DETECTION OF THE START AND END OF FOG/HAZE IN A VIDEO

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Introduction :-

Characteristics of the foggy Image :-

- **decrease of the visibility distance on the image**,
- scene blurring (**color degradation**) due to the **loss of high frequency components**.

The fog density mainly depends on the depth information.

Detection based on the Computer Vision techniques

This method is based on two clues:

- **estimation of the visibility distance**, which is calculated from the camera projection equations
- the **blurred effect due to the fog**

Detection by estimating The Haze Degree factor

- This method is based on the **atmospheric scattering model analysis** and the statistics of various outdoor images.
- we propose a **haze degree estimation function** to automatically distinguish foggy images and label images with their corresponding haze degrees.

DETECTION OF FOG BY ESTIMATING THE HAZE DEGREE FACTOR

Literature Survey (Atmospheric Scattering Model Analysis) :

This analysis uses the **RGB color model**. Based on **Koschmieder Law**, physical model for foggy image is

I(x) = J(x)*t(x) + A*(1 - t(x))

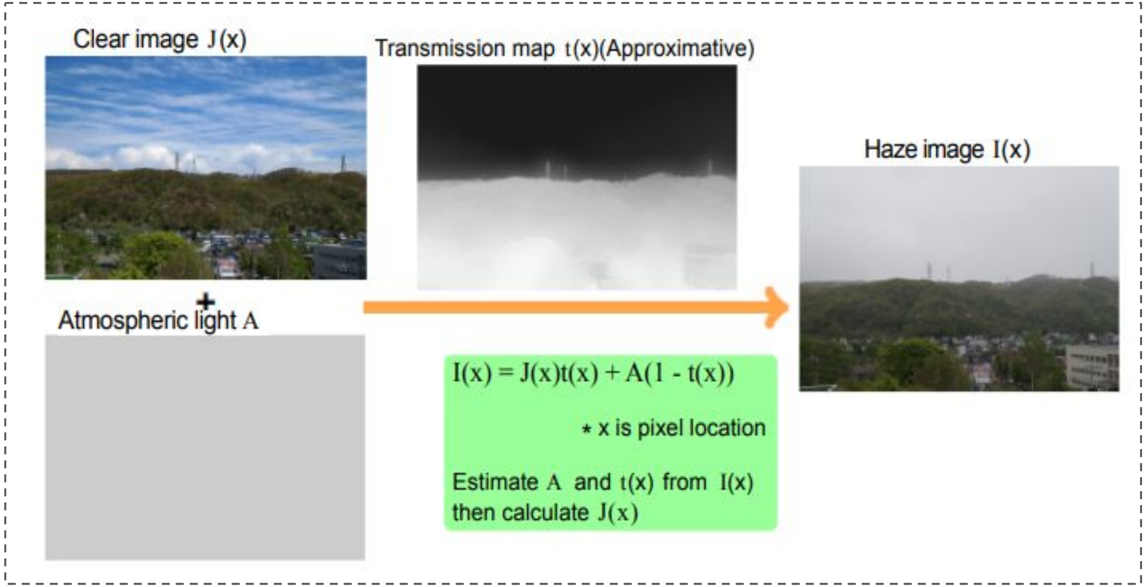
where x denotes the **pixel location**,

I(x) is the **observed haze image**,

J(x) is the **haze-free image**,

A is the **global atmosphere light**,

t(x) is the **medium transmission**.



Estimation of the Atmospheric light (A):

- **d(x) and b(x) are the minimum and maximum values** of three channels at a pixel location.
- d and c (average values of dI (x) and cI (x)) are referred to as the dark and contrast values, respectively
- we assume that the size of image I is |Sx * Sy|
- Therefore, the values d and c may be correlated with the overall haze degree of an image.

$$\mathbf{d}^{\mathbf{I}}(\mathbf{x}) = \min_{n \in \{r,g,b\}} \mathbf{I}^{n}(\mathbf{x})$$

$$\mathbf{b}^{\mathbf{I}}(\mathbf{x}) = \max_{n \in \{r,g,b\}} \mathbf{I}^{n}(\mathbf{x}),$$

$$\mathbf{c}^{\mathbf{I}}(\mathbf{x}) = \mathbf{b}^{\mathbf{I}}(\mathbf{x}) - \mathbf{d}^{\mathbf{I}}(\mathbf{x})$$

$$d = \frac{\sum_{\mathbf{x} \in \mathbf{X}} \mathbf{d}^{\mathbf{I}}(\mathbf{x})}{|S_x \times S_y|}, \; b = \frac{\sum_{\mathbf{x} \in \mathbf{X}} \mathbf{b}^{\mathbf{I}}(\mathbf{x})}{|S_x \times S_y|}$$

$$\mathrm{c} = \mathrm{d} - \mathrm{b},$$

$$b \le \mathrm{A}_0 \le \max_{\mathbf{X} \in \mathbf{X}} \mathbf{b}^{\mathbf{I}}(\mathbf{x})$$

- A0 can be expressed as, (we set λ = 1/3)

$$\mathrm{A}_0 = \lambda \max \mathbf{b}^{\mathbf{I}}(\mathbf{x}) + (1-\lambda) b, 0 \le \lambda \le 1$$

Haze Degree Estimation Function:

- For **most foggy images, (A0−d) is less than 75 and c is less than 50** and for **most haze-free images (A0−d) is greater than 100 and c is larger**.
- ln(w) is a linear function of x1, x2 and σ. To limit ω ∈ (0, 1), we introduce the following to estimate the haze factor ω:

$$\omega = \exp\left\{-\frac{1}{2}(\mu x_1 + \nu x_2) + \sigma\right\}, x_1 = \frac{A_0 - d}{A_0}, x_2 = \frac{c}{A_0}$$

- Using 300 outdoor images that use the RGB color model and **multiple linear regression analysis** on our **data set** { **ln(w), x1, x2** } the model is trained and the final coefficients are obtained as

μ = 5.1, v = 2.9, σ = 0.2461

- The **Foggy Road Image Database (FRIDA)** is used to test the haze factor estimation function

- A is generally a fixed element A0 in all three color channels.
- t(x) is supposed to be same in all three color channels at one pixel location.
- When the atmosphere is homogeneous, **$t(x) = \exp(-\beta \cdot dep(x))$**, where β is the **scattering coefficient** of the atmosphere, and dep(x) is **the scene depth**
- The property that **the difference between the maximum value and the minimum value of RGB color channel is larger as the fog becomes darker** for designing our classical model is used.

Assumptions:-

- **Atmosphere is homogeneous**
- The picture has **no monochrome light source** because A was not the same in three channels if image has a monochrome light source

- After calculating haze degree of all nearly 300 images we found ranges of w by dividing them into four groups for different intensities of fog levels in the image.

w <= 0.6	→ sunny / fog-free image
w > 0.6 and w <= 0.7	→ low foggy image
w > 0.7 and w <= 0.8	→ moderate foggy image
w > 0.8	→ high foggy image

- Note that the **<u>sky area of images from the data set images is different from a real situation</u>**. So, Real fog-free image in our experimental results, have a degree of below 0.4.
- 48 real images are taken and found an approx ranges of w by dividing them into three groups for different intensity of fog levels in an image.

w <= 0.4	→ sunny / fog-free image
w > 0.4 and w <= 0.7	→ foggy image
w > 0.7	→ high foggy image

Failing examples:

- During night time the atmospheric light is affected by artificial light (which are monochromatic light sources), such as street lights and car lights.
- **Atmospheric light value at night is not uniform,** so haze degree factor estimation method is not valid.
- In the shown image, **A was not the same in three channels** which make our model fail.

Example: Shown Image is foggy image so,

haze degree factor must be above 0.6 but

Haze degree factor (w) = 0.246 which says that image is

fog-free image.

Characteristics of night time images:-

1. Difficult to determine the illumination intensity and range of artificial light sources,
2. In contrast to sunlight, the light emitted by artificial light sources is colored

Possible solution for estimating A in night time images:

- In the atmospheric scattering model [**$I(x) = J(x)*t(x) + A*(1 - t(x))$**], we will split the atmospheric light value **A into $L(x)*\eta(x)$**

$$I(x) = L(x)*\eta(x)*R(x)*t(x) + L(x)*\eta(x)*(1 - t(x))$$

where, $L(x)$ represents the **ambient illumination**,

$\eta(x)$ represents the **environmental color coefficient**,

$R(x)$ is the **scene reflection** (high frequency component)

- The initial atmospheric light value is corrected by the **light source influence matrix**.
- The transmittance near the light source can be adaptively adjusted to reduce the glow effect near the light source by the light intensity matrix.

Estimation of A in 3 different channels for night time images:

- **photometric map** of image is extracted by converting the image to HSI space.
- The average value of the pixels in the **top 0.5%** of the photometric value is selected as the light source candidate **threshold Cmax**.
- The light source pixel points are filtered whose photometric values are greater than or equal to the threshold value.
- Pixel blocks in **top 2%** of the photometric value are defined as the **near light source region Ω**.
- Ambient illumination A on each **local patch j∈Ωi** is assumed to be constant, intensity Lj and color map ηj of ambient illumination are assumed constant.

- Under the action of light, **maximum reflectance** is approximated as 1.

$$\max_{j\in\Omega_i} R_j^\lambda \approx 1$$

- The **atmospheric light deviation coefficient A0** is introduced to modify the atmospheric light value Aλ _i near the light source
- The dehazing effect of A0 in the range of **0.1–0.16** is better.

$$A_i^\lambda = \begin{cases} \bar{A}_i^\lambda + A_0, i \in \Omega \\ \bar{A}_i^\lambda, i \notin \Omega \end{cases}$$

$$\begin{aligned} M_{\Omega_i}^\lambda &= \max_{j\in\Omega_i} I_j^\lambda \\ &= \max_{j\in\Omega_i} \left(L_{\Omega_i}\eta_{\Omega_i}^\lambda R_j^\lambda t_{\Omega_i} + L_{\Omega_i}\eta_{\Omega_i}^\lambda (1 - t_{\Omega_i}) \right) \\ &= \max_{j\in\Omega_i} R_j^\lambda \left(L_{\Omega_i}\eta_{\Omega_i}^\lambda t_{\Omega_i} \right) + L_{\Omega_i}\eta_{\Omega_i}^\lambda (1 - t_{\Omega_i}) \end{aligned}$$

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$$M_{\Omega(x)}^c = L_{\Omega(y)}\eta_{\Omega(y)}^c \rightarrow \eta_{\Omega(y)}^c = \frac{M_{\Omega(x)}^c}{L_{\Omega(y)}}$$

$$L_{\Omega(y)} = \max_{c\in\{r,g,b\}} \left(\max_{x\in\Omega(y)} \widetilde{I}_x^c \right)$$

Accuracy for real time images:

- About **94%** haze-free images get a haze-factor value below 0.4, **88%** haze images get a value between 0.4 and 0.6, and, **85%** thick images get a value between 0.7 and 1.

How to apply this method for video:

- **A frame** of the video is **inputted as image** to the haze degree function.
- **Each frame was performed in this method independently of other frames**. So we obtain the starting and ending frames of fog, from that we will get their respective time intervals.
- As cut-off ''W'' (haze degree factor) is not same for all environment conditions. We have chosen some average w by observing all type of videos, so we may miss some of the foggy frames.

Execution time:

- Execution time for a single image is **8ms - 15ms** for 100 x 100 Pixels
- Execution time for a single frame in video is **10 ms - 15 ms** for 100 x 100 Pixels

Cut - off value of Haze Degree Factor (w):

- If a frame has its haze degree factor(w) less than W_cut_off then it is non-foggy frame and greater than W_cut_off means foggy frame.
- Depending on weather conditions W_cut_off value changes because day is cloudy then that frame results into a low foggy image rather than non-foggy.
- Calculated W_cut_off is in between 0.6 and 0.62.

Conclusion:

- The fog with opacity level greater than 30% is being detected in a frame.

Future Aspects:

- Detection of starting and ending of fog in the night time.
- Dehazing of fog in the day and night time.

References :

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