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Visibility estimation based on camera data and algorithm of snow recognition on traffic signs

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Abstract

Finnish Meteorological Institute (FMI) and JAMK University of Applied Sciences have developed algorithms to monitor safety condition on roads using new methods, like machine learning and image recognition. The idea is to estimate visibility on the roads based on camera data and recognize snow on the traffic signs.

The idea to solve the first problem is to classify the observed visibility into three classes (normal, poor and very poor) and clarify the reason for the reduced visibility (snowfall, sleet, drifting/blowing snow on the road surface). Visibility information can be delivered to drivers who are driving to the area where horizontal visibility is reduced.

The algorithm for the second issue is analyzing camera images to find the traffic sign, identify it and estimate amount of snow on the traffic sign. As a result, maintenance services can monitor traffic signs condition remotely which would help to save some resources and time.

Keywords: Machine learning, image recognition, road safety, road maintenance.

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1. Introduction and background

Finnish Meteorological Institute (FMI) and JAMK University of Applied Sciences have developed algorithms to monitor safety condition on roads using new methods, like machine learning and image recognition. The idea is to estimate visibility on the roads based on camera data and recognize snow on the traffic signs.

Visibility estimation is based on classifying the observed visibility into three classes (normal, poor and very poor) and clarify the reason for the reduced visibility (snowfall, sleet, drifting/blowing snow on the road surface). Also, weather observations from the nearest weather station can be used to identify the precipitation form (snow, sleet or rain) and intensity of the precipitation. In the meteorological point of view very poor visibility means that the horizontal visibility is 1000 meters or less.

Juga et al. have studied massive wintertime pile-up cases taken place in Finland (Juga et. al 2005, Juga et al 2014) and low visibility has played a significant role in those cases. Low visibility and icy road surface with low friction is a challenging combination for road safety. The aim of this study is to develop an image recognition system that could be used in targeted warnings about reduced visibility which can be delivered to drivers for example via wireless networks (Sukuvaara et. al 2006).

An image recognition algorithm was developed to analyze camera images to find traffic sign and snow on it. Applying this algorithm into mobile application can help maintenance services to monitor the condition of speed traffic signs remotely which would help to save some resources and time. The aim of this work is improve road safety, because driving with proper speed on winter period can help drivers keep vehicles under better control (Rune 2012).

2. Neural network architecture and training process for visibility classification

Today terms like artificial intelligence (AI), machine learning (ML), and deep learning (DL) are big topics to deal for example big data. In this study, the deep learning algorithms are used to recognize the visibility from the images. Machine and deep learning algorithms can be used to building an approximate model of some function, such as extracting visibility from an image. The models are trained with a large dataset of training examples. The general overview of the neural network configuration is shown in Figure 1.

The algorithm relies on a convolutional neural network which is used to predict a single visibility from the input image. Convolutional neural networks are one of the most widely used neural network models in image recognition and other image-based regression tasks (Dumoulin and Visin 2016). The main advantage of convolution networks is the ability to detect the same features independent of location within the input image.

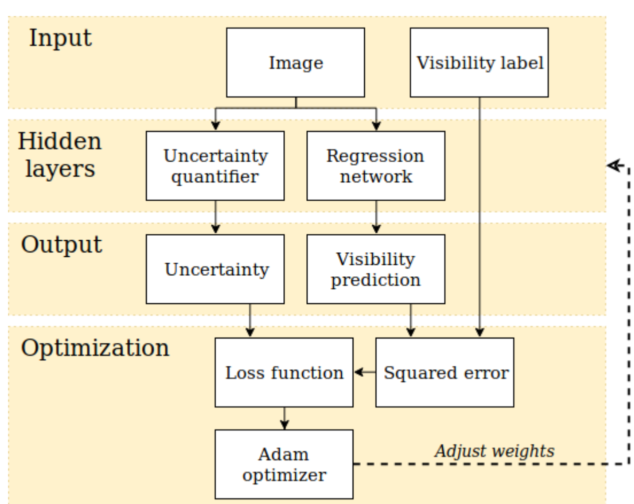

Fig. 1. Architectural diagram of the neural network

A dataset of images with varying levels of visibility are chosen to train the network. A small portion of this dataset is extracted to be the evaluation dataset, which is used to test the performance of the network. The rest of the data is used as training data. Only the image is used as an input: no other variables are used when predicting the visibility.

Due to the limited amount of training data and to avoid overfitting, several dataset augmentation techniques are used to grow the size of the dataset. Tools such as cropping, padding, rotation, flipping, contrast adjustment and random noise are used to alter the original training image data.

An ensemble of four networks is trained for the task. The networks are convolutional neural networks with varying architectures, consisting primarily of convolutional layers and a final fully connected layer. Two of the networks in the ensemble include residual connections as well. All layers use Rectified Linear Unit, (ReLU) (Zagoruyko and Komodakis 2016) as their activation function, other than the final fully connected layer which uses linear activation. An uncertainty quantifier algorithm (Gurevich and Stuke 2017) is implemented to measure the quality of the network output. The networks are trained with the Adam optimization algorithm (Kingma and Ba 2014).

Analyzed visibilities from road weather camera picture are presented on figures 2a – 2d. Percent values on the left-hand side present the relative visibility, where 100 indicates good visibility and 0 very poor visibility. The percent value on top is the median prediction of the neural network ensemble. Also, an uncertainty of the visibility estimation is given as a percent from 0 to 100. The bigger number the better estimation. Reflections from sun or from other cars, dirty lens or icy/snowy/moist lens can cause problems and visibility estimation will be very hard, or impossible, to do.

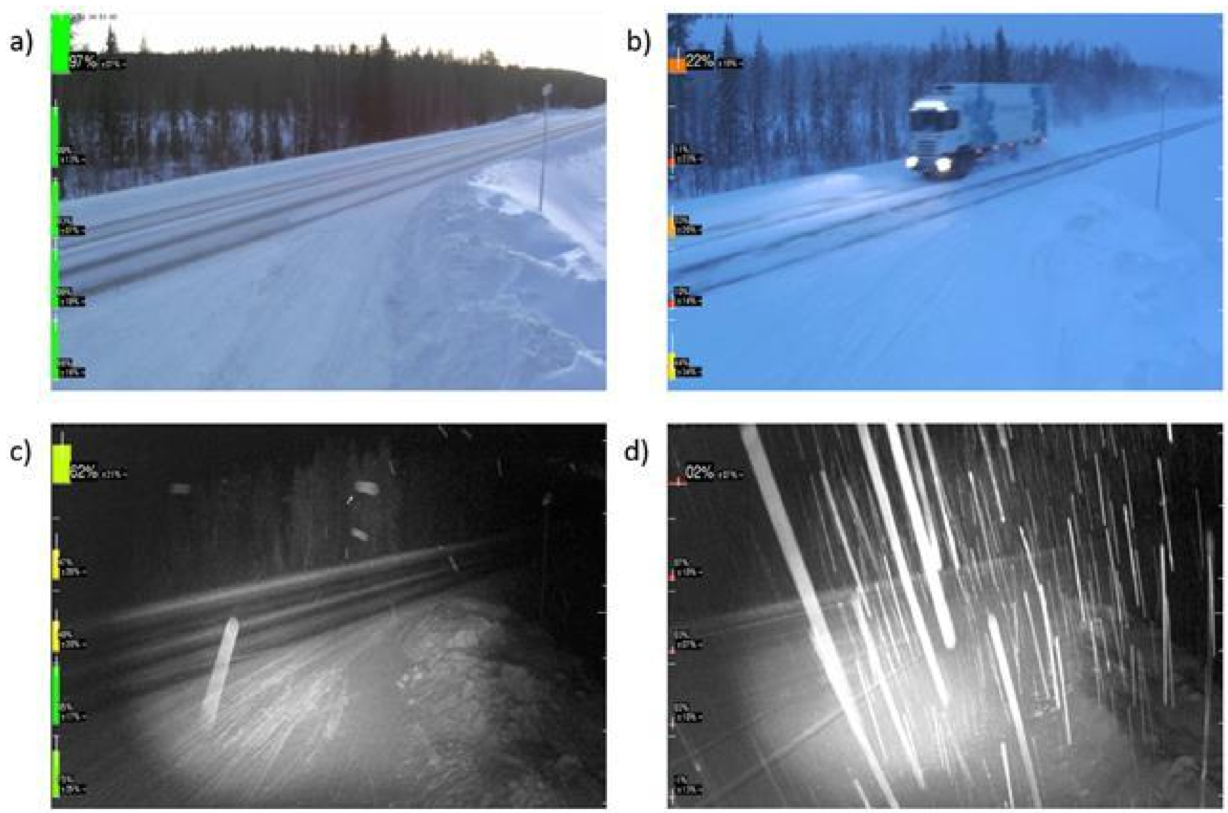

Fig. 2. Different visibility classes based on neural network analyse of road weather camera pictures. Panel a) presents good visibility, b) very poor visibility (blowing snow), c) poor visibility (snowfall) and d) very poor visibility (snowfall).

3. Algorithm to recognize snowy traffic signs

Awareness about speed limits is extremely important for the safety on the roads (Rune 2012); in winter during heavy snowfalls, snow can cover most of the traffic signs so that drivers cannot see speed limits. It may takes weeks before traffic signs will be cleared. In this chapter, we describe algorithm to ease monitoring of traffic sign condition during winter.

Python 2.7 was chosen as the programming language. To analyze images we use OpenCV library. Main task can be divided to three subtasks:

1. Find area where potentially can be traffic sign
2. Find traffic sign
3. Find snow and determine its amount on the sign.

Different parts of algorithm are present on Figure 3. First, we search for traffic sign colors to crop areas where most probably sign are and try to find round objects at those areas. For that, Hough circle transform are used (OpenCV-Python Tutorial Hough Circle Transform, 2018). Second part is traffic signs recognition, which performed by using flat objects search (OpenCV-Python Tutorial Feature Matching 2018). As templates for that search we use images of numbers from road signs (see figure 4). Finally, we analyze cropped images to find snow: each pixel splits to RGB components and pixels with color components in some specific range counts as snow.

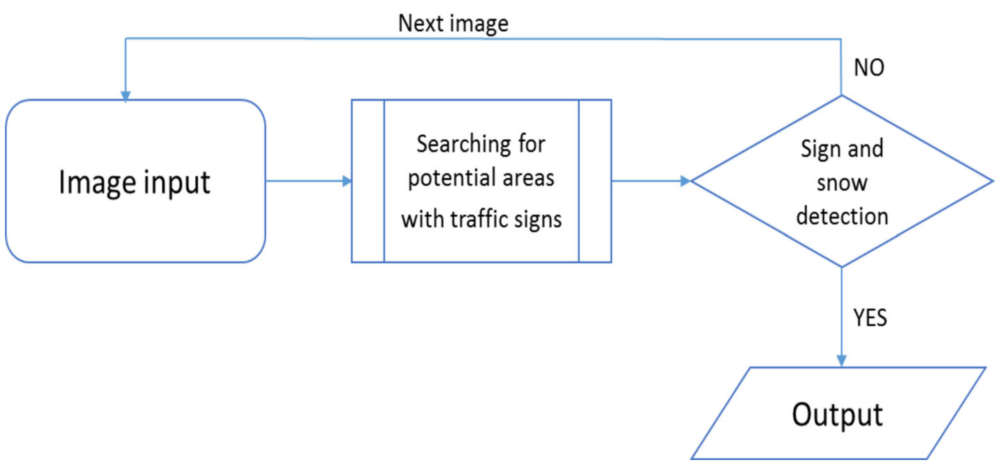

Fig 3. Algorithm of traffic sign and snow recognition.

Fig 4. Patterns for searching images.

According to the testing results, the algorithm works well for during daylight, but darkness and twilight increase the number of errors. Reason for false recognition can be traffic lights, streetlights and car lights. RGB color components of those light have quite similar range to snow; also, snow reflection can be misinterpret. Example results of the snow recognition algorithm shown on the figure 5.

Presented algorithm can be employ as a part of mobile service to analyze images after they been collected from roads. For example, cameras can be install into regional buses; this will provide updating road images from the same routes regularly. Also damaged or dirty traffic signs can be recognized using this same method.

Fig 5. Snow recognition.

4. Results and conclusions

This research is directed to create services which will assist to monitor driving conditions and road or roadside condition. Image recognition and machine learning techniques enables automatic systems to recognize different things from pictures. Automatic techniques are not only fast and efficient but they also save human resources when there is no need to do manual work.

The first results of the methods presented in this study have been promising. Visibility seems to be possible to estimate from road weather camera pictures. Next step is to study how the developed method works when using other road weather cameras or inboard cameras, like smartphones in car. When monitoring snow on the traffic signs remotely that help to save some resources and time when there is no need to drive along the roads to monitor the snowy traffic signs manually.

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