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Analysis of factors temporarily impacting traffic sign readability

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ABSTRACT

Traffic sign readability can be affected by the existence of dirt on traffic sign faces. However, among damaged signs, dirty traffic signs are unique since their damage is not permanent and they just can be cleaned instead of replaced. This study aimed to identify the most important factors contributing to traffic sign dirt. To do so, a large number of traffic signs in Utah were measured by deploying a vehicle instrumented with mobile LiDAR imaging and digital photolog technologies. Each individual daytime digital image was inspected for dirt. Location and climate observations obtained from official sources were compiled using ArcGIS throughout the process. To identify contributing factors to traffic sign dirt, the chi-square test was employed. To analyze the data and rank all of the factors based on their importance to the sign dirt, Random forests statistical model was utilized. After analyzing the data, it can be concluded that ground elevation, sign mount height, and air pollution had the highest effect on making traffic signs dirty. The findings of this investigation assist transportation agencies in determining traffic signs with a higher likelihood of sign dirt. In this way, agencies would schedule to clean such traffic signs more frequently.

Introduction

The standard retroreflectivity values established by the Manual on Uniform Traffic Control Devices (MUTCD, 2012) require transportation agencies to maintain compliance with these minimum levels. The goal of establishing minimum retroreflectivity requirements was to improve safety on transportation networks (Re and Carlson, 2012). While retroreflectivity efficiency ensures the visibility of traffic sign, damage on the face of sign has effects on its legibility (Boggs et al., 2013). It is worth noting that the existence of dirt on the face of the traffic signs has effects on both visibility and legibility. Of various forms of damaged signs, the dirty signs are unique since the damage is not permanent. Importantly, dirty signs can be cleaned rather than replaced. A previous study stated that the retroreflective performance of dirty traffic signs is dramatically different before and after cleaning (Rasdorf et al., 2006). Another study showed a significant increase in average sign visibility can be achieved just by cleaning dirty signs (Wolshon et al., 2002). It is imperative to note that when conducting their tasks, clean-up workers are exposed to being hit by vehicles. Moreover, the washing-related activities can lead to unacceptable delays and lengthy queues, and cost transportation agencies and tax payers a tremendous amount of money. Thus, it is critical to determine the contributing factors to traffic signs dirt. In this way, transportation agencies would be able to determine traffic signs (and other roadway infrastructures) that are more likely to be dirty and develop and schedule cleaning plans.

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To accomplish this goal, data on over 97,000 traffic signs was collected in Utah. Several official sources were utilized to acquire climate and location observations. To obtain the desired data for each individual traffic sign, ArcGIS was then employed. After integrating sign attributes data with climate and location observations, this entire data set was analyzed. During data analysis, it was observed that a number of measured signs were dirty. The identify the factors that most notably contribute to traffic sign dirt, various statistical methods and models were taken into consideration. In order to address statistical modeling related issues, such as nonlinearity, complexity, varied data structure, interactions, and multicollinearity, we applied random forests model. At the completion, the variables were ranked based on their importance in contributing to dirt on traffic signs.

Background

Transportation agencies continually make efforts to improve safety (Williamson et al., 2015; Pour-Rouholamin and Zhou, 2016). As a part of transportation infrastructure, traffic signs provide road users with key information through warning, guiding, and regulating them. To ensure traffic sign visibility for drivers to help them better comprehend and detect traffic signs, MUTCD mandate established standard levels for traffic sign retroreflectivity with respects to sign background color and sheeting type. This mandate necessitated the replacement of traffic signs that were not in compliance with the minimum levels. The MUTCD also defined five methods for guiding agencies in maintaining the standard levels, including retroreflectivity assessment methods (nighttime visual inspection and retroreflectivity measurement) and management methods (expected sign life, blanket replacement, and control signs).

After the mandate establishment, many studies have been conducted discussing traffic sign data collection methods, traffic signs' comprehensibility and driver recognition of signs, traffic signs attributes, and factors affecting traffic sign visibility and legibility. For example, the assessment and management of traffic signs have been discussed by multiple studies (Carlson and Lupes, 2007; Kipp et al., 2009; Harris et al., 2009; Liang et al., 2012; Brimley and Carlson, 2013), and some methods were proposed for agencies to manage traffic signs with regards to the retroreflective characteristics of sign background sheeting (Evans et al., 2012a,b). A study discussed traffic sign vandalism to determine signs that are more vulnerable to damage caused by humans (Khalilikhah et al., 2016). In addition, studies were conducted to examine the association between air pollutants and traffic sign deterioration (Khalilikhah and Heaslip, 2016). Moreover, (Hildebrand, 2003) examined the effects of frost and dew on traffic sign retroreflectivity. A study showed that traffic signs lose their effectiveness when dirty (London Department for Transport, 1982). However, little research exists focusing on the identification of contributing factors to traffic sign dirt. The current study is conducted to bridge this gap.

Sign data description

Data collection method

Recently, advanced methods have been used to collect data in various fields, e.g., bridge management (Zolghadri et al., 2014), pedestrian (Sharifi et al., 2015a,b), and transportation planning (Asgari and Jin, 2015). Multiple studies lately utilized novel methods to collect roadway asset data remotely. Most of these methods included mounting a variety of devices, such as sensors, lasers, image/video log, and Global Positioning System (GPS) simultaneously on an inspection vehicle (Khalilikhah et al., 2015). The Utah Department of Transportation (UDOT) conducted a mobile-based data collection in 2012. The effort included data collection on roadway assets along over 6000 miles of state routes and interstates. The surveyed roads were paved roads. This was carried out by an instrumented vehicle driving at freeway speeds and collecting asset data on the roadway. In addition, to automatically collect high-resolution detailed images from the roadway assets, imaging technologies were integrated (Ellsworth, 2013).

After conducting post-processing analysis by survey, data on more than 97,000 traffic signs under the jurisdiction of UDOT was derived. The surveyed data included sign attributes, including location, size, orientation, and mount height. In addition, operators examined the captured daytime digital images, and the dirty traffic signs were noted throughout the entire data set using manual vision inspection. It is necessary to note that only traffic signs wherein legibility was influenced by dirt were labeled as dirty signs. To ensure the accuracy of the data, we used photos from Google Street View 2013 (Fig. 1). After analysis of the collected data, we observed that over 600 of measured signs were dirty. Fig. 2 shows the locations of the measured signs, including dirty signs. During the modeling process, we examined various variables corresponding to traffic sign attributes, location and climate observations. We used the chi-square statistical test to identify the variables that have potential effects on making traffic signs dirty. The next section provides a summary of the chosen variables with regard to their association with traffic sign dirt.

Explanatory variables

For this study, several different sources were used to obtain various climate, location, and emission observations for traffic signs. Afterwards, ArcGIS software was employed to combine this data information with sign location (latitude and longitude). The resulting values of climate and location data for each individual traffic sign were extracted from the raster data.

Fig. 1. Examples of dirty traffic signs. *Source:* Google street view images.

Then, the association between these variables and dirt rates was tested using the chi-square test. The following is the variables potentially affecting traffic sign dirtiness chosen for this study.

Sign height above the road

According to the summary of sign dirt by mount height in Table 1, higher placed signs were less likely to get dirty. The rate of dirtiness for traffic signs installed 10 or more feet above the road was only 0.18%. According to the results of the chi-square test, there is evidence of an association between the dirtiness of the sign and mount height.

Direction of sign face

The percentage of dirty signs with regards to the direction that sign faced is summarizes in Table 2. As shown in the table, the changes in the percentage of dirty signs with respect to the direction of the sign faces were little.

Ground elevation

The National Elevation Dataset (NED) 30 digital elevation model from the United States Geological Survey (USGS, 2013) were used to obtain ground elevation of the location that traffic sign is placed. After creating raster data using ArcGIS, we extracted ground elevation measurements for every single sign. Table 3 shows the results of this extraction. The likelihood of traffic sign dirtiness increased as the elevation increased. The highest percentage of dirty signs was observed in areas with an elevation higher than 6500 feet. The result of the chi-square test also showed evidence of an association between the rate of dirtiness and ground elevation.

Geographical area

Boggs et al. (2013) discussed that the rate of traffic sign damage and deterioration is different for urban areas than rural areas. Thus, based on the environment surrounding the traffic sign, we defined an explanatory variable. This variable categorized the surveyed traffic signs into two groups: rural and urban. To obtain geographical area data, the Geographic Information Database of Utah's Automated Geographic Reference Center (AGRC, 2008) website was used. Then, rural and urban signs were identified using ArcGIS. Table 4 summarizes the effects of traffic sign geographical area on dirt rate. As seen in the table, more rural signs were dirty than urban signs. The chi-square value was also statistically significant. Therefore, the association between the area surrounding traffic sign and number of dirty signs was evident.

Precipitation

In order to examine the association between traffic sign dirtiness and precipitation, we used the Parameter-elevation Regressions on Independent Slope Model (PRISM, 2010) climate mapping system to obtain the 30-year average (1981–2010) of annual precipitation data across the state of Utah. The mean precipitation measurements for each individual traffic sign were extracted from the raster data using ArcGIS. Table 5 summarizes the results. The result of the chi-square test showed evidence of an association between sign dirtiness and precipitation.

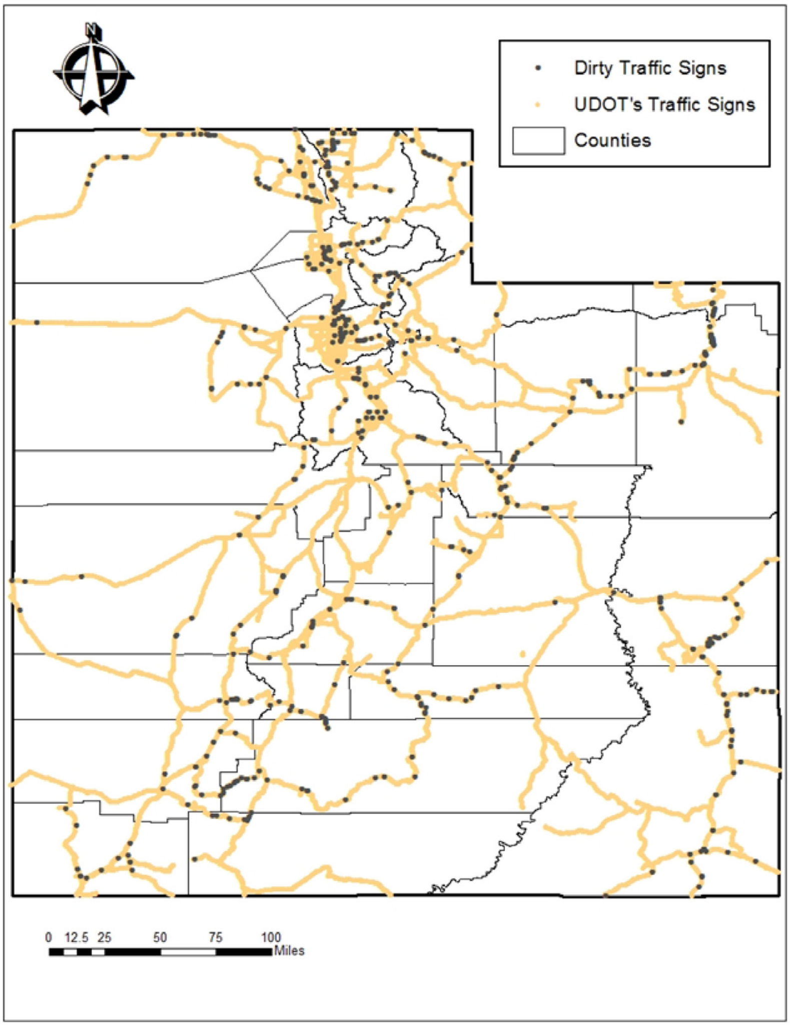

Fig. 2. Locations of dirty traffic signs in Utah.

Table 1
Dirty traffic signs by sign mount height.

Sign height above road (ft)	# of signs	Dirty		% Dirty
		Yes	No	
<5	17,160	73	17,087	0.43
5–7	25,707	269	25,438	1.05
7–8	24,020	181	23,839	0.75
8–10	17,718	76	17,642	0.43
>10	12,709	23	12,686	0.18

Chi-square test statistic = 138.77.
p-Value < 0.001.

Wind

An estimate of annual average wind resource is provided in the National Renewable Energy Laboratory (NREL, 2013) database. For this study, the 165-feet height above surface data for the state of Utah was obtained from NREL. After analyzing the data, it was observed that 92.4% of the signs were in areas with similar wind speeds (class1) though (see Table 6).

Sulfur Dioxide (SO_2)

Some areas of Utah are severely engulfed by air pollutants. Since emissions are among the potential factors contributing to traffic sign deterioration, we examined the association between traffic sign dirtiness and air pollution, and it was found

Table 2
Dirty traffic signs by sign direction.

Sign facing direction	# of signs	Dirty		% Dirty
		Yes	No	
North	16,129	89	16,040	0.55
Northeast	9044	58	8986	0.64
Northwest	8662	68	8594	0.79
East	14,672	116	14,556	0.79
West	14,441	82	14,359	0.57
Southeast	8458	53	8405	0.63
Southwest	9076	40	9036	0.44
South	16,860	116	16,744	0.69

Chi-square test statistic = 17.59.
p-Value = 0.01.

Table 3
Dirty traffic signs by ground elevation.

Elevation (ft)	# of signs	Dirty		% Dirty
		Yes	No	
<3200	1870	6	1864	0.32
3200–5000	49,165	258	48,907	0.52
5000–6500	34,198	239	33,959	0.70
6500–8200	9728	98	9630	1.01
>8200	2353	21	2332	0.89

Chi-square test statistic = 38.18.
p-Value < 0.001.

Table 4
Dirty traffic signs by geographical area.

Geographical area	# of signs	Dirty		% Dirty
		Yes	No	
Urban	46,611	183	46,428	0.39
Rural	50,703	439	50,264	0.87

Chi-square test statistic = 84.89.
p-Value < 0.001.

Table 5
Dirty traffic signs by precipitation.

Mean precipitation (in)	# of signs	Dirty		% Dirty
		Yes	No	
<9	9195	54	9141	0.59
9–11	11,518	93	11,425	0.81
11–14	13,823	115	13,708	0.83
14–17	16,916	73	16,843	0.43
17–19	20,199	128	20,071	0.63
19–22	10,363	69	10,294	0.67
>22	15,300	90	15,210	0.59

Chi-square test statistic = 25.52.
p-Value < 0.001.

that the association was strongly evident. For this study, Sulfur Dioxide (SO_2) values were used as a proxy of air pollutants to examine their impacts on signs dirtiness. SO_2 is produced from the burning of fossil fuels containing sulfur (coal and oil) (World Bank Group, 1999; Burtraw and Szambelan, 2009). In order to determine the impacts of SO_2 on traffic sign dirt, the Utah Department of Environmental Quality's (DEQ, 2014) observations were used. The Division of Air Quality (DAQ) conducts the air-related data collection. For this study, DAQ's observation was obtained from (AGRC, 2008). The DAQ's air emissions inventory includes 317 stations placed across the state of Utah. After obtaining the observations from the official source, we imported the data into ArcGIS software. To obtain the quantitative values of SO_2 for each individual traffic sign, it was necessary to define a field based on discrete data. Using interpolation function provided by ArcGIS, a raster data of

Table 6
Dirty traffic signs by wind.

Wind power	Wind power density (W/m^2)	Wind speed (mph)	# of signs	Dirty		% Dirty
				Yes	No	
Class #1	0–200	0.0–12.5	89,887	600	89,287	0.67
Class #2	200–300	12.5–14.3	7018	19	6999	0.27
Class #3	300–400	14.3–15.7	345	3	342	0.87
Class #4, 5, or 6	400–800	15.7–19.7	64	0	64	0.00

Chi-square test statistic = 16.84.
p-Value = 0.001.

emission components across the state was created. The value for each sign was then extracted from the raster data. After running a chi-square test, the strong association between the traffic sign dirt rates and SO_2 compounds was evident (chi-square value of 50.16 and p-value less than 0.001).

Statistical model

Throughout the analysis of collected data, variables that potentially had association with number of dirty traffic signs were identified. The final data set of more than 97,000 traffic signs included traffic sign dirty (yes/no) as dependent variable and seven explanatory variables (sign mount height, sign facing direction, ground elevation, geographical area, precipitation, wind, and sulfur dioxide). In order to choose an appropriate statistical model, several different models were considered including analysis of variance, log linear models, and logistic regression model. However, a number of issues existed in this large data set that these traditional approaches could not address. Firstly, a few number of dirty signs, almost 1% of measured signs caused the response variable to be extremely biased. Moreover, the data structure of multiple explanatory variables was enormously varied (nominal or ordinal, continuous or categorical, quantitative or qualitative). The relationships among the explanatory variables was also thoroughly complex, some of which may are confound variables, while others may have interaction. The relationship between response and predictors was also unknown, but likely, nonlinear. Instead, random forests model is able to simultaneously handle these challenges (Breiman and Cutler, 2007; Moisen, 2008). Thus, to compare the effects of factors on the rate of traffic sign dirt, random forests model was developed. At the end, the random forests model determined which factors are most important for sign dirt. This section of the paper firstly discusses the model structure. Then, the results obtained from developed model are provided.

Random forests

As a tree-based statistical procedure, random forests (RF) model has been widely used in different fields of transportation. RF includes a very large number of decision trees (James et al., 2013). Due to two randomization schemes processed when the model is building, RF tends to have lower variance. Firstly, when splitting tree's nodes, a subset of m predictors is randomly selected from the full set of p predictors. Secondly, random bootstrap samples are generated to construct the trees (Palczewska et al., 2013). In comparison with the single decision tree, RF model is more accurate and able to predict better. However, since hundreds of trees are developed, the interpretation of model is challenging. To address this issue, sorting predictors based on their importance on the response variable is suggested for random forests. A greater importance value indicates that the predictor has a greater role in the final response.

After digging into the data, a variety of predictors were observed with their own units. In order to avoid the possible bias caused by a varied scale, all of the predictors were standardized. To do this, standard transformation was used, where the difference between each observation and the variable's mean was divided by the variable's standard error. After standardization, the measurements of all predictors ranged from -1 to +1. Then, a random forests package was created in R software (Team R, 2014). The subset of variables considered in each splitting is suggested to be $m = \sqrt{p}$ $(p = 7,\ m = 3)$ in previous studies (James et al., 2013). For the number of trees, no optimal number was suggested in the literature. A larger number of trees do not necessarily lead to consistently better performance though (Oshiro et al., 2012). For the current study, 1500 trees were developed that is an appropriate number for such sample sizes.

Results

Fig. 3 provides a plot of the variables importance ranking on traffic signs dirtiness. As Fig. 3 depicts, the ground elevation and the height of sign above the road were the most important predictors for traffic signs dirtiness. The importance of ground elevation perhaps reflects the fact that more frequent snowfall occurs in areas with higher elevation (Boggs et al., 2013). A number of traffic signs gets dirty because of snow and roadway debris. Regarding sign mount height, traffic signs close to the ground were more likely to get dirty because of snow and roadway debris, tree sap, agriculture dust or other airborne dust (McGee, 2010). In addition, the variable of sulfur dioxide compounds was also important to traffic signs dirt-

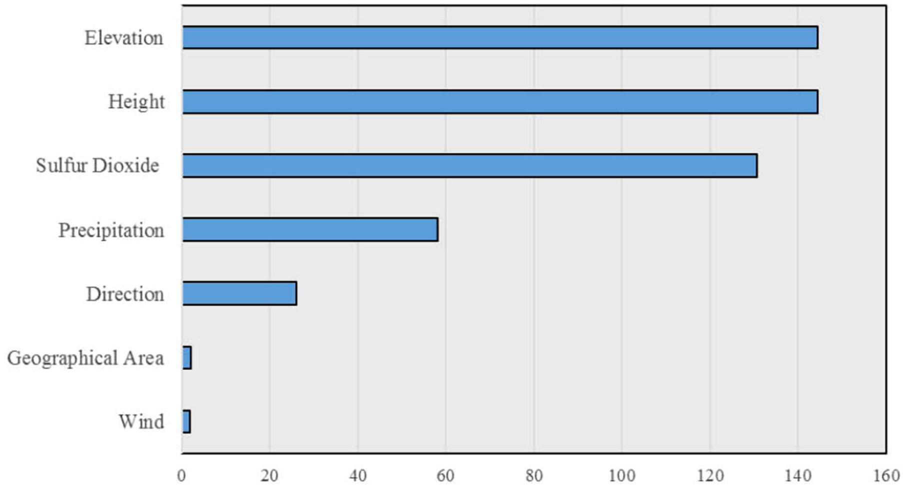

Fig. 3. Variable importance ranking for traffic sign dirt.

iness. Traffic signs installed in areas with higher concentration of air pollutants such as industrial areas or along routes with heavy traffic are more likely to get dirty. Average annual precipitation was also a variable that plays a role in the dirtiness rate of traffic signs. Although regular rainfall has the potential to clean the sign face (McGee, 2010), frequent snow is a contributing factor to dirtiness. As shown in the figure, sign face direction, geographical area, and wind variables were not as important as the other factors in making signs dirty.

Conclusions

The existence of dirt on the faces of traffic signs has effects on sign readability. Issues with traffic sign readability can lead to an increase in unsafe driving behaviors. However, cleaning traffic signs is very expensive and can potentially lead to safety issues for workers, and traffic delays for road users. Thus, it is important to identify traffic signs that are more likely to get dirty. The goal of this study was to reveal the effects of sign attributes, climate, and location observations on the number of dirty traffic signs. To do this, data on more than 97,000 traffic signs was collected in the state of Utah. In addition, official sources were used to obtain climate and location data. Then, sign attributes, climate, and location observations were integrated using ArcGIS. The chi-square test was then employed to identify contributing factors to traffic sign dirt. After utilizing random forests model, the variable importance ranking of the predictors on the rate of traffic sign dirt was extracted. Once sorted, it can be stated that ground elevation, the height of sign above the road, and sulfur dioxide compounds had the highest effect on making traffic signs dirty.

The analysis of the dirty signs surveyed in Utah showed that the average ground elevation of the places that they were placed was approximately 5500 feet. The dirty signs also had a height at 6.85 feet above the road, on average. Taking the standard deviation values into consideration, traffic signs under UDOT's jurisdiction that cleaning them may be warranted include:

- Signs placed in areas with higher ground elevation (in Utah, higher than 5000 feet) that experience frequent snowfall.
- Ground mount traffic signs not placing high (in Utah, with mount height less than eight feet).
- Signs installed in areas with higher concentration of air pollutants, such as industrial areas or along roadways with heavy traffic.

The findings of this study assist transportation agencies in determining traffic signs with a higher likelihood of dirt based on sign attributes, climate, and location data. Thus, agencies should schedule more frequent inspections in the areas with a higher likelihood of sign dirtiness. As a result, agencies are able to make informed decisions regarding cleaning plans and reduce the amount of unnecessary cleaning activities and improve the safety of workers. The next step is to establish a cost-benefit analysis to assess the cost of cleaning signs versus its effects on the improvement of sign readability. In this way, the importance of such activities would be quantified.

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