Fog detection from camera images

Roberto Castelli [*] Peter Frolkovič [†] Christian Reinhardt [‡]
Christiaan C. Stolk [§] Jakub Tomczyk [¶] Arthur Vromans [‖]

Abstract

Fog is one of the most dangerous weather types with more fatalities than winter storms. It is in the interest of general public that a precise, predictive and accurate fog density map with high spatial resolution can be created. Currently, the definition of fog as used by national weather services is so detailed and technical that the fog can be identified only at a few locations by means of the prescribed light scattering experiments. With the rising availability of cameras in public places such as airports, streets and highways, a large amount of data on the occurrence of fog becomes available to researchers. In this article we describe methods for determining not necessary only the existence of fog, but sometimes a visibility distance - a type of optical penetration length - as well. We will show that digital cameras can be a reliable alternative or complementary method for creating fog visibility maps when processing of image data is used.

KEYWORDS: fog detection, Dark Channel Prior, edge detection, colour detection, visibility distance

1 Introduction

Fog is the weather phenomenon of light scattering particles - usually water droplets - suspended in air causing an attenuation of light and therefore a severely reducing a visibility of objects. The sudden appearance of fog - especially a dense fog - can lead to such reduced visibility that transportation networks can be affected or even fully compromised: for example massive car collisions resulting in long traffic jams, grounding of airplanes or even closing of airports and reduced speed of trains to

[*] VU Amsterdam
[†] STU Bratislava
[‡] VU Amsterdam, corresponding author
[§] UvA Amsterdam
[¶] Univ. Sydney
[‖] TU Eindhoven

prevent derailment. Some of these effects can be alleviated or even prevented when a transportation network can adjust to a fog density map of high spatial resolution accuracy by issuing warnings or decreasing the speed limit. Unfortunately such a density map needs a dense network of sensors that are capable of detecting the fog and measuring the visibility distance, a network weather services are now lacking.

Current fog detection systems measure the amount of scattering of a collimated beam of infrared light to determine the Meteorological Optical Range (MOR): the distance at which a collimated beam of incandescent light with a light colour of 2700K has reduced to an amount of 5% of the emitted flux. In the Netherlands there are 25 sites, see Figure 1 for the locations, capable of determining the MOR resulting in a spatial resolution that is significantly larger than typical length scales on which fog varies that can be as low as a few meters in the neighbourhood of surface water. Therefore a new and complementary method based on new data sources is needed.

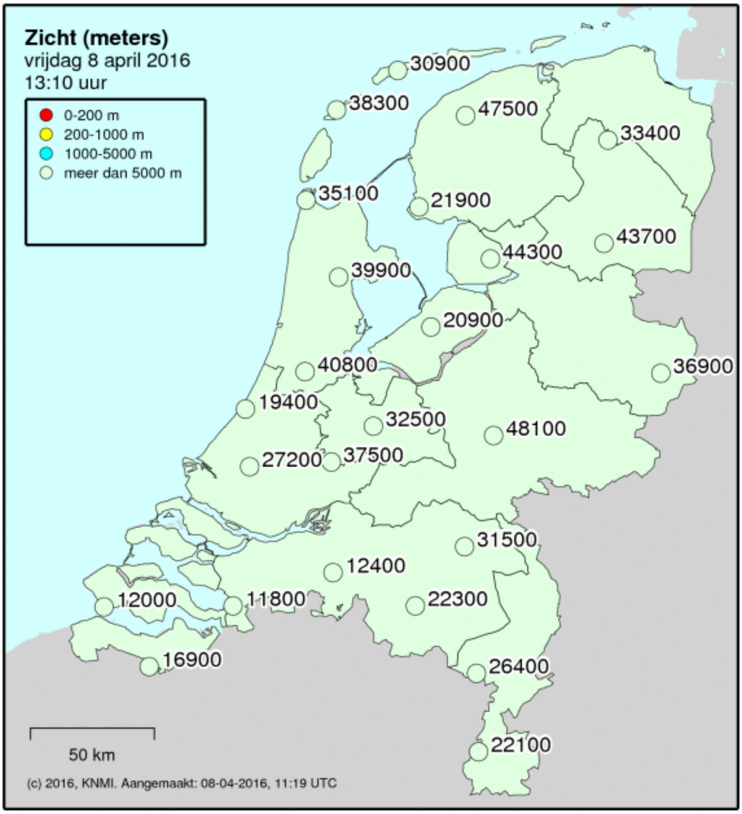

Figure 1: Map of the Netherlands showing the Meteorological Optical Range (MOR) measured at 25 sites capable of determining the MOR. Image from the real time updated public KNMI website: http://knmi.nl/nederland-nu/weer/waarnemingen.

A possible new source of data are public cameras. The rising spread of public cameras for control, security and safety allows for a much denser network of fog detecting sensors. For example The Netherlands had about 2200 state owned traffic cams der Staten Generaal (2010) in 2010, which would yield a spatial resolution of about 2.5 km if the cameras are distributed uniformly. Unfortunately the meteorological definition of fog is incompatible with the data gathered by cameras. Cameras do not see a constant light colour of 2700 K nor have a reference level of the emitted flux. Therefore different properties of fog have to be used in a camera involved in a fog detection system. For validation such fog system must correlate to the MOR and to the fog detection and classification based on human perception.

Properties of fog and their measurement As we stated before fog is the weather phenomenon of light scattering particles, suspended in air causing an attenuation of light and therefore a severe reduction of the visibility of objects. This description already hints to several characteristic properties. The most important parts of this description are the “light scattering particles" and the “reduced visibility of objects". The first part implies that the light of a source can be seen from a direction different than the source direction. As a result the total amount of light scattered into one specific direction will lead to a shift of an object colour towards white or grey. This property will be called Colour Level Shift. Furthermore, the attenuation due to the scattering leads to a gradual change of the fog colour from white to black depending on the attenuation length of the fog, the thickness of the fog layer and the intensity of the light source.
The second part of the description indicates a loss of resolution. It indicates that visibility is a relative quantity depending on the no fog perception of an object. An object becomes “fuzzy" and less detailed. This property will be called Shape Level Decrease.
In general both the Colour Level Shift and the Shape Level Decrease can be interpreted as some combinations of smearing and averaging effects. The smearing implies the existence of a diffusion process like scattering, which is the reason why objects are perceived “fuzzy" and with shifted colour levels, and the averaging indicates the direction of the Colour Level Shift: towards a specific grey level.
The MOR detection method is fully based on scattering and therefore it is by definition a colour level method: a decrease of flux in a specific small wavelength interval will indicate a colour level shift. The MOR detection method does not determine the loss of resolution or the absolute change of colour. Therefore camera data can complement the MOR detection method by determining both the loss of resolution and the absolute change of colour. A loss of resolution can be quantified by edge detection realized e.g. via gradient thresholding, high level wavelet transforms or total variability measures. The colour shift can be quantified by comparison between the RGB-channels of camera.

2 Fog detection based on Dark Channel Prior

In this chapter we introduce fog detection methods that are based on so called Dark Prior Channel from RGB colour images.

2.1 Description of available data

Although in general a video data can be available for our purposes, we note that the video footage is in principle a sequence of photographs, where each photograph is only shown for a very short time interval, usually too short to be perceived as a single photograph. Therefore we will only discuss the datasets consisting of single pictures. Each colour picture consists of three channels - Red, Blue and Green (RGB) - where each channel is a picture: an intensity map of the light received after passing through a specific band pass filter. The combination of the three channels yields the real life colour picture. Current camera technology is typically based on digital data obtained from a CCD (Charged Coupled Device), where the CCD is an array of integrating capacitors Rieke (2009). Each pixel of the picture is identified with a single integrating capacitor. The amount of charge collected by the capacitor is a direct measure of the intensity of the light. The relation is linear except for high values of charge. Current CCDs use a pixel with three integrating capacitors, one for each of the RGB channels Kitchin (2009). A CCD will give an electronic signal, the read-out signal, that consists of sequence of voltage spikes, one for each pixel channel. The data is therefore immediately in an analogue format which is easily and automatically converted into a digital signal.
Camera data will therefore consists of three digital RGB channel data sets in our study. In particular, the methods that will be discussed in this paper are applied to pictures provided by Koninklijk Nederlands Meteorologisch Instituut (KNMI), see Figures 2 or 4 later for an illustration. The pictures obtained from camera images are taken from a single location - KNMI institute terrain at De Bilt, Utrecht, the Netherlands (52.0990 N, 5.1766 E) - and pointed in a single steady direction towards the horizon (NNE). The pictures have a size of about 60 degrees wide and 40 degrees high with the horizon centered at about 18 degrees from the bottom, in pixel sizes 768×562. The temporal resolution is 10 minutes.
Complementary to the camera data the KNMI provided the Meteorological Optical Range (MOR) values of the same weather station location at the same times. The MOR values are in meters and are determined with the same temporal resolution. However the MOR is determined for the air directly at the location of the detector, while the camera has a solid angle to probe with a certain angular resolution resulting in multiple probes of fog of locations at least several tens of meters away from the camera. We assume that the fog is spatially homogeneous on the visible length scales and therefore probed in the same way by the MOR detector and the camera.

Transmission and Dark Channel Prior If we see the i-th image channel as an intensity density mapping I_i, $i = r, g, b$, then the density mapping can be decomposed into two mappings: the transmission mapping and the air scattering mapping, see e.g. Fattal (2008); Narasimhan and Nayar (2000, 2002). The transmission mapping is the perfect visibility image (or the scene radiance) J_i weighted with a transmission density t indicating the amount of transmission of the medium - in this case air. The air scattering mapping is the additive complement of the transmission mapping depending on the global atmospheric radiance A_i indicating the amount of intensity of air radiance being scattered in the direction of the camera.

$$\mathbf{I}(\mathbf{x}) = \mathbf{J}(\mathbf{x})t(\mathbf{x}) + \mathbf{A}(\mathbf{1} - t(\mathbf{x})), \tag{1}$$

Mathematically speaking, the mappings $\mathbf{I} = [I_r, I_g, I_b]^\top, \mathbf{J} = [J_r, J_g, J_b]^T, \mathbf{A} = [A_r, A_g, A_b]^\top$ are defined on $[1, n] \times [1, m]$, the image of size $n \times m$ pixels, and with their values in $[0, 1]^3$, the relative colour intensities for each RGB channel. Remark that the RGB intensity is rescaled to 1 instead of the to the usual value of $2^B - 1$ for B-bits colour coding.
We are interested in the transmission coefficient $t \in [0, 1]$, since $1 - t$ is a measure of the amount of fog at the location depicted by the image pixel. Therefore one must be able to remove the fog from the image and create the scene radiance image $\mathbf{J}$. The procedure for doing this is called dehazing, because it is the inverse operation of applying fog or haze to an image He et al. (2011).
The objective of dehazing is to estimate $\mathbf{J}$, $\mathbf{A}$ and t in (1) from a single image $\mathbf{I}$. Naturally this procedure is a priori ill-posed since the output is 7/3 times greater than the input from the image. Therefore the relation (1) cannot be solved without extra constraints.

It was empirically observed in He et al. (2011) that patches in haze-free outdoor (day) images in the non-sky regions have very low intensities in at least one channel at some pixels belonging to the patch. These very low intensity pixels are due to large deviations in the intensity of a channel, which is by itself a measure of object resolution (pixel to pixel deviations) and transmission (channel to channel deviations). One expects that for foggy (day) images the scattering causes both a decrease in the object resolution as well as a colour shift to white or grey. Note that the grey scale colours are by a definition unbiased to any of the RGB channels. Therefore the RGB channels must have small deviations in the intensity of the channels, which can be interpreted as a loss of resolution (pixel to pixel) and colour shift (channel to channel).

Consequently, we can introduce the dark channel J_{dark}, which is the minimum over all channels of the minimum of all pixels in a (small) neighbourhood, a patch $\Omega(\mathbf{x})$, centered at a pixel $\mathbf{x}$,

$$J_{dark}(\mathbf{x}) := \min_{c \in \{r,g,b\}} \left(\min_{\mathbf{y} \in \Omega(\mathbf{x})} (J_c(\mathbf{y})) \right), \tag{2}$$

The dark channel is therefore a prior knowledge for dehazing. Note that this Dark Channel Prior is depending on the choice of a patch. If the patch is too large, then the Dark Channel Prior will be almost uniform in the image, while a too small patch will go beyond the effective resolution of the image causing a Dark Channel Prior with almost the same variability as the original RGB channels.

The scene radiance image is the "no fog" transmission image, which is assumed to have zero values in the dark channel prior, i.e. $J_{dark} = 0$. Therefore the minimal values over all channels for the observed image are fully caused by the scattering mapping. Thus using (1) and supposing an estimate $\hat{\mathbf{A}}$ of $\mathbf{A}$ is known, we can estimate the transmission density mapping by

$$\hat{t}(\mathbf{x}) = 1 - \omega \min_{c \in r,g,b} \left(\min_{\mathbf{y} \in \Omega(\mathbf{x})} \left(\frac{\mathbf{I}_c(\mathbf{y})}{\hat{\mathbf{A}}_c} \right) \right), \tag{3}$$

where $\omega \in [0, 1]$ is a constant parameter introducing a small amount of haze to preserve a correct perception of distant objects. The haze indicated by the factor $1 - \omega$ can be attributed to other effects than scattering by water vapour, such as Rayleigh scattering of air, thermal deviations of the refractive index, or lens problems such as defocussing, chromatic aberration and astigmatism F.L. Pedrotti (2007). In our applications we set $\omega = 1$, since the camera is assumed to have no lens problems and the unobstructed view distance of 250 meter (a typical value in our test images) is assumed to be too small to allow other natural scattering effects.

To determine $\hat{\mathbf{A}}$ we pick the top 0.1% brightest pixels in the dark channel and then the pixels with highest intensity in the input image $\mathbf{I}$ to estimate the atmospheric light $\hat{\mathbf{A}}$, see He et al. (2011) for more details

In the following fog detection methods we make use of smoothed transmission t. The smoothing is permormed using Guided Filter, where we filter $\hat{t}$ and the filtering process is guided by $\mathbf{I}$ He et al. (2011).

In next sections we present particular fog detection methods based on Dark Channel Prior and transmission image. To obtain them for images in our computations we have used an available Matlab implementation, see Tierney (2014).

2.2 Classification Tree methods for fog detection

We assume we have obtained a smoothed transmission t for all pixels of the image from RGB data. Afterwards we compute the average of the smoothed transmission for each row. The resulting function of one variable indicates the transition between sky/air and the ground. One expects that a fog will create a smooth transition between the two, while clear days will have a sharp distinction between the two. In Figures 2 - 5 one can see examples how a clear day and a foggy day will change the transmission function. Hence this horizontal averaged smooth transmission function can be a good indicator for fog.

To test this approach we compute horizontal average for smoothed transmissions t for 4458 images from October 2015 (the dataset *Oct15*) and for 2554 images from

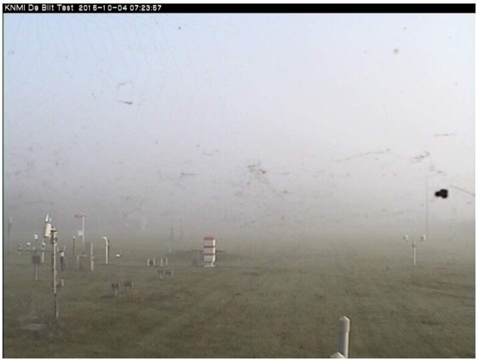

Figure 2: Image with a fog.

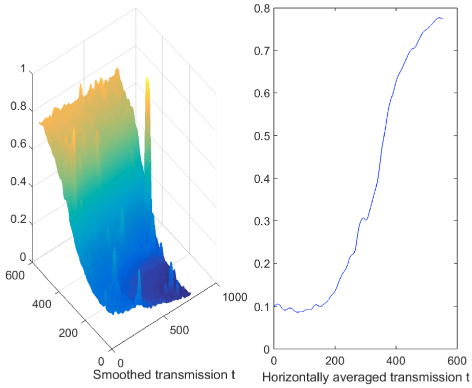

Figure 3: Smoothed transmission t and horizontal averaged function.

November 2015 (the dataset *Nov15*). Thanks to MOR method we have accurate estimation of visibility for these two datasets. We discard images for which visibility measurement is not available. Our goal is to be able to distinguish 3 classes:

- Class 1 - visibility $\leq 250m$,
- Class 2 - visibility $> 250m$ and ≤ 1000 m,
- Class 3 - visibility >1000 m.

Based on the MOR data one can easily determine to which class an image belongs, see Table 1.

Table 1: Number of images for each class and each dataset based on MOR data

	Class 1	Class 2	Class 3
Oct15	171	194	4092
Nov15	3	17	2451

However to determine these classes we intend to use the image datasets only. Therefore to distinguish between the three classes we use machine learning techniques on image data only and the predetermined partition of the images by the MOR data.

We proceeded as follows. We randomly partition the images into training and validation sets for each dataset. The 50% of each dataset is used for the training and the rest for the validation. We report in Figures 6 - 9 the results for two machine learning techniques: Single Classification Tree (SCT) and Bagged Classification Trees (BCT) Breiman et al. (1984) .

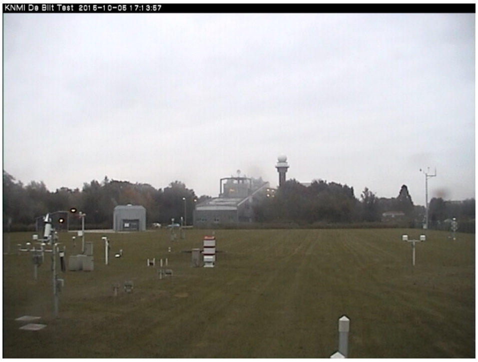

Figure 4: Image without fog.

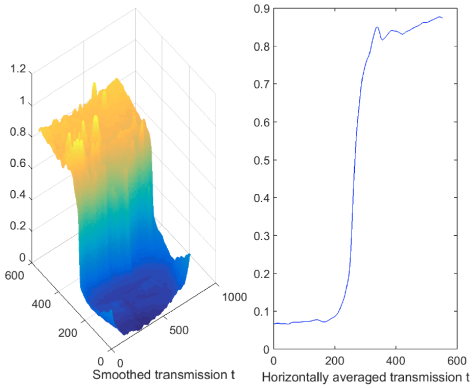

Figure 5: Smoothed transmission t and horizontal averaged function.

We find that the BCT outperforms the SCT for the November 2015 dataset in both Class 1 and 3. In Class 2 both methods are equally bad with 1 in 4 images wrongly classified.

For the October 2015 dataset the both methods are equally correct with a wrong classification of only 1 in 6 of the Class 1 (dense fog) images, 2 in 5 of the Class 2 (moderate fog) images, and 1 in 100 of the Class 3 (no fog) images. However due to the low amount of images with Class 1 and 2 classification it is premature to conclude that the methods are useful for fog classification.

We note that from the point of safety it is not problematic if a method has a bias for a higher probability on false positives towards lower Classes (more fog) images. However from the point of view of disruption, public awareness, believability and costs for society such a method is problematic if the bias is significant. Therefore a machine learning method should be combined with another fog detection method to decrease false positives and false negatives.

2.3 Transmittance Method

A second method exploiting the transmission function, called the transmittance method, is based on two consequences of the model (1).

The first one is the diffusion of the air region in the image into the ground region. This can cause an effective lowering of the horizon in pixel height. In the transmission function this effect can be seen as a shift of the location of the largest transmission jump to lower pixel height values.

The second consequence is the smoothing of the colour level due to the air intensity

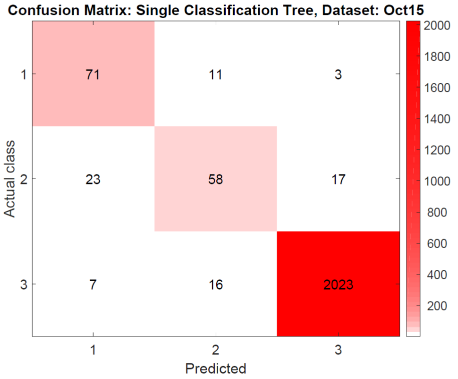

Figure 6: The SCT for dataset *Oct15*.

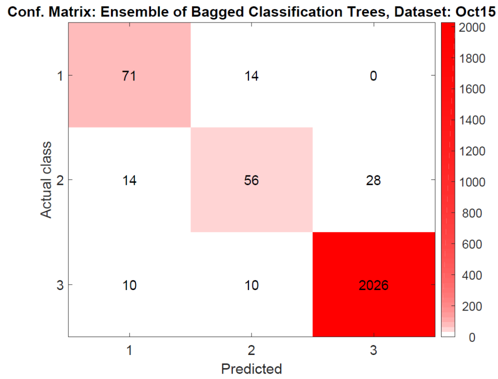

Figure 7: The BCT for dataset *Oct15*.

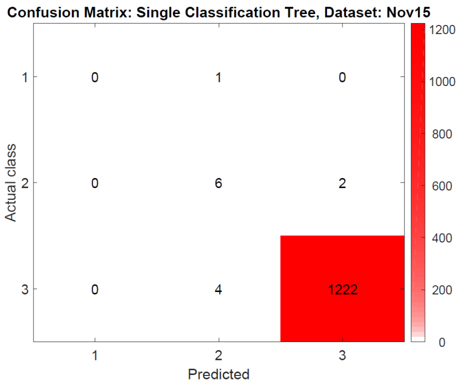

Figure 8: The SCT for dataset *Nov15*.

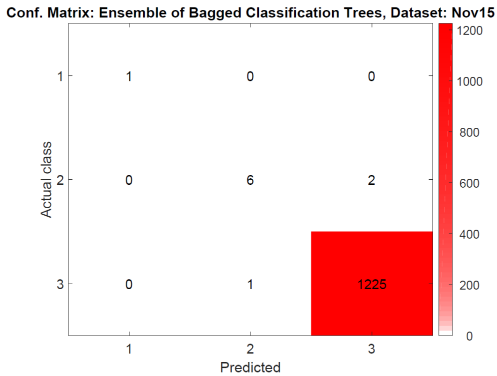

Figure 9: The BCT for dataset *Nov15*.

mixing with the strength $1-t$ in (1). This smoothing of color level can easily be seen by applying a column average of the transmission. The obtained function will be very noisy if there is no fog, while it will be smooth if there is a homogeneous fog.

A clear problem with the determination of the jump location is the smoothing itself. The smoothing implies smaller and more gradual jumps due to the horizon as the horizon itself becomes fuzzier and less clear. However large objects can still create large local deviations resulting in contamination of the jump location. The jump location can therefore only be used for extreme cases (dense fog or no fog conditions). As a result one can see that the jump location is usually at large values when there is fog and at small values when there is no fog. Unfortunately still a significant fraction of fog conditions according to both MOR and total variability data has a small jump location value.

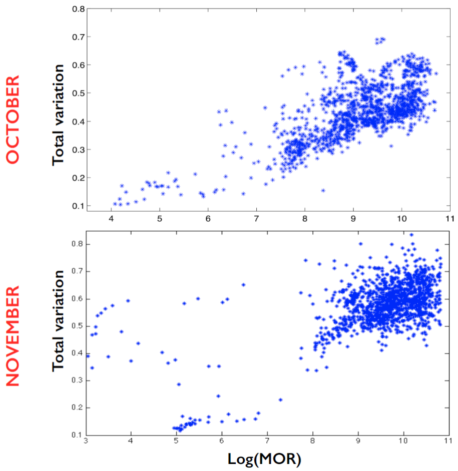

Figure 10: Total variability against the logarithm of MOR for the Oct15 and Nov15 data sets.

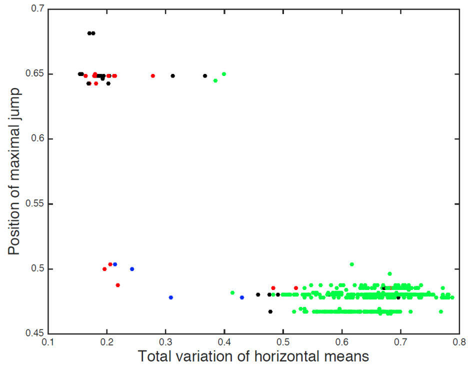

Figure 11: Jump location as the percentage of the height of image (from the top of image) against the total variability for 500 day pictures. Dot colour indication: black for MOR $<$ 200m, red for 200m$<$MOR$<$500m, blue for 500m$<$MOR$<$1km and green for MOR $>$ 1km.

A problem with the usage of total variability method is its dependence on the variability of no fog image. If a camera is pointed at a low variability location such as a snowy landscape or a calm sea, then foggy and clear weather conditions can be difficult to distinguish. Furthermore, the total variability method is only applicable when the camera is focussed at infinity. If a camera is focussed at a nearby location such as an object on the lens, then the resulting defocussing of the background will directly imply low variability, while the actual weather condition might be a clear day.

2.4 Fog Indicator method

The third method related to the transmission function will be called the Fog Indicator method. This method applies the horizontal averaging to the estimated transmission. The method combines the slope change of the obtained horizontal averaged transmission function f with the location of the biggest jump. An elementary observation is the large difference between the transmission values of the sky and the ground. Furthermore, the horizon is a sharp drop during clear days and a shallow drop during foggy days. Thus the horizontal averaged transmission function f for clear days looks more like a step function than in the case of foggy days. Hence the Fog Indicator F_{ind} can be suggested as the squared L^2 norm of the difference between the (discrete) horizontal averaging function f and the fitted step function S_f with respect to f, see

Figures 13 and 12 for an illustration.

Figure 12: An image without fog.

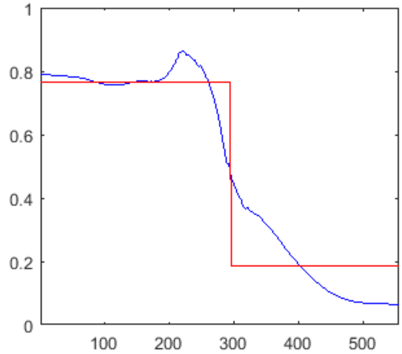

Figure 13: The horizontal averaged transmission function f (blue) and the fitted step function S_f (red).

Consequently, the low values of F_{ind} indicate clear days, while high values indicate foggy conditions. We summarize the obtained results for available data sets in Figures 14 and 15.

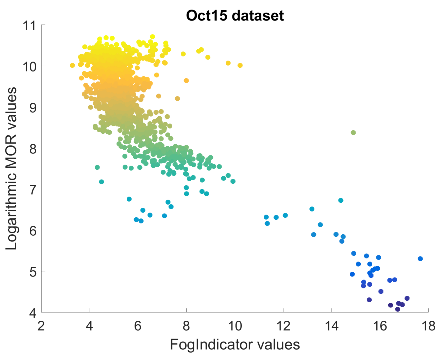

Figure 14: Logarithmic MOR values against Fog Indicator values for the Oct15 dataset. The colours are directly related to the logarithmic MOR values.

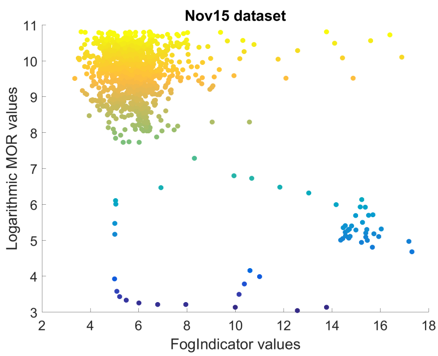

Figure 15: Logarithmic MOR values against Fog Indicator values for the Nov15 dataset. The colours are directly related to the logarithmic MOR values.

When considering the data of October 2015 the Fog Indicator seems like a good predictor for fog or even MOR values. However for the data of November 2015 one can see two additional groups of points that indicate a discrepancy between the two methods. One group (the blue points in the lower and left part of graph) is probably caused by a faulty MOR reading as the images do not show fog (as indicated by the low Fog Indicator value as well). The other group (the orange points in the top and right part of graph) is due to dark images because of the decreased length of days in winter in the Netherlands. It is natural that the second group did not occur in October as the days are not yet short enough to cause problems for the daily time intervals we are looking at. For typical representative pictures of each group see see Figure 16 and 17.

Figure 16: An image with a faulty low MOR value.

Figure 17: An image with a faulty large Fog Indicator value.

Clearly, the Fog Indicator method has some issues. Dark and nightlike images will yield wrong values. Moreover, the amount of clouds in the sky will influence the Fog Indicator value even though they do not cause fog. In general the Fog Indicator method depends on the visibility of a horizon in the image. If a camera is pointed towards the ground in such a way that the horizon is not visible, then the Fog Indicator method may fail for clear day images.

3 Fog detection methods from shapes in images

Fog is known to affect visibility by reducing the contrast. Multiple methods are possible for determining an effective value for the contrast. We were not successful to create fog detection methods with some of them. For example Fourier analysis methods did not show clear characteristics for discriminating between fog and clear conditions. Other methods like wavelet analysis were relatively complex and computationally expensive compared to the reliability of the data. Therefore we have chosen to do only two related methods: gradient thresholding and local contrast correlation.

3.1 Gradient Threshold method

This method is based on the assumption that the fog has a tendency to smooth colour values, creating a less pronounced colour gradient between an object and a background, the edge.

For simplicity we have converted the RGB colour images into grey scale images. Having this grey scale image we calculate the local gradient vector and its norm. Afterwards we count the number of pixels with a local gradient norm larger than a certain threshold. Our experience is that for a well chosen threshold one can distinguish for the chosen image between fog and clear days, see Figures 18 and 19 for an illustration.

Figure 18: The chosen image for gradient treshold method.

Figure 19: An image representation of gradient thresholding: the white pixels denote locations with sufficiently large gradients (the detected edges), while the black pixels indicate gradients below the threshold.

To compute the gradient we apply a finite difference method, usually a second order one, which implies that the local gradient is a patch size dependent given by the order of the finite difference method.

The proposed Gradient Threshold method seems to be a good fog indicator for at least the presence of fog, see Figures 20 and 21. Concerning the visibility distance we still see a large spread that can give unacceptably large deviations in the visibility distance.

The gradient method is still sensitive to defocussing, a presence of objects on the lens, and ground fog when it can give errors and incorrect interpretations of the data, but it is quite robust in the sense that the problems like astigmatism, chromatic aberration or night images will affect the method far less then colour dependent methods.

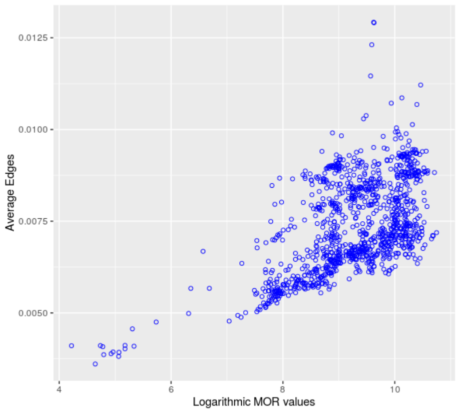

Figure 20: Average edges against the logarithmic MOR for October.

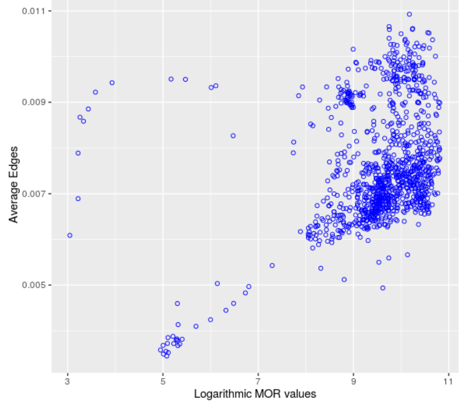

Figure 21: Same as Figure 20 for November.

3.2 Local Contrast Correlation method

In the Local Contrast Correlation method we make use of the fact that we have a sequence of images taken from the same viewpoint. The method proceeds in two phases. First we analyze a set of reference images from the past and determine specific, small-scale, contrast-rich features that are present in this set of images. Secondly, we take the current image, and determine whether the features that have been identified in previous images can be observed in the current image. In other words, the Local Contrast Correlation method tests specifically for the presence of certain contrast-rich features identified from reference images, and not directly for the presence of fog. But since fogs blurs the features of the image one might expect a good correlation with the presence of fog. The first phase will be called the analysis phase, the second phase the test phase. Analogous to the Gradient Threshold method we convert the RGB images to grey scale images. In the examples we only used daytime images.

The main motivation for this method, as compared to the previous, gradient threshold method, is to address the issue of contamination on the shape level, see section 4 below. For example, theoretically it is possible that in a situation of fog, a bird flies close the camera and introduces a lot of extra contrast, compensating for the loss of contrast elsewhere in the picture due to the fog. In the local contrast correlation method, the contrast from the bird will be discarded because it was not present in the set of reference images.

We next describe the analysis phase. For each reference image, we identify the small-scale, contrast-rich features as follows. We subdivide the image into a specified number of patches of a certain size. In each patch, we set the zeroth and first moments of the local grey scale expansion to zero. The constants are chosen to equal the average constant value and gradients within a patch. The remaining grey scale image for a certain patch will have highly pronounced edges (if edges are present in the patch). The corresponding patches obtained from the different reference images are averaged, to keep only contrast present in many of the images. A set of patches is selected where contrast is above a certain threshold. These will be used for testing the presence of specific features in the test image. Patches can e.g. be of size 16×16 and 100 patches can be selected. After moment removal, the patches where normalized, so that, as a vector, they had unit length. We denote by $\hat{R}_{\alpha,\beta}(j,k)$ the patches after moment removal, averaging and normalization, with α, β the index of the patch and (j,k) the coordinates of each pixel in the patch, and by $S = \{(\alpha_1, \beta_1), (\alpha_2, \beta_2), \ldots, (\alpha_M, \beta_M)\}$ the set of patches selected for testing. See Figure 22 and 23 for an illustration.

In the test phase, one subdivides the test image $I(j,k)$ in patches $I_{\alpha,\beta}(j,k)$ in the same way as for the analysis phase. To find whether a certain feature is present in the image, we consider the inner product (correlation)

$$t_{\alpha,\beta} = \sum_{j,k} I_{\alpha,\beta}(j,k)\hat{R}_{\alpha,\beta}(j,k).$$

A large value of $t_{\alpha,\beta}$ means that the detailed features, observed in the reference images, are present in the test image. Small values for $t_{\alpha,\beta}$ can mean either that there is no contrast present in the specific patch, or that there is an altogether *different* contrast present, e.g. due to an object with a different shape that is present in the image. The logarithms of the values $t_{\alpha,\beta}$ can be summed to give a first indication of the "fogginess".

Figure 22: An RGB reference image used for the analysis phase of the Local Contrast Correlation method.

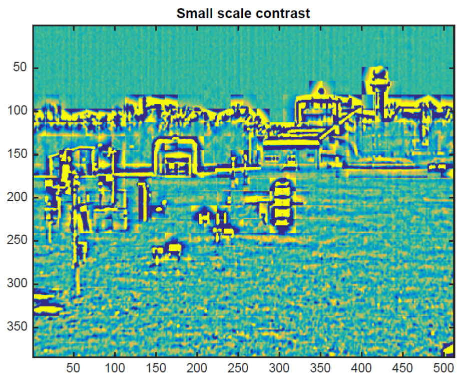

Figure 23: An outtake of the greyscale image of which the zeroth and first moments are removed in grid patches. The colouring is from dark blue for value -1 to bright yellow for value +1.

The indicator value of the proposed Local Contrast Correlation method is actually a good indicator for the October 2015 data with no deviations from a specific functional form with respect to the MOR data. However for November 2015 we see again a group of points deviating from the October functional dependence. Again these points seem false positives of the MOR data as the values of the edge detection are similar to the values of the clear days. It is highly likely that this group is the same false positive group as found by the Fog Indicator method.

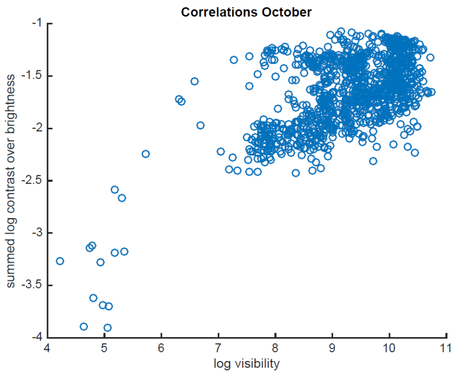

Figure 24: Local contrast correlation indicator values against MORvalues for images of October 2015 dataset.

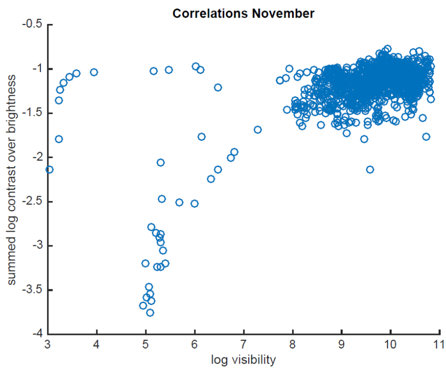

Figure 25: Local contrast correlation indicator values against MOR values for images of November 2015 dataset.

The Local Contrast Correlation method shares some properties of Gradient Tresholding method. But there is also a number of differences. An important difference is the use of reference images, showing what was previously visible at the site. As explained, this could address the issue of shape contamination. In principle, using more of the available information should lead to a reduction of the statistical uncertainty. However, it is unclear whether this is the case when including information from reference images, because there are also potential complications. The use of patches in principle allows the use of different statistics than simply summing the values $t_{\alpha,\beta}$. Each low $t_{\alpha,\beta}$ value is an indicator of reduced contrast in some part of the image which could be caused by fog. However, it is not easy to say anything in general about the relation between the $t_{\alpha,\beta}$ and the fog conditions. Reasons for this are for example that the depth- and height-maps of the pictures are unknown, that the distribution of contrast over the picture can vary and that fog can have different characteristics.

4 Error sourcess in fog detection methods

All methods for determining the existence of fog are subjected to three types of error sources: difficult weather conditions, camera errors and errors in the method itself.

We assume that all errors in the method itself, for example ill-posed matrices for inversion or other problems resulting in non-uniqueness, are negligible, while all other errors are due to the difficult weather conditions or camera errors.

In what follows we discuss contaminating conditions in fog detection methods.

Contamination on the colour level The colour level depends on the properties of the objects seen in the picture, the intensity of the light, the position of the sun and the weather conditions. Several combinations of these factors can lead to false positives in the colour level methods for fog detection. Due to the variable nature of weather, light intensity and solar position in the sky one expects the colour level contamination to be highly variable with predictable time dependencies.

Contamination on the shape level The shape level depends on the local variability in colour (or grey scale), which ultimately depends on the resolution and the intensity of the light. Therefore the same contamination problems as with colour level are present. If the objects in the images vary with time, as it is the case for traffic cameras, then the shape level depends on the amount, shape, size and colour of objects visible in the clear image as well. An empty road should not be classified as foggy just because no car is visible, while a foggy traffic jam should not be classified as clear just because a lot of cars are visible. Therefore only not hidable stationary objects should be used in the determination of the shape level, e.g.one does not want to use the lines on a highway as objects, because they can be hidden from the camera by another objects such as a car or a truck.

Weather conditions A crucial part in the colour level methods is the Dark Channel Prior. By definition this Dark Channel Prior is the minimal value over all channels for all pixels within a patch. As a consequence the Dark Channel Prior is biased towards dark images: darker images are perceived as clearer pictures. Therefore every weather condition that creates dark images will artificially be interpreted as clear. Thick rain clouds, clouds during dusk or dawn and night images can all give the wrong interpretation of fog. Night images are even more problematic because of the vanishing horizon.

A second problem is the imitation of fog by other weather conditions. Heavy precipitation in any form will create a decrease in the visibility distance, but it is not fog and therefore not seen by the MOR (if the sensor is encased for protection purposes). Therefore false positives of the image methods with respect to fog and false negatives of the MOR method with respect to visibility distance will occur.

One can pose the question what the ultimate goal of the KNMI (or any other user of these tools) is: fog detection or visibility distance determination? This question is crucial in the evaluation of the data, for example in the determination of the influence of the MOR values compared to the image data indicators.

A third problem is the inhomogeneous distribution of fog. If fog is only present in a part of the image, then even dense fog can be classified as moderate fog. Clear examples are thin layers of dense ground fog. They can result in multiple effective horizons or a high spatial discrepancy in edge detection.

Camera errors Camera errors are systematic errors that effect all image data indicators. The most prominent problems are defocussing, chromatic aberration and astigmatism.

Defocussing implies a large scale averaging on the entire perfect image resulting in an artificial dense fog condition. Almost all colours of the image are mixed resulting in a fog like Dark Channel Prior. Chromatic aberration is an effect when a lens does not work equally for all wavelengths. Chromatic aberration occurs in two types: different focal lengths or different foci. Different focal lengths imply different magnifications for different colors. Therefore edges become less pronounced and blurring occurs on the edges of the image resulting in artificial fog. Different foci implies a homogeneous defocussing of different strength for different colours. This results in a local averaging for different colours implying higher values for the Dark Channel Prior, hence the method can classify the image as slightly foggy. Astigmatism is an effect when different lens axes have different foci, resulting in an effective blurring of the image. Naturally the Dark Channel Prior can again classify the image as slightly foggy.

Miscellaneous errors There are other reasons why errors are introduced. For example animal interference. If a spider creates a cobweb on a camera, then it will influence the determination of fog or visibility distance. Similarly wind can blow leaves or cloths on the camera, while animals like bugs or arachnids can stay on the lens. Precipitation can cause blurring as well just by exposure of the lens to weather. Water droplets or ice severely influence the viewing angle or distort the view. Furthermore, dew and crystallization of moisture can cause fast changing operating conditions with total blockage of the camera lens in extreme cases. Aging of the lens due to degrading lens surfaces by sand, salt or other effects can create optical effects that persist. Moreover, CCD aging due to long exposures to high intensities of light or other effects can create permanent artifacts on images.

5 Conclusions

In this paper we present several fog detection methods based purely on processing of image data obtained from digital cameras. We can classify these methods into two groups. The first group is based on well established Dark Channel Prior method that was originally proposed to dehaze foggy images, and it includes Classification Trees methods, Transmittance methods, and Fog Indicator method. The second group works with converted grey scale images, and it includes Gradient Tresholding and Local Contrast Correlation method.

We note that not only the fog detection but also the visibility correlated to the current meteorological standard for visibility ranging can be obtained from camera images in several cases. For practical usage one may propose a combination of presented methods supported by proper statistical tools to create a fog detection method that is robust against false positives and false negatives of individual methods. In fact, using proposed fog detection methods we could recognize faulty data in Meteorological Optical Range (MOR) measurements.

References

L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen. *Classification and regression trees*. CRC press, 1984.

T. K. der Staten Generaal. Vragen van het lid jansen (sp) aan de minister van verkeer en waterstaat over cameras langs de wegen (ingezonden 21 juli 2010). antwoord van minister eurlings (verkeer en waterstaat) (ontvangen 17 augustus 2010). *Kamervragen (Aanhangsel)*, 2009-2010(3118), 2010.

R. Fattal. Single image dehazing. *SIGGRAPH*, pages 1–9, 2008.

L. P. F.L. Pedrotti, L.S. Pedrotti. Introduction to optics. *Pearson - Prentice Hall*, 3rd edition:355–357,438–456, 2007.

K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(12):2341–2353, Dec 2011. ISSN 0162-8828. doi: 10.1109/TPAMI.2010.168.

C. Kitchin. Astrophysical techniques. *CRC Press*, 5th edition:17–30, 2009.

S. Narasimhan and S. Nayar. Chromatic framework for vision in bad weather. *CVPR*, pages 598–605, 2000.

S. Narasimhan and S. Nayar. Vision and the atmosphere. *IJCV*, 48(233-254), 2002.

G. Rieke. Detection of light - from the ultraviolet to the submillimeter. *Cambridge University Press*, 2nd edition digitally transferred:151–175, 2009.

S. Tierney. Matlab implementation of "single image haze removal using dark channel prior". https://github.com/sjtrny/Dark-Channel-Haze-Removal, 2014.