

**KOLEJ UNIVERSITI TUNKU ABDUL RAHMAN**

**FACULTY OF COMPUTING AND INFORMATION TECHNOLOGY**

**Assignment**

**BMCS3003 DISTRIBUTED SYSTEMS AND PARALLEL COMPUTING**

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| Student’s Name / ID Number | : | Sandra Tang Poh Yi / 22WMR13625 |
| Student’s Name / ID Number | : | Saw Hui Lin / 22WMR13626 |
| Programme | : | RSW |
| Tutorial Group | : | G3 |
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1. **Introduction**

Haze is an effect that occurs when airborne particles such as smoke, water, or pollution, scatter light as it travels through the atmosphere. It dulls the image and makes the landscape aspects appear blurry like in inclement weather, outdoor photos typically lose quality and contrast (Marr, 2021; Qingsong Zhu, Jiaming Mai and Ling Shao, 2015). It is an unpleasant disadvantage for photographers because it alters the colours and blurs the distinction of everyday photos, reduces the visibility of the scenes, and compromises the reliability of numerous applications like object detection, outdoor police work, and satellite and underwater photography. Other than that, the deteriorated pictures cause the majority of automated systems, which heavily rely on the input image definition, to malfunction. As a result, eliminating haze from images is a crucial and rarely requested area in image processing (Sri Krishna & Professor, 2021, Qingsong Zhu, Jiaming Mai and Ling Shao, 2015).

Additionally, low contrast, low signal-to-noise ratio, and colour distortion are characteristics of hazy photographs. Thus, noise reduction, edge highlighting, contrast enhancement, and colour restoration are the main goals of picture dehazing algorithm. The technique for picture dehazing is evolving along with image processing technologies. The picture dehazing issue was first approached as an image enhancement challenge, employing defogging algorithms like Retinex and contrast enhancement. Later, the atmospheric scattering model-based picture restoration techniques are used to address the image dehazing problem. For example, it includes Non-local Dehazing, Dark Channel Prior, and others. Fusion-based techniques are developed when the researchers combine many of the approaches to improve performance due to the intricacy of the picture dehazing challenge. Nowadays, the researchers have proposed many more algorithms such as DehazeNet, AOD-Net, and FFA-Net, the robustness and dehazing impact of the algorithms have significantly improved (Guo et al., 2023).

Moreover, the image restoration and image enhancement are two primary methods used by researchers to remove haze from a single image. The Koschmieder atmospheric scattering model, which describes how haze develops as a result of light scattering and attenuation brought on by minute particles like dust or water droplets, is the foundation of image restoration. However, the two unknown variables in this model make it difficult to solve. The Dark Channel Prior (DCP), which detects pixels with extremely low intensity in at least one colour channel in non-sky areas, was developed by He et al. to solve this issue. DCP helps to remove the haze by accurately estimating the transmission medium’s extinction coefficients (Ngo et al., 2020).

In this paper, we utilize the DCP as the core technique for haze removal. We can evaluate and account for the effects of haze-induced light attenuation and scattering by using DCP. By improving visibility and bringing back more distinct elements in the picture, this technique aids in the recovery of the original scenario. This enhances the overall clarity of the dehazed image by making it look crisper and more visually correct. Figure 1 shows a sample result of using DCP.

A collage of different images of buildings

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**Figure 1: Haze removal result**

Top: Input haze images. Middle: Restored haze-free images. Bottom: Depth maps. The rectangles in the top row indicate where the method automatically obtains the atmospheric light.

1. **Literature Review**

Image dehazing can minimize the negative effects of inclement weather on the quality of pictures while also effectively enhance contrast and appearance (Xu et al., 2016). In addition to improving the efficacy and accessibility of remote sensing data, haze removal lessens the restrictions imposed by weather conditions on aerial images (Long, Shi and Tang, 2012). Besides that, Tan eliminates the haze by optimizing the local contrast of the newly created image after noticing that the haze-free image needs to have a higher contrast than the one containing the haze image (Tan, 2008). By assuming that surface shading and transmission are uncorrelated locally, Fattal estimates the scene's albedo and infers its medium transmission (Fattal, 2008). Nevertheless, this method may not work well in situations where the presumption is violated and is unable to handle pictures with a lot of haze (He, Sun and Tang, 2009).

Apart from that, the Dark Channel Prior (DCP) approach, which was first presented by He, Sun, and Tang (2009), has become one of the most prevalent and significant dehazing approaches among the many that have been proposed over the previous 20 years (He, Sun and Tang, 2009). Moreover, an image statistical property known as the dark channel prior predicts that in small patchy parts of haze-free outdoor images, the darkest pixels will be very dark, so close to zero (Golts, Freedman and Elad, 2020). Stated differently, a dark channel derived from an unobstructed daylight picture would primarily consist of black pixels, with the exception of sky places, while a channel derived from a hazy image would contain grey pixels of varying intensities (Koley, Roy and Dhar, 2021).

**Atmospheric Scattering Model**

The following atmospheric scattering model is frequently used in computer vision and computer graphics to explain how a haze image forms:

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**Figure 1**

According to Xu (2012), I represent the observed image with haze, J represents the object’s light source, A represents ambient light while the ratio is established by the medium transmission value t. Moreover, X represents the image’s coordinate. In order to recover J, A and t from I, haze needs to be removed (Xu et al., 2012). Consequently, it is important to estimate t(x) and A first (Xu et al., 2016). Haze removal becomes more difficult as a result. In addition, taking a look at the right side of the equation, the first term J(x)t(x) is called direct attenuation while the second term which is A(1-t(x)) called airlight. The scene's radiance and its degradation in the medium are described by direct attenuation, whereas the scene's colour shift is caused by airlight, which is the result of previously scattered light (Xie, Guo and Cai, 2010).

**Dark Channel Prior**

According to He et al (2009), an indicator of the haze-free outdoor photos is the dark channel prior. It is predicated on the crucial finding that the majority of local patches in haze-free outdoor photos have a few pixels with extremely low magnitudes in at least a single-color channel (Xie, Guo and Cai, 2010). Officially, for an image J, the equation as below:

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**Figure 1.1**

From the Figure 1.1 where Ω(x) is a local patch centered at x and Jc is a colour channel of J. With the exception of the sky area, the intensity of Jdark is extremely low and nearly zero if J is an image taken without any outdoor haze, except the bright region:

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**Figure 1.2**

Moreover, numerous photos have been used to confirm this observation (Long, Shi and Tang, 2012). According to He et al. (2011), to test this assumption, he personally removes the sky regions from 5,000 haze-free landscape and cityscape photos. It is discovered that 90% of the dark channel's pixels have intensity values below 25, and 75% of its pixels have zero values. These findings provide strong support for the dark channel prior. Hence, the primary cause of the lack of contrast in the dark channel is the vibrant, shadow-rich nature of authentic pictures (Kaiming He, Jian Sun and Xiaoou Tang, 2011). When the transmission t is low, a haze image is brighter than its haze-free counterpart because of the additive airlight. Therefore, in areas with denser haze, the dark channel of the haze image will be more intense (Wang and Wu, 2010).

Although effective, the Dark Channel Prior (DCP) technique has several well-known shortcomings. The algorithm struggles in sky areas where the dark channel conjecture is inherently broken, resulting in poor sky region coding (He et al., 2010). It also has problems with white objects that are close in colour to the background light and does not satisfactorily remove the haze or distorts the colours (Fattal, 2014). DCP's performance is poor when the haze is thick, and it often fails to remove enough of the haze or ends up overdoing it when the parameters are changed too much (Tarel and Hautiere, 2009). The original method's computational burden, mainly with regard to the soft matting step of composing the transmission map, makes it unable to be used in real time without some sort of hardware acceleration (He et al., 2013). Moreover, the approach can produce excessive noise in low transmission areas and leads to colour distortion due to the complex real scene illumination that the global atmospheric light assumption fails to consider (Meng et al., 2013).

**Transmission Estimation**

After dark channel prior, estimating transmission t(x) is necessary in order to continue working on the solution. It is also necessary to assume that atmospheric light A is known. Below Figure 2 will be the diagram by dividing both sides of A:

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**Figure 2**

We are handling colour images; thus, we must normalize each colour channel separately. For most of the images, the depth does not change too drastically so it can be considered constant over small regions. This hypothesis needs modification for edges of images. Let Ω(x) is a small patch over which transmission stays constant. We use the dark channel on both sides of the below equation which is Figure 2.1:

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**Figure 2.1**

Since t(x) is assumed to be constant over a small patch, it can be excluded from the minimum operator. Since J(x) is a fog-free image, its Dark Channel value is close to zero. This results in the following outcome:

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**Figure 2.2**

The reduction of transmission t(x) to:

A close up of a math equation

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**Figure 2.3**

The right-hand term in figure 2.3 is referred to as dark channel of a normalized hazy image: it gives an estimate of the transmission for a scene point. While dark channel prediction works well for the majority of images, it is not an accurate recreation for the sky’s regions. The color of fog is very similar to the color of the sky, which is significant because it makes estimating atmospheric light, A, easier. The sky area is practically at infinity distance; therefore, we expect next to no light from the distant sky. Using this reasoning and the dark channel model for estimating the transmission in trouble regions of images, we can determine, for sky region, the transmission as:

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**Figure 2.4**

Even on a day with no clouds, the atmosphere always contains some moisture, which causes some of the light to become dispersed. Thus, clear daytime photos that contain a small amount of fog are also known as "Aerial Prospective." In order to account for this phenomenon, Figure 2.3 introduces a variable w, which yields:

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**Figure 2.5**

Based on Figure 2.5, applications determine the value of w, which ranges from 0 to 1. At a pixel x, the variable w efficiently decreases the dark channel and raises t(x), resulting in lower reduction in the reestablished photograph.

**Approximation of Atmospheric Light (A)**

The accurate colour regeneration of the pictures is crucial for atmospheric light estimation. An incorrect estimate will cause in comparison colour changes in the recovered image J in the RGB plane (Ieee.org, 2025). Besides that, according to this article, the atmospheric light A has been assumed to be recognized. According to previous works, A or A's first guess is the colour of the region with the greatest amount of haze. Moreover, the most haze-opaque pixels in the fuzzy pictures are those that are the brightest (Ieee.org, 2025). This is only true in cloudy conditions where it is possible to ignore the sun. In this instance, the scene's sole source of lighting is the ambient light. Thus, every single hue channel's scene radiance is determined by:

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**Figure 3**

In this case, R ≤ 1 is the reflectance of the scene points. As shown in the equation, haze imaging equation in Figure 3 can be expressed as follows:

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**Figure 3.1**

When the image contains pixels at infinite distance (t≈0), the brightest I is the most haze-opaque and roughly equals A. Sadly, we hardly ever get to ignore the sun in real life. Taking into account the sunlight S, we alter the equation in Figure 3 by:

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**Figure 3.2**

Apart from that, we also modify the equation in Figure 3.1 as below:

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**Figure 3.3**

Below will be the example of the situation, the image's brightest pixel may be more brilliant than the ambient light. They could be on a white vehicle or a white structure in figure 3.4 (d) and (e).

A collage of a city

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**Figure 3.4**

Figure 3.4. Estimating the atmospheric light. (a) Input image. (b) Dark channel and the most haze-opaque region. (c) The patch from where our method automatically obtains the atmospheric light. (d), (e) Two patches that contain pixels brighter than the atmospheric light.

According to the above Figure 3.4 (b), a hazy image's dark channel roughly represents the density of the haze. In order to enhance the estimation of the surrounding light, we can use the dark channel to identify the area that is most obscured by haze. First, we select the dark channel's top 0.1 percent brightest pixels. These pixels, which are delineated by yellow lines in Figure 3.4 (b), are typically the most haze opaque. The pixels in the source picture I that have the highest intensity among these pixels are chosen to represent the atmospheric light. In Figure 3.4 (a), these pixels are located in the red rectangle.

**Soft Matting**

Initially, He et al. (2009) used the soft matting approach delineated by Levin et al. (2008) to enhance the transmission map. The main idea is that both the alpha matting and image composition functionalities are problems in the refinement of the transmission map. In this context, the transmission map t functions as the alpha matte that is to be improved upon with respect to the given hazy image (Levin, Lischinski and Weiss, 2008). The refinement is formulated as an optimization problem using the soft matting approach:

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**Figure 4**

According to Figure 4, where t̃ is the coarse transmission map estimated using the dark channel prior, t is the refined transmission map, λ is a regularization parameter that balances the fidelity to the coarse map and the smoothness constraint, and L is the matting Laplacian matrix defined as:

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**Figure 4.1**

The equation in Figure 4.1 where δij is the Kronecker delta, μk and Σk are the mean and covariance matrix of the colors in window wk, U3 is a 3×3 identity matrix, ε is a regularizing parameter, |wk| is the number of pixels in window wk, and Ii and Ij are the colours of the input image I at pixels i and j.

Other than that, by solving the following sparse linear system, the optimal t can be found:

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**Figure 4.2**

In the aforementioned equation, U represents an identity matrix with the same size as L. In order to softly constrain t by t~, we set λ to a small value (He, Sun and Tang, 2009).

By solving this optimization problem, we get a more accurate transmission map that reduces block artifacts while keeping edges and depth discontinuities. One caveat is that the soft matting approach is very costly from a computational standpoint, as it has a time complexity of O(N), where N is the image pixel count. For instance, on an average CPU, a refinement step may take a few minutes for an image of 600×400 pixels.

**Scene Radiance Recovery**

The last step is to recover the scene radiance (haze free image) after obtaining the refined transmission map through soft matting. Using the atmospheric scattering model, the scene radiance J can be recovered as:

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**Figure 5**

It maps the J image to the x pixel location. This equation takes I, a hazy image, as input along with an estimate of the A atmospheric light. The value of A is passed as an input parameter alongside t(x), the refined transmission map, and t₀, a lower bound (usually 0.1) set to minimize the effects of noise in areas of low transmission (He, Sun and Tang, 2009). This lower bound value is significant for far away objects since the amount of value for transmission goes close to zero. The visibility of the recovered image J is increased, the color contrast is restored, and there is also less haze in the effects however, due to the estimation errors in either the transmission map or atmospheric light some artifacts still exist (Tarel and Hautière, 2009). For certain cases like autonomous navigation systems that need immediate processing, a number of optimizations have been suggested to improve the speed of execution without exceedingly undermining the quality of the dehazing including parallel implementations on multicore CPUs or GPUs (Huang, Chen and Wang, 2014). Recent research has investigated further hardware accelerated versions to cope with the processing load that DCP comes with, achieving a range of 3 GPUs.

1. **Methodology**

**3.1 Explanation of Serial Code for Dark Channel Prior (DCP)**

The foundation of the Dark Channel Prior (DCP) method of picture dehazing is a fundamental finding regarding naturally occurring outdoor haze-free photographs like in the majority of these images’ patches, at least one colour channel typically has extremely low intensity values. With a number of useful stages, this implementation adheres to this idea.

To enable appropriate mathematical operations, the technique first transforms the input fuzzy picture into a normalised double-precision format. The dark channel for this image is then calculated by looking at the local patches (15 x 15 pixels) around each pixel. It creates a dark channel map that reflects the original image’s “darkness” by determining the lowest value of each patch across all the three RGB channels. The technique finds the brightest spots in the black channel, which usually correlate to foggy areas, for estimating atmospheric light. In order to provide a more reliable estimate of the atmospheric light, this solution averages the colour values of the top 0.1% brightest pixels from the dark channel rather than relying just on the brightest pixel.

After determining the ambient light, the algorithm divides each colour channel by the relevant atmospheric light component to normalise the picture. The transmission map, a critical component that indicates how much light travels through the haze to reach the camera, is then estimated using this normalized picture to compute another dark channel. The transmission is calculated as 1 minus a weighted dark channel value, where the weight (0.95) helps preserve some atmospheric perspective. The patch-based method frequently results in a blocky initial transmission map. In order to improve it, the implementation uses a fast guided filter rather than the original paper's computationally costly soft matting. Using the original picture as a guide, this filter sharpens the margins of the transmission map without affecting its general structure.

Lastly, the program uses the atmospheric scattering model to reconstruct the image free of haze. In order to avoid excessive noise in extremely cloudy areas, it adds a lower bound of 0.1 to the transmission values. By removing the atmospheric light, dividing by the transmission, and then adding the atmospheric light component back, it uses these components to recreate each colour channel separately. The output is normalised and returned to the standard picture format once the channels have been combined.

This method, which makes use of robust ambient light estimate and rapid guided filtering, strikes a compromise between theoretical accuracy and practical efficiency. Usually, the result is a brighter, clearer image with features that were previously hidden by haze. Natural colour tones are preserved, and noise or artefacts are not unnaturally amplified.

* 1. **Parallel Computing Techniques**

In order to accelerate the performance of haze removal, reduce the processing time, and handle the large datasets, parallel computing techniques such as Open Multi-processing (OpenMP) technique and Computed Unified Device Architecture (CUDA) technique are applied. For performance acceleration, OpenMP uses many CPU cores to conduct these tasks concurrently while CUDA makes use of GPUs. In addition, real-time haze reduction is necessary for applications such as drones, surveillance systems, and driverless cars. Processing times may be shortened from seconds to milliseconds. Additionally, millions of pixels make up high-resolution photos. By sharing the burden, parallel computing makes it possible to handle very big datasets effectively.

* + 1. **Open Multi-processing (OpenMP) Technique**

A simpler method of parallelisation with common multi-core CPUs is provided by OpenMP. OpenMP directives can divide the burden across the available CPU cores for the dark channel calculation, allowing each core to handle a different piece of the image. This method offers a considerable speedup on contemporary multi-core CPUs with little code modification. By having each thread gather values from the designated image region and store them in thread-local storage before combining the findings, the atmospheric light estimation may be optimised. OpenMP may parallelise the box filter operations directly with layered parallelism directives and use parallel sections to execute several filtering operations simultaneously for the guided filter implementation.

Because of data transfers between various memory areas don’t need to be explicitly managed, OpenMP’s shared-memory paradigm makes implementation easier. For the smaller pictures or systems without dedicated GPUs, this makes it great starting point for parallelisation.

* + 1. **Computed Unified Device Architecture (CUDA) Technique**

In order to speed up the GPU programming, NVIDIA created a CUDA parallel programming methodology. Complex control-intensive activities can be handled by the CPU, while computing-intensive tasks can be processed by the GPU (Wu et al., 2020). Therefore, the Dark Channel Prior technique is perfect for GPU acceleration via CUDA since it includes a number of computationally demanding processes. By allocating each pixel to its own GPU thread, CUDA allows for huge parallelisation of the dark channel calculation, which is the most time-consuming stage. By examining local patches surrounding each pixel concurrently, these threads would significantly cut down on processing time as compared to sequential processing.

Furthermore, CUDA can effectively detect the brightest pixels in the dark channel for atmospheric light estimate by utilising parallel reduction algorithms. Another computationally intensive phase that can profit from pixel-level parallelism across thousands of GPU cores is the transmission map calculation. Several box filters that may be implemented as separable convolutions are employed in the guided filtering stage for transmission refinement. These filters operate incredibly well on GPUs that leverage texture memory for optimal memory access patterns.

Besides, the last scene recovery step is ideal for parallel execution as it applies the atmospheric scattering equation to each pixel separately. A CUDA implementation could be able to dehaze high-resolution photos in real time with proper memory management to control the transfer between host and device memory. This would be useful for applications like surveillance systems or autonomous driving.

* 1. **Performance Evaluation Techniques**

In evaluating the performance of the Dark Channel Prior algorithm for image haze removal, several key criteria are considered to assess its effectiveness and efficiency in enhancing visibility and restoring natural colors in hazy scenes. Metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are useful for evaluating performance in a variety of fields. When assessing image processing algorithms, these objective quality evaluation tools offer quantifiable metrics that remove subjectivity. They make it possible to compare various methods fairly and consistently by creating standardised standards, which aids researchers and developers in identifying better strategies. Because it identifies certain algorithm flaws that may be fixed, this assessment procedure is essential for optimization.

* + 1. **Peak Signal -to-Noise Ratio (PSNR)**

The mean squared error (MSE) between the original and processed pictures is used to compute PSNR, a metric that accesses the quality of reconstructed or processed images in comparison to their original forms as shown below. The MAX is the maximum possible pixel value, which is 255 for 8-bit images. The result will be expressed in decibels (dB), and the typical range is 20 to 50 dB for the image processing. The higher the value indicate that the quality is better.

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**Figure 3.1**

* + 1. **Structural Similarity Index (SSIM)**

A perception-based measure called SSIM takes into account an image’s structural information. In contrast to PSNR, which assesses each pixel individually, SSIM evaluates the brightness, contrast and structural similarity. These factors are taken into account by the SSIM formula, which yields a result between -1 and 1, where 1 denotes perfect similarity.

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**Figure 3.2**

1. **References (Harvard)**

Marr, A. (2021). *How to Handle Haze in a Landscape Photo*. [online] Explore Landscape Photography, viewed on 8 March 2025. Available at: <<https://explorelandscapephotography.com/how-to-handle-haze-in-a-landscape-photo/>>

Qingsong Zhu, Jiaming Mai and Ling Shao (2015). A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior. *IEEE Transactions on Image Processing*, 24(11), pp.3522–3533, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/tip.2015.2446191>>

Sumitha .j (2021). Haze Removal Techniques in Image Processing. *Nigerian Journal of Botany*, [online] 9(9), pp.144–146, viewed on 8 March 2025, <<https://www.researchgate.net/publication/351273043_Haze_Removal_Techniques_in_Image_Processing>>

Guo, F., Yang, J., Liu, Z. and Tang, J. (2023). Haze removal for single image: A comprehensive review. *Neurocomputing*, 537, pp.85–109, viewed on 8 March 2025. doi:

<<https://doi.org/10.1016/j.neucom.2023.03.061>>

Lee, S., Yun, S., Nam, J.-H., Won, C.S. and Jung, S.-W. (2016). A review on dark channel prior based image dehazing algorithms. *EURASIP Journal on Image and Video Processing*, 2016(1), viewed on 8 March 2025. doi: <<https://doi.org/10.1186/s13640-016-0104-y>>

Kermani, E. and Asemani, D. (2014). A robust adaptive algorithm of moving object detection for video surveillance. *EURASIP Journal on Image and Video Processing*, 2014(1), viewed on 8 March 2025. doi: <<https://doi.org/10.1186/1687-5281-2014-27>>

‌Ozaki, M., Kakimuma, K., Hashimoto, M. and Takahashi, K. (2012). Laser-Based Pedestrian Tracking in Outdoor Environments by Multiple Mobile Robots. *Sensors*, 12(11), pp.14489–14507, viewed on 8 March 2025. doi: <<https://doi.org/10.3390/s121114489>>

Xu, Y., Guo, X., Wang, H., Zhao, F. and Peng, L. (2016). Single image haze removal using light and dark channel prior, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/iccchina.2016.7636813>>

Tan, R.T. (2008). Visibility in bad weather from a single image. *2008 IEEE Conference on Computer Vision and Pattern Recognition*, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/cvpr.2008.4587643>>

Long, J., Shi, Z. and Tang, W. (2012). Fast haze removal for a single remote sensing image using dark channel prior, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/cvrs.2012.6421247>>

Fattal, R. (2008). Single image dehazing, viewed on 8 March 2025. doi: <<https://doi.org/10.1145/1399504.1360671>>

He, K., Sun, J. and Tang, X. (2009). *Single image haze removal using dark channel prior*. [online] IEEE Xplore, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/CVPR.2009.5206515>>

Golts, A., Freedman, D. and Elad, M. (2020). Unsupervised Single Image Dehazing Using Dark Channel Prior Loss. *IEEE Transactions on Image Processing*, 29, pp.2692–2701, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/tip.2019.2952032>>

Koley, S., Roy, H. and Dhar, S. (2021). A wavelet-based low frequency prior for single-image dehazing. [online] Academic Press, pp.245–262, viewed on 8 March 2025. doi: <<https://doi.org/10.1016/B978-0-12-822844-9.00038-4>>

Ngo, D., Lee, S., Nguyen, Q.-H., Ngo, T.M., Lee, G.-D. and Kang, B. (2020). Single Image Haze Removal from Image Enhancement Perspective for Real-Time Vision-Based Systems. *Sensors*, 20(18), p.5170, viewed on 8 March 2025. doi:

<<https://doi.org/10.3390/s20185170>>

Xu, H., Guo, J., Qing Huo Liu and Ye, L. (2012). Fast image dehazing using improved dark channel prior, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/icist.2012.6221729>>

Xu, Y., Guo, X., Wang, H., Zhao, F. and Peng, L. (2016). Single image haze removal using light and dark channel prior, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/iccchina.2016.7636813>>

Xie, B.-H., Guo, F. and Cai, Z. (2010). Improved Single Image Dehazing Using Dark Channel Prior and Multi-scale Retinex, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/isdea.2010.141>>

Kaiming He, Jian Sun and Xiaoou Tang (2011). Single Image Haze Removal Using Dark Channel Prior. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(12), pp.2341–2353, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/tpami.2010.168>>

Wang, Y. and Wu, B. (2010). Improved single image dehazing using dark channel prior, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/icicisys.2010.5658614>>

‌Ieee.org. (2025). *Single image haze removal using improved dark channel prior*, viewed on 8 March 2025. [online] Available at: <<https://ieeexplore.ieee.org/abstract/document/6642199>>

‌Wu, X., Wang, K., Li, Y., Liu, K. and Huang, B. (2020). Accelerating Haze Removal Algorithm Using CUDA. Remote Sensing, [online] 13(1), p.85, viewed on 8 March 2025. doi:

<<https://doi.org/10.3390/rs13010085>>

Levin, A., Lischinski, D. and Weiss, Y. (2008). A Closed-Form Solution to Natural Image Matting. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, [online] 30(2), pp.228–242, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/tpami.2007.1177>>

‌ Fattal, R. (2014). Dehazing Using Color-Lines. *ACM Transactions on Graphics*, 34(1), pp.1–14, viewed on 8 March 2025. doi: <<https://doi.org/10.1145/2651362>>

‌ Koesdwiady, A., Soua, R., Karray, F. and Kamel, M.S. (2017). Recent Trends in Driver Safety Monitoring Systems: State of the Art and Challenges. *IEEE Transactions on Vehicular Technology*, 66(6), pp.4550–4563, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/tvt.2016.2631604>>

‌Tarel, J.-P. and Hautiere, N. (2009). Fast visibility restoration from a single color or gray level image. *2009 IEEE 12th International Conference on Computer Vision*, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/iccv.2009.5459251>>

‌Meng, G., Wang, Y., Duan, J., Xiang, S. and Pan, C. (2013). Efficient Image Dehazing with Boundary Constraint and Contextual Regularization. *International Conference on Computer Vision*, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/iccv.2013.82>>

‌Huang, S.-C., Chen, B.-H. and Wang, W.-J. (2014). Visibility Restoration of Single Hazy Images Captured in Real-World Weather Conditions. *IEEE Transactions on Circuits and Systems for Video Technology*, 24(10), pp.1814–1824, viewed on 8 March 2025. doi: <<https://doi.org/10.1109/tcsvt.2014.2317854>>

‌Tarel, J.-P. and Hautiere, N. (2009). Fast visibility restoration from a single color or gray level image. *2009 IEEE 12th International Conference on Computer Vision,* viewed on 8 March 2025. doi: <<https://doi.org/10.1109/iccv.2009.5459251>>

Name(s): Sandra Tang Poh Yi, Saw Hui Lin Program: RSW3S2 Group: 3 Date: 24/4/2025

**Program (60%) - CLO1**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **No** | **Item** | **Criteria** | | | **Final Marks** |
| **Poor** | **Accomplished** | **Good** |
| 1 | Output (10) | Inadequate information/outputs needed are  generated.  Most of the information/outputs generated are less accurate.  Results visualization is overly cluttered or the design seems inappropriate for problem area.  Lack of information that are  useful for the user  0-4 | Adequate information/outputs needed are  generated.  The information/output generated are accurate but some with errors.  Pleasant looking, clean, well-organized results visualization  The information displayed are useful for the user, but some details are  omitted.  5-7 | All the necessary information/outputs are  generated.  All or most of the information/outputs generated are accurate. Minor errors can be ignored.  The results are visually pleasing and appealing.  Great use of colors, fonts, graphics and layout.  The information displayed are useful to the users and complete with necessary details.  8-10 |  |
| 2 | Programming (10) | The end product fails with many logic errors, many actions lacked exception handling. Solutions are over-simplified. Programming skill needs improvement.  0-4 | Major parts are logical, but some steps to complete a specific job may be tedious or unnecessarilycomplicated.  Program algorithm demonstrates acceptable level of complexity. The student is qualified to be a programmer    5-7 | Correct and logical flow, exceptions are handled well. Demonstrates appropriate or high level of complex algorithms and programming skills.  8-10 |  |
| 3 | Degree of completion  (10) | Too much still remain to be done. Basic  requirements are not fulfilled.  The end product produces enormous errors, faults or incorrect results.  0-4 | All required features present in the interface  within the required scope, but some are simplified. Or one or two features are missing. The system is able to run with minor errors.  5-7 | All required features present in the interface  within or beyond the required scope.  No bugs apparent during demonstration.  8-10 |  |
| 4 | Program Model Optimization  (10) | The model is not optimized.  Most of the processes are executed in serial.  Only 1 parallel program model is used.  0-4 | The model is optimized by using more than 1 parallel program model, i.e. SPMD, loop parallelism.  5-7 | The model is optimized by using more than 1 parallel program model, i.e. SPMD, loop parallelism.  The model is tested on different parallel platform, i.e. OpenMP (Homogenous), CUDA, OpenCL (Heterogenous).  8-10 |  |

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| --- | --- | --- | --- | --- | --- |
| **No** | **Item** | **Criteria** | | | **Final Marks** |
| **Poor** | **Accomplished** | **Good** |
| 5 | System implementation  (10) | The end product is produced with different  system design or approach, which is not related to the initial proposal.  0-4 | The end product conforms to most of the  system design, but some are different from the specification.  5-7 | The end product fully conforms to the  proposed system design.  8-10 |  |
| 6 | Presentation (10) | The student is unclear about the work produced, sometimes not even knowing  where to find the source code.  0-4 | The student knows the code whereabouts, but sometimes may not be clear why the work  was done in such a way.  5-7 | The student is clear about every piece of the work done.  8-10 |  |
| Sum of Score | | | | |  |

**Final Report (40%) – CLO3**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **No** | **Item** | **Criteria** | | | | **Final Marks** |
| **Missing or Unacceptable** | **Poor** | **Accomplished** | **Good** |
| 1 | Title and abstract (10) | Title or abstract were omitted or inappropriate given the problem, research questions and method  0-2 | Title or abstract lacks relevance or fails to offer appropriate details about the education issue, variables, context, or methods of the proposed study.  3-4 | Title and abstract are relevant, offering details about the proposed research study.  5-7 | Title and abstract are informative, succinct, and offer sufficiently specific details about the educational issue, variables, context, and proposed methods of the study.  8-10 |  |
| 2 | Results  (Performance measurement) (10) | Analytical methods were missing  or inappropriately aligned with data and research design. Results were confusing.  0-2 | Analytical method was  identified but the results were confusing, incomplete or lacked relevance to the research questions, data, or research design.  3-4 | The analytical methods were  identified. Results were presented. All were related to the research question and design. Sufficient metric or measurement is applied.  5-7 | Analytical methods and results  presentation were sufficient, specific, clear, structured and appropriate based on the research questions and research design. Extra metric or measurement is applied.  8-10 |  |
| 3 | Discussion and  Conclusion  (10) | Discussions or answers to the  research question and system performance were omitted or confusing. No or very little conclusion could be yielded.  0-2 | Little discussions were  presented. Answers to the research question and system performance were unclear or confusing.  3-4 | Discussions of the results were  presented. The research question and system performance were answered and identified.  5-7 | The significance of the results of the work  was discussed, sufficiently inclusive of the information that concluded and answered the research question and system performance is evaluated comprehensively. Limitations and future improvements of the studies were identified.  8-10 |  |
| 4 | Organization  (5) | The structure of the paper was  incomprehensible, irrelevant, or confusing. Transition was awkward.  0-1 | The structure of the paper was  weak. Transition was weak and difficult to understand.  0-2 | A workable structure was  presented for presenting ideas. Transition was smooth and clear.  3-4 | Structure was intuitive and sufficiently  inclusive of important information of the research. Transition from one to another was smooth and organized.  5 |  |
| 5 | Spelling,  Grammar and Writing Mechanics (5) | There were so many errors that  meaning was obscured, make the content became difficult to understand  0-1 | Some grammar or spelling  errors were spotted. Some sentences were awkwardly constructed so that the reader was occasionally distracted.  0-2 | There were occasional errors, but  they did not represent a major distraction or obscure meaning.  3-4 | Sentences were well-phrased. The writing  was free or almost free of errors.  5 |  |
| Sum of Score | | | | | |  |
| **Final score = sum of scores/100\*60 (base 60%)** | | | | | |  |