity of distress comparing with the quantity from Superpixels automatic distress inspection and the NCU Semi-Automatic Inspection. Below is showing the quantity of Patching, Ravels, Potholes and Expansion Joints as shown in the Table 3. Superpixels automatic distress inspection has 91% of coincidence rate in Patching detection, 25% of coincidence rate in Ravels detection, 100% of coincidence rate in Potholes detection and 100% of coincidence rate in Expansion Joints detection. Since the image space in Semi-auto inspection is 25 meters, it could not detect completely distress.

	Manual	NCU Semi-Auto	Auto-Superpixel
Numbers of image		40pic/km	250pic/km
Pothole	8	3	7
Severity	5M+2H+1L	3M	7M
PCI	43	71	54
Accuracy		34.9%	74.4%

Table 2: Methods Comparison

		Patching	Ravels	Potholes	Expansion Joints
1.Man-eye	11		4	3	1
2.NCU Semi-Auto	5		1	1	1
3.Auto-Superpixel	10		1	3	1
Coincidence rate (1 vs 3)	91%		25%	1	1

Table 3: Coincidence Rate Comparison in 2nd Taiwan Provincial Rd

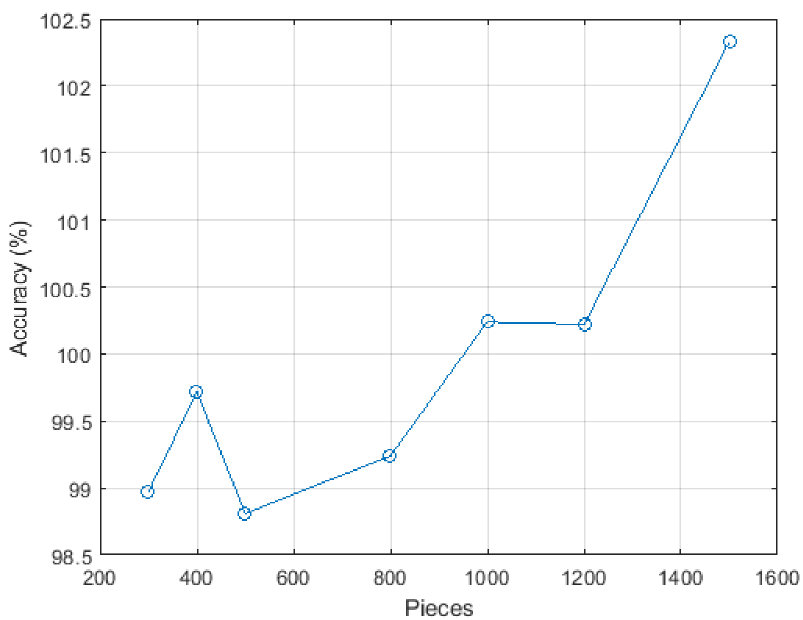

Figure 7: The accuracy of Superpixels

The Following Table 4 is showing the analyze result in 16km to 13 km of 31th Taiwan Provincial Rd inspection. The total number is showing that the number of distress inspect from the site, and the Superpixels automatic distress inspection could successfully find out 87.5% of Alligator Cracking, 83.3% of Weathering and Raveling, 77.8% of Patching, 66.7% of Potholes and 55.6% of Long/Trans Cracking. The following Table 5 is showing the distraction region comparison between the Superpixels automatic distress inspection

Distress Type	Alligator Cracking	Weathering & Raveling	Patching	Potholes	Long/Trans Cracking
Total	4	6	9	3	9
Check	3.5	5	7	2	5
	87.5%	83.3%	77.8%	66.7%	55.6%

Table 4: Detection Rate of Superpixels Automatic Distress Inspection

and the Semi-Automatic inspection which shows that the distress measuring in area has better extracting performance in this software since the resolution is not good enough to measure the width of cracking completely. In this study, five engineers would select the distress through the visual ways. And using the

Distress Type	1	19	11	13	10
Total	4	6	9	3	9
Check	3.5	5	7	2	5
	87.5%	83.3%	77.8%	66.7%	55.6%

Table 5: Superpixels-Auto comparing with the Manual Inspection

average distress makes the reproducibility of the automatic inspection method. The standard deviation (σ) of potholes is 0.3%, σ of patching is 2.71%, σ of trans/long cracking is 5.3 as shown in the Table 6.

Semi-Auto Selection							
	SA1	SA2	SA3	SA4	SA5	Avg.	
Potholes	6.2%	6.92%	7.08%	6.74%	6.56%	6.7%	0.3%
Patching	35.46%	33.18%	28.95%	29.66%	33.16%	32.08%	2.71%
Trans/Long Cracking	184.95	196.47	193.55	192.92	184.95	190.57	5.3

Table 6: True Value from Multiple Semi-Auto Selection

The distress quantity recognizes by the superpixels automatic distress recognize software is in 95% percent confidence level of the semi-auto selection software. The interval of the pothole is 6.1% to 7.3% and the Superpixels method is 6.34%, the 95% confidence level interval of the Patching is 26.76% to 37.40% and the Superpixels method is 37.26% and the 95% confidence level interval of the long/trans cracking is 180.19 to 200.95 and the Superpixels method is 181.75.

3.4 Software Introduction

In this study, Microsoft Visual C++ is the software to combine all different functions from Matlab including the video capturing system, image calibration, superpixels clustering, K-means clustering, distress classify and PCI value calculation. There are four steps need user to do, Step 1 is selecting the road inspection video; step 2 is camera calibration, select 4 points of the traffic marking and using image coordinate and the size known traffic marking to transfer the selecting area into reality scale since that the software could calculate the distress pixel into the reality size, the selecting model is shown on Fig.6. Step 3 is selecting the analysis area, user could select the area from the from the image and the software would cut the following image by the area and only analyze the selecting area by this step as shown on the Fig.9. After these three steps, user have to input the frame interval according the driving speed to cover the completely road. And input cutting number for the superpixels clustering which would usually take 200 and the Number for the

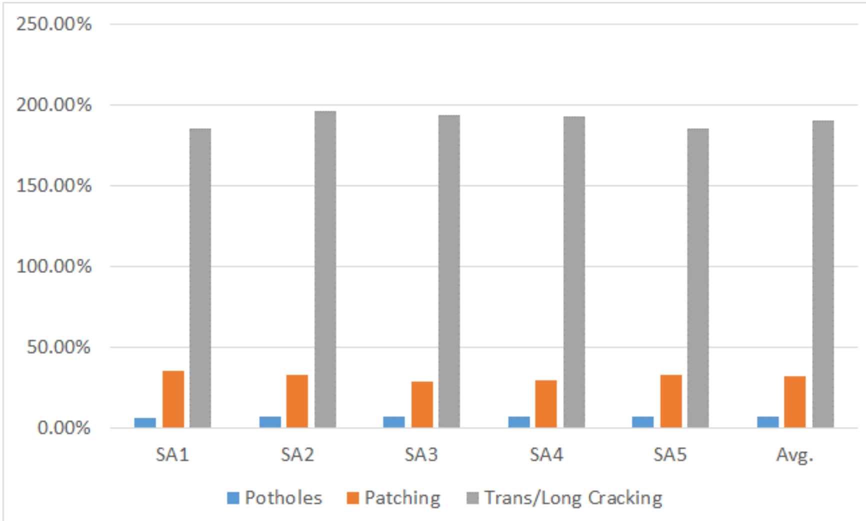

Figure 8: True Ratio from Multiple Semi-Auto Selection

K-Means Clustering which would always be 3. Then the last step is input the SD value for filtering the image from good condition road image and makes the software more efficiency.

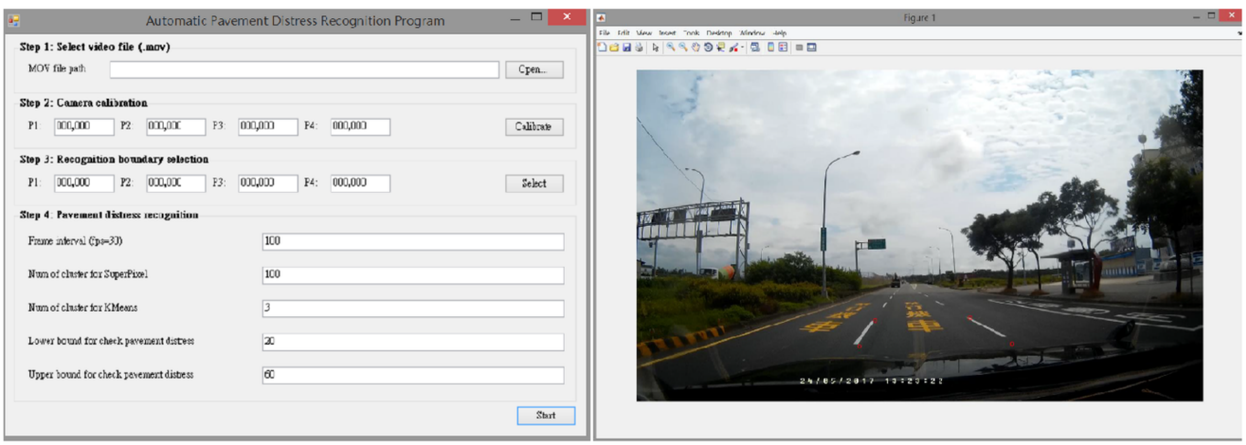

Figure 9: Automatic Image Recognition Software

4 Conclusion and Recommendation

Superpixels Automatic method has better performance than the traditional image binary method since it only need two setting parameters for image extraction without trying other methods and it could be a real automatic method for recognizing distress from the pavement inspection video. The software could get comprehensive road images through adjust the capture number from the film and the driving speed. This study would calculate 6 images in freeway assuming the driving speed is 90km/h and 4images in urban road assuming the speed is 50km/h, using the SD value to filter the distress pavement from good condition pavement to make the software more efficient and selecting the analysis region to remove unnecessary parts of the image. The Superpixels automatic image recognition in pavement distress has 95 percent confidence level with the semi-automatic distress recognition representing the software could replace the current method in the future. The result in Taiwan 31th Provincial Road inspection could match 85.7

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