REAL TIME IMAGE ANALYSIS OF LIVE CAMERA FOR DETECTION OF ACCUMULATED SNOW

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ABSTRACT

Surveillance of road surface conditions is essential to quality road management, especially in cases of snowfall. The area of snow coverage over the road's surface is particularly important. While some sensors exist for detection of snowfall such as microwave and thermography sensors, their high cost and immobility can make them prohibitive. On the other hand, a live camera is also a sensor that can judge the road surface state visually. Moreover, live camera can grasp a situation in-field and makes it easy to perform point deployment because of its comparatively cheap price. In Japan, a network of road cameras is already being monitored by eye. However, this is difficult and time consuming for people to perform continuously. Utilizing this automated camera network to detect road surface conditions for snowfall, image analysis is performed using discriminant analysis and branch condition logic based on the characteristics of intensity in image histograms. This algorithm shows positive results, although improvements continue to be developed.

1. PURPOSE

On expressways in Japan, the weather phenomenon responsible for most traffic stoppage is heavy snowfall. (Japan National Police Agency White Paper, 2010) Therefore, it is very important for road management to monitor road surface conditions in real time during winter. Conditions can be precisely monitored by microwave sensor, radiometer or road surface temperature sensor. However, the manufacture and installation of such sensors is prohibitively expensive. On the other hand, network cameras are significantly more affordable and an existing infrastructure is already in place for real time monitoring by eye. Since it isn't feasible to check so many images simultaneously for evidence of snow accumulation, an image recognition algorithm has been developed to solve the problem and aid the road managers.

In this paper, an attempt is made to algorithmically quantify the observed snowfall road condition from a set of network camera images. The calculated values are validated against human observation of one of four road states - no snow, partial slush, all slush, or snow. While such image processing and recognition applications to road surface condition are increasing in recent years, an original method is utilized. This method combines Aoki and Sano's (2007) image processing and detection of snow in images with discriminant analysis (Otsu, 1979) and finally, includes original branch conditional logic based on image characteristics.

2. METHOD

The linear discriminant analysis method of image processing as proposed by Otsu (1979) is initially applied. Firstly, each road image is converted into a grayscale intensity distribution for all pixels in the image. The decision is made to process the image into three categories or classes. The algorithm calculates an optimal intensity threshold that maximizes the between-class variance and equivalently minimizes the within-class variance. The result is an image that is divided into three distinct classes that can be correlated to typical road conditions with respect to snowfall. The classes are defined as relatively dark (Class 1), median (Class 2), and relatively bright (Class 3). See Figure 1 – Histogram and classes.

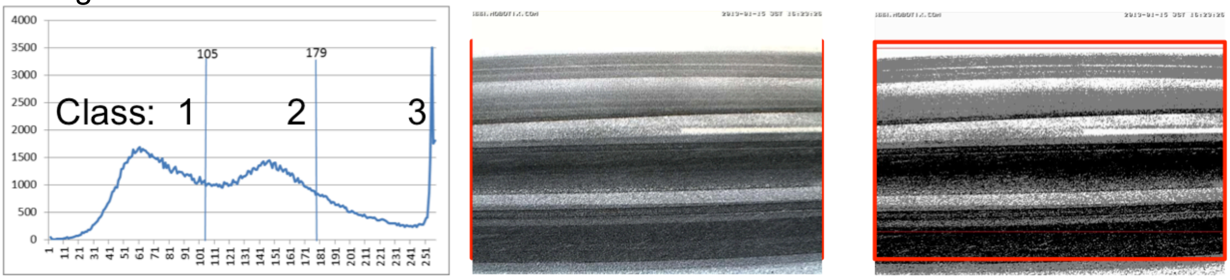


Figure 1 - Histogram and classes. The left figure is the pixel intensity histogram and the threshold value solved from the discriminant analysis for three class. The histogram was made from the center image. The third image from the left is a post-processed, three intensity value (black, gray, white) image using the threshold values.

By noting the relationship between the algorithmic delineation of the classes and corresponding observed road conditions, three basic cases were discovered. Figure 2 – Class versus case, shows these three cases.

	Case 1	Case 2	Case 3
Class 1	road (darker)	road	slush (darker snow)
Class 2	road (bright)	slush (darker snow)	snow & white line
Class 3	white line	snow & white line	snow & white line

Figure 2 - Class versus case. Table of three cases assumed from the combination of a class and a road surface state.

In Case 1, an image of a dry road surface, the area of the distribution with relatively dark pixels (Class 1) represent darker road surface, the median pixels (Class 2) are bright road surface, and the bright pixels (Class 3) are associated with white traffic lines on the road.

In Case 2, an image of a road only partially covered in snow and slush, the area of the distribution with relatively dark pixels (Class 1) represent darker road surface, the median pixels (Class 2) are slush, and the bright pixels (Class 3) are associated with snow and white traffic lines.

In case 3, an image of a completely snow-covered road, the relatively dark pixels (Class 1) correspond to darker snow such as slush, while both the median (Class 2) and bright pixels (Class 3) are snow surfaces.

As the next step, an attempt is made to classify these cases using other information acquired from the brightness of a camera image. The discriminant analysis algorithm outputs 2 threshold values that are essentially between-class separators for the 3 classes. Using the lower threshold that divides class 1 and class 2, we test against a threshold pixel intensity of 150. If the value is greater than this threshold, then the image is almost completely gray or white and is classified as case 3, all snow case.

In the next conditional, if the count of white pixels, defined as intensity greater than 200, is less than a reference white pixel count, then the image is also classified as case 3. The reference white pixel count was found by analyzing the typical number of white pixels that correspond to traffic lines in a dry road image. Therefore, if we reach this conditional branch and in this case the traffic lines are covered by slush or snow, then there is a high probability that the image is if a snow covered surface.

For the next conditional, we look at the intensity transition along the Y-axis of images. The images used in this study were photographed top-down with the Y-axis of the image perpendicular to the direction of the road. So, if there is partial snow cover in the form of a track, the grayscale intensity along the Y-axis should have a periodic large gradient compared to a dry road surface. Therefore, when the large gradient change is repeated, the image is classified as Case 2. See Figure 3 – Steep pixel intensity gradient.

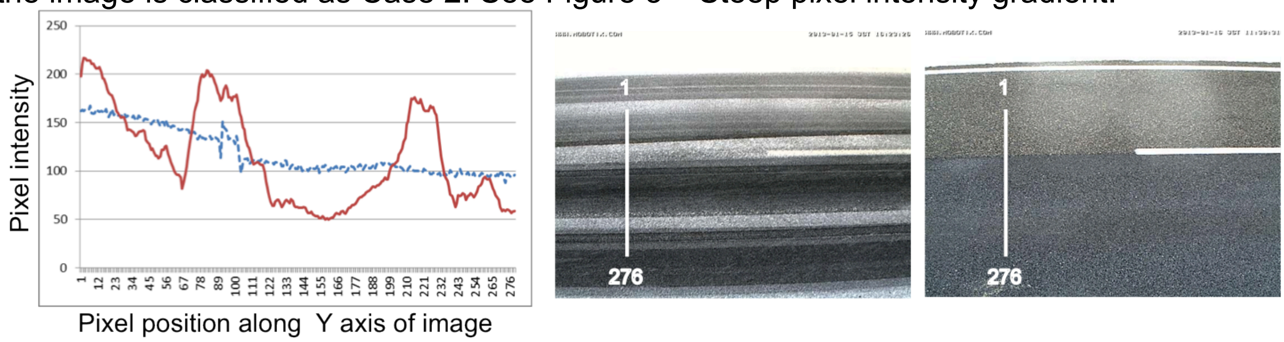


Figure 3 - Steep pixel intensity gradient. The graph on the left shows pixel distribution along the image's vertical axis (perpendicular to road direction) as a function of intensity. The sold line is calculated from the center image, the case of partial snow. The dashed line is calculated from the right image, the case of dry road. A large gradient (differential) is seen in pixel intensity for the case of partial snow. There is almost no differential for no snow case.

For the final conditional, it may be impossible to judge the partial snow cover only by the gradient along the Y-axis, so we check between-class variance, which indicates amount of separation between classes. If the variance is high, then the classes were divided into three discrete classes. After qualitative analysis, it was noted that a minimum between-class variance of 0.8 correlates well to partial snow cover, Case 2.

The complete flow chart with the above conditional logic is shown in Figure 4 – Complete flow chart for case classification.

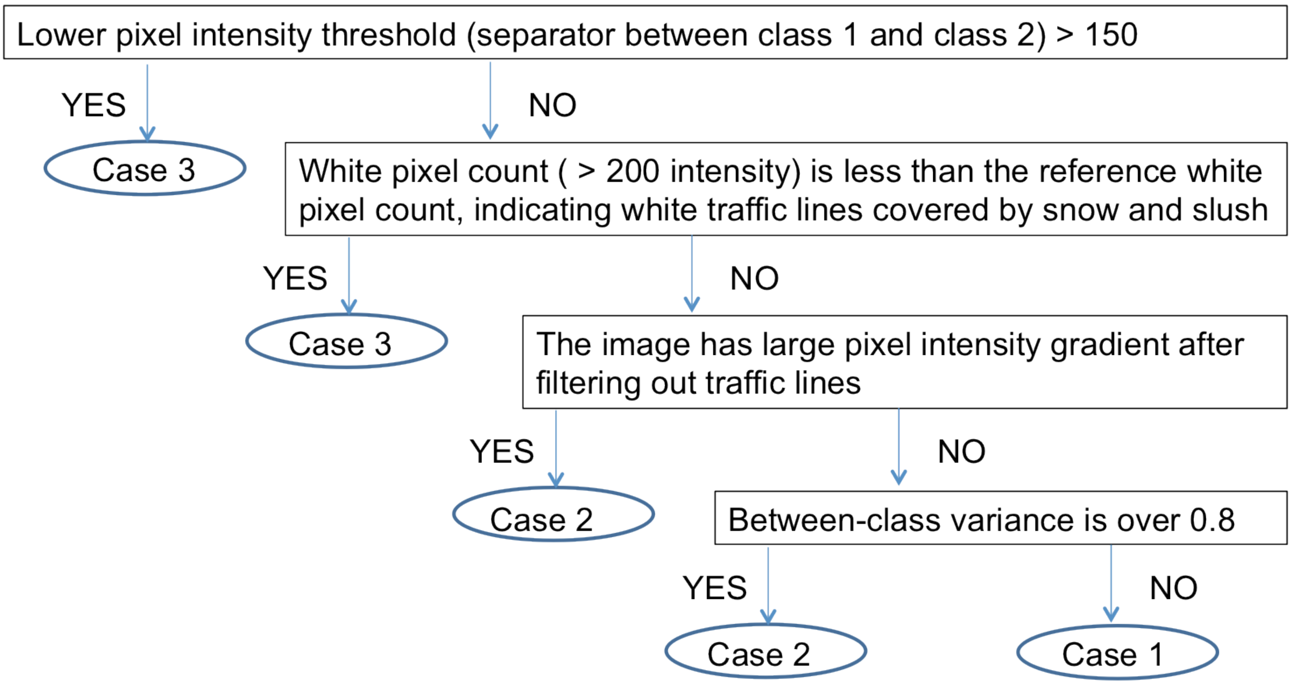
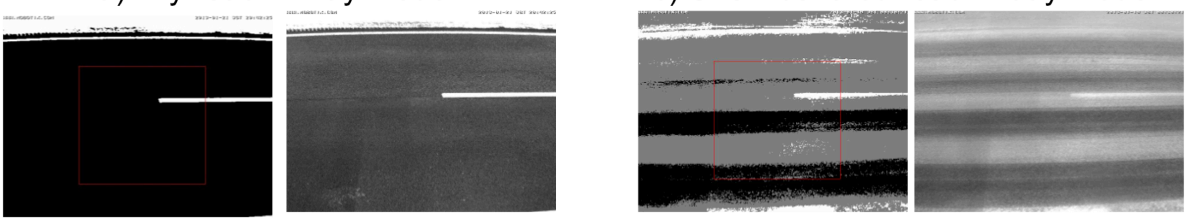


Figure 4 - Complete flow chart for case classification.

Figure 5 – Example cases, shows the processing of road images into 3 colors based on the classification result of performing the algorithm.

a) Dry road in Day mode   c) Snow covered road in day mode



b) Dry road in Night mode   d) Snow covered road in night mode

Figure 5 - Example cases. Examples of the result of the algorithm. Left images are the result of image processing after splitting images into classes. Pixels are changed to black for road surface, gray for slush, and white for snow. Right images are the original images.

We correlate this result to 5 ranks that are necessary for road surface management. See Figure 6 – Road management ranking of road conditions versus algorithm categorization rule.

Rank	Road Management Categorization	Algorithm Rule For Categorization
1,2	no snow	
3	partial snow	snow + slush > 10%
4	slush	snow + slush > 80% & snow < 20%
5	snow	snow + slush > 80% & snow > 20%

Figure 6 - Road management ranking of road conditions versus algorithm categorization rule.

3. RESULTS

For verification of the algorithm, a set of 1168 images are used that were gathered by photographing once every 20 minutes for a two week period in January, 2013. Since the cameras also take infrared photos, the images of night mode were processed the same as for day mode. Figure 7 – Time series, is a time series plot of the 5 road conditions.

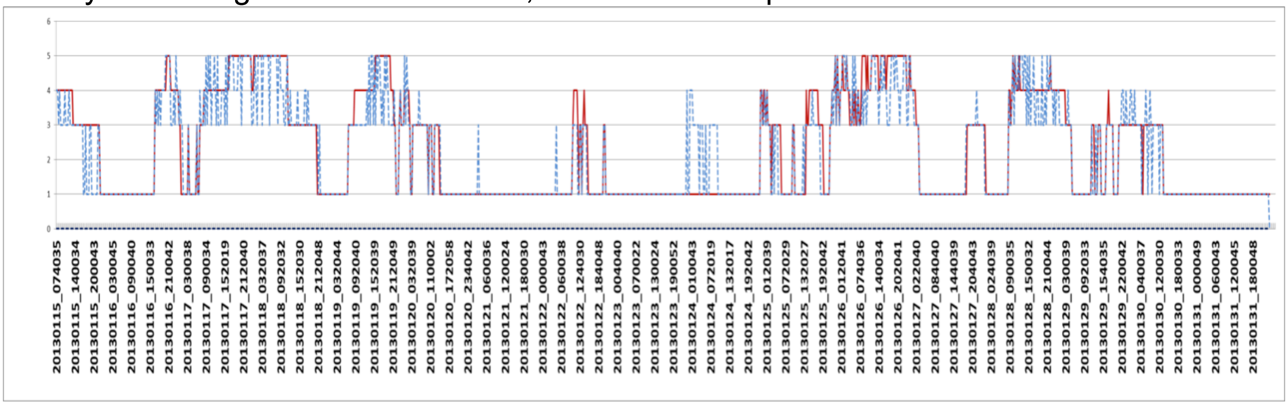


Figure 7 - Time series. Road management road condition ranking, comparison between human judgment (dashed red line) and algorithm result (solid blue line) in a time series.

Lines are plotted for both human judgment and algorithm result of the 5 road condition ranks described in Figure 6 – Road management ranking of road conditions versus algorithm categorization rule. Figure 8 – Count matrix, is a table comparing the algorithm result with human judgment.

Algorithm result

		1, 2		3	4	5
Human judgment	1, 2	599		30	4	0
	3	28		176	21	0
	4	0		94	66	31
	5	0		17	34	68

Figure 8 - Count matrix. Count matrix representing road management road condition ranking, vertical by human judgment, horizontal by algorithm result.

The overall coincidence rate calculated from the value in Figure 8 – Count matrix, is 0.802, or 80.2% success. However, since human judgment is somewhat ambiguous, an allowance is made for 1 road condition rank difference in the case where there is some snow. This calculation resulted in an improved coincidence rate of 0.915, or 91.5% success. Finally, a coincidence rate of 0.923, or 92.3% success, was calculated for the case where there is some snow or no snow. The similarity between human judgment and algorithm result were very encouraging.

While Figure 9 – Successful shadow example, shows the case where a shadow in the image does not generate an erroneous result, there were some cases that the algorithm was found to miss.

Figure 9 - Successful shadow example. An example of the result of the algorithm in the case of a shadow. Successfully classified as dry road.

Firstly, there were 28 cases in which humans identified snow on the road but the result of the algorithm was a miss. In these cases, classification based on the Y-axis intensity gradient and between-class variance thresholding was impossible. Conversely, there were 34 cases in which humans identified a snow-free road whereas the algorithm indicated snow accumulation. Figure 10 – Failed road salt example, shows an example of this missed case.

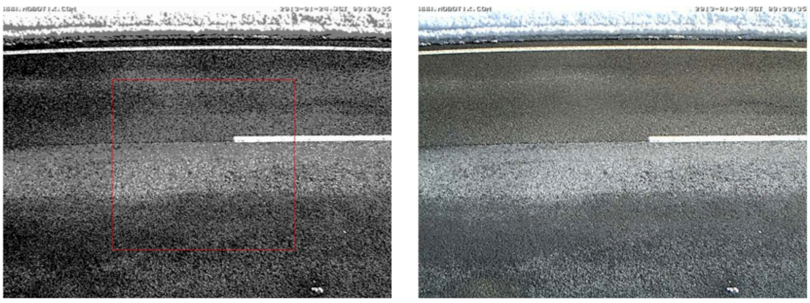


Figure 10 - Failed road salt example. An example of the algorithm failing to judge the road condition. Snow removal salt on the road is falsely classified as partial slush.

The road surface is white due to snow removal salt despite being completely dry. In the future, other data should be considered in addition to pixel intensity for the judgment of this case.

4. CONCLUSION

The goal of this study was to accurately judge the road surface condition using real-time network camera. This was attempted through discriminant analysis and branch condition logic based on characteristics of pixel intensity in images. A comparison of human judgment and the result of this algorithm using 5 road condition ranks shows a coincidence rate and therefore agreement of over 90%. While this conclusion is very encouraging, more work can be done to limit missed cases by including other kinds of data.

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