Black Sea Journal of Engineering and Science
doi: 10.34248/bsengineering.1349643

Open Access Journal
e-ISSN: 2619 – 8991

Research Article
Volume 6 - Issue 4: 604-612 / October 2023

ESTIMATION OF AIR LIGHT WITH DEEP LEARNING FOR A NEAR REAL-TIME IMAGE DEHAZING SYSTEM

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Abstract: Haze which can be created by natural or synthetic factors, degrades the visual quality and human sight distance. Visible objects become invisible or scarcely visible. The physics of the degrading function due to haze has been modelled by Atmospheric Light Scattering (ALS) Model. Therefore, from a single hazy image, by using proper methods, it is possible to recover the original scene. In dehazing methods, which solve the ALS function, there are basically two steps: First one is the estimation of the air light present at the time of the image capturing and the second one is the estimation of transmission of the corresponding scene. One of the most effective method which is used for air light estimation is QuadTree decomposition. For this method, tests show that the most amount of the dehazing time is consumed to estimate the air light. For the case of High Definition (HD) imagery, the estimation of air light consumes huge time. Therefore, it cannot be possible to achieve a real-time or near real-time dehazing on traditional hardware. In this study, a novel convolutional neural network model is developed to estimate the air light directly from the hazy image quickly. The estimated air light then is used with Atmospheric Light Scattering model to handle the recovered image. Results show that the time cost is reduced by 56.0% and 65% for image resolutions of (640x480) and (1920x1080) compared to the QuadTree Decomposition method used in ALS based dehazing methods, without losing the visual quality of the dehazed image.

Keywords: Depth map, Image quality, Distortion, Image blur, Real-time systems

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Received: August 25, 2023
Accepted: September 30, 2023
Published: October 15, 2023
Cite as: Çimtay Y. 2023. Estimation of air light with deep learning for a near real-time image dehazing system. BSJ Eng Sci, 6(4): 604-612.

1. Introduction

Dehazing is crucial for a better human visual quality in the conditions of bad weather and for improving the success of the computer and machine vision applications needed in the field of transportation and military. For the last decade, many researchers have contributed to the subject of image enhancement and restoration (Wang and Yuan, 2017). As being one of the areas of image restoration, dehazing, depends on the estimation of the air light presents at the time of image capturing and the depth of the scene from the observing device. The success of dehazing is mostly determined by the success of these estimations. Another important problem related to dehazing is the homogeneity of the haze cover on the scene, since, it can be at local and/or global levels. Therefore the air light and transmission estimation may not be achieved properly for each pixel of the hazy image. The distance of the object from the scene is another important factor for the estimation of transmission term. As the distance from the sensor increases, the transmission of the light through the haze cover decreases and the estimation error becomes higher. In addition, as the amount of haze increases, the reconstruction error becomes larger and the success of dehazing goes down. Figure 1 shows the hazy images with low and high amount of haze, taken from CHIC dataset (El Khoury et al., 2018) and the reconstructed images with Dark Channel Prior method (Park et al., 2014). It can be observed that when the amount of haze is higher the reconstruction performance is poor.

Fundamentally, there are 2 approaches in the context of image dehazing which are traditional methods and learning based methods. In traditional methods, contrast enhancement and image restoration are applied in the very first studies (Tan and Oakley, 2001; Kim et al., 2011; Hao et al., 2011; Al-Sammaraie, 2015). Secondly, ALS model of haze is studied to be solved. DCP and the DCP-based methods are frequently applied for this purpose (Kaiming et al., 2011; Park et al., 2014). Due to the limitations on the accurate estimation of transmission and/or air light, researchers have developed deep models to be trained with hazy and clear image pairs. Therefore, many learning based methods based on Convolutional Neural Network (CNN) (Cai et al., 2016; Li et al., 2018; Li et al., 2018; Rashid et al., 2019; Haouassi and Di, 2020), Generative Adversarial Networks (GAN) (Khatun et al., 2020; Ren et al., 2022), Vision Transformers (Guo et al., 2022; Li et al., 2023; Yuda et al., 2023) structures have been developed. By this way, several hazy image datasets were created and provided as open access (Ancuti et al., 2016; El Khoury et al., 2018; Ancuti et al., 2019; Ancuti et al., 2019; Li et al., 2019).

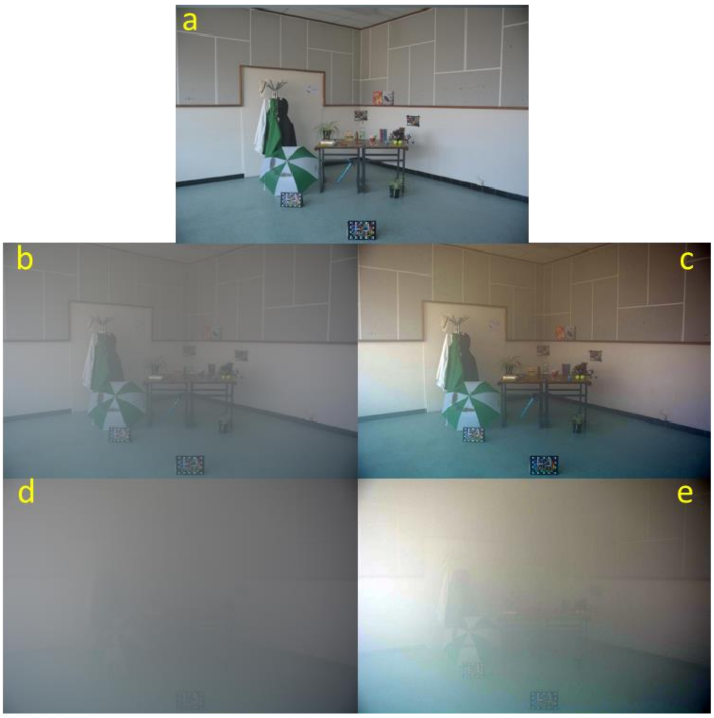

Figure 1. (a) Clear image, (b) low-level hazy image, (c) dehazed image from (b), (d) high-level hazy image, (e) dehazed image from (d).

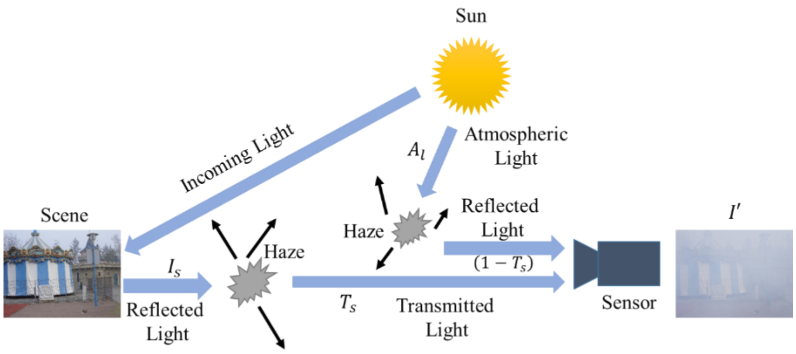

Figure 2. Atmospheric light scattering model.

However the most important bottleneck of the learning based methods are the capability of the generalization. A deep model which was trained on a specific dataset generally cannot achieve the same performance when tested on a different hazy image dataset. To solve this problem several studies based on domain adaptation have been employed for last 3-4 years (Shao et al., 2020; Meng et al., 2022).

In this study, we address the problem of real-time and/or near real-time dehazing which is needed in many real-time applications. When the complexity of the method or model increases, the response time to single image frame increases which makes real-time processing harder or impossible. Since the generalization capacity is more effective than many learning based models, (Park et al., 2014) is taken as the reference in this study. As shown in Figure 2, ALS model, needs the transmission map of the scene and air light (incoming light) present at the time of image capturing to be estimated from a hazy image. According to the prior implementations, it was observed that the most percentage of the total dehazing process is spent in the air light estimation part (Cimtay. 2020; Cimtay, 2021). Therefore, as the image size increases, the estimation time also increases dramatically. In order to reduce this cost, in this study, the estimation of air light is embedded in a deep model which was trained with hazy images and the corresponding air light values handled by employing the Quadtree Decomposition method, applied in (Park et al., 2014). Therefore, the contribution of this study is, reducing the estimation time of air light by using a deep model and by this way achieving a near real-time dehazing performance on traditional hardware.

2. Motivation

ALS model formulates the physics of the deterioration due to haze, very well. Figure 2 shows the graphical structure of the formation of hazy image on the sensor. ALS equations are given in (Equation 1) where I' is the hazy image, I_s is the clear image of the scene (ground truth), and A_l is the air light (incoming light in Figure 2).

$$I' = I_s * T_s + A_l * (1 - T_s) + E_r \quad (1)$$

The sensor integrates the air light reflected from haze particles and the light reflected from scene and transmitted through haze. In Equation 1, T_s is scene transmission map and E_r is the reconstruction error of ALS model. Although there will be still some amount of error due to the multiple reflections and/or transmission terms from/through haze particles and the absorbed energy by haze, for a perfect recover of the original scene from the hazy image, estimation of transmission and air light is crucial.

2.1. Preliminary Study

The time spent on the estimation of the transmission and air light is based on the size of the image to be dehazed. To measure the processing time, 3 images with various resolutions were dehazed by using (Park et al., 2014). The time spent for transmission estimation and air light estimation is measured and given in Table 1. It can be observed from the table, as the resolution of the image increases from 480p to 4K, the time spent for both transmission and air light increases. In addition the ratio of the spent time for air light estimation changes from 83% to 70.67%. This experiment shows that the most amount of the time spent for dehazing is used for the estimation of air light. In addition, time spent increases as the resolution of the image increases.

The interest point of this study is reducing the time spent for estimation of air light. By this way a real-time or near real-time dehazing can be achieved. Therefore, this study develops a deep CNN model which extracts the spatial features from the hazy images and employs a regression between these features and the estimated air light by (Park et al., 2014).

2.1. QuadTree Decomposition

The study in (Park et al., 2014) proposes an optimal approach to improve the previous air light estimation methods (Tan et al., 2001). It is presumed that air light which is present over much of the hazy image, has its intensity as greatest in a local region of the image scene. Then air light is estimated by using QuadTree subdivision on a transformed image. The grayscale version of the color hazy image is divided into non-overlapping sub-blocks with the size of NxN.

The minimum value over each block is assigned to each pixels inside each block, defined as B_k^{block} reduce the negative effects of a local object's bright values (Equation 2).

$$L_k^{block} = \min B(x), x \in B_k^{block} \quad (2)$$

N as the block size is chosen as 30×30 to keep the accuracy and reliability optimal. The transformed image has lower brightness values, in average, compare to the original gray image. As a result, the suggested QuadTree decomposition strategy can pick the candidate region to estimate the air light more accurately. By this way, after several iteration, the sky region in a sample image can be selected as the final candidate region even if the image includes some white floors. Air light is estimated more accurately by considering the final region. By calculating the Euclidean distance, given in Equation 3, for each pixel in that region, the color values of the pixel which minimizes the distance is chosen as the air light.

$$\left\| P_{(R,G,B)} - (1,1,1) \right\| \quad (3)$$

3. Related Work

Beyond the traditional dehazing methods, deep learning is the main technique used recently. For single-image dehazing, GANs and CNNs have lately been employed in the creation of deep learning-based techniques. The transmission maps and/or atmospheric light are directly learned from data using CNN-based algorithms (Cai et al., 2016; Boyi et al., 2017). It has also been demonstrated that utilizing multi-scale features collected by pyramid networks can enhance the effectiveness of CNN-based dehazing (Singh et al., 2020). GAN-based techniques (Zhang et al., 2018; Tran et al., 2022) have been developed to address the light attenuation effect caused by haze from the original scene.

However, the dehazing performance suffers if deep learning-based dehazing algorithms are unable to predict physical model parameters precisely. Furthermore, the success of the deep models are more accurate when tested on the same samples from the same dataset whereas the success reduces on different datasets. And due to the extensive training time and hardware requirements, deep learning-based dehazing methods are typically computationally inefficient. The literature has a lot of effective image dehazing approaches. The intricacy of the algorithms, hardware limitations, and high cost should all be taken into account when real-time implementation is the main focus.

Table 1. Time spent for various image resolutions

Image resolution	Time Spent (ms)		Ratio (%)
	Air light	Transmission	
640x480	130	20	86.6
1280x720	373	67	84.7
1920x1080 (HD)	720	250	74.2
3840x2160 (4K)	2530	1050	70.67

By combining the Central Process Unit (CPU) and Graphics Processing Unit (GPU), the study in (Yuanyuan and Yue, 2015) provides a parallel processing dehazing method for mobile devices and reports 1.12s per frame processing time for HD imagery on a Phone with Windows operating system. The researchers use a mean filter instead of the guided filter to speed up image processing in (Lu and Dong, 2019). A 25 frames per second processing rate is achieved over a DSP device (C6748 pure DSP device data sheet, 2023).

In the research in (Vazquez et al., 2020), a hazy color image is converted to an Hue, Saturation, Value (HSV) color space, and the value component is subjected to a global histogram flattening, the saturation component is changed to be consistent with the previous lowered value, and the value component is subjected to contrast enhancement. For HD images, it achieves 90ms of dehazing time on GPU. The study in (Yang et al., 2017) carries out two level image processing in an intelligent manner. If the final image satisfies the system requirements after applying histogram enhancement, no further action is necessary. If not, DCP is employed to clear the haze. It performs real-time processing and saves a lot of time by adopting a clever method.

The work in (Cheng et al., 2020) decomposes the picture into brightness and contrast components while parallelizing the fundamental Retinex model. Gamma correction and non-parametric mapping are used to restore the image, and the parallel GPU system achieves a processing time of 1.12ms for a high quality 1024x2048 image. Genetic programming is used in the work in (Hernandez et al., 2019) to create a transmission function estimator. The transmission map is then computed using this function. To obtain the haze-free pictures, a transmission map and a hazy image are utilized. The system processes both synthetic and real-world images at high rates. In (Kopf et al., 2008) to combine a virtual series of candidates for haze-free images into the desired single haze-free image, a unique pixel-level optimum dehazing criteria is suggested. By using every conceivable value of the discretely sampled depth of the scene, the calculation for this series of pictures is performed from the input hazy image. The benefit of this approach is that it can compute any individual pixel location without affecting the others. Therefore, employing a fully parallel GPU system makes it simple to implement this strategy.

In (Nguyen et al., 2022) a multiscale guided filtering-based real-time dehazing method is proposed. Since the estimation of the transmission map and atmospheric light in ALS model takes the longest time in the dehazing process, atmospheric light and transmission map are estimated by computing them in the low-resolution images which are created as image pyramids of the original hazy image. Then by using guided filtering for each pyramidal level, the transmission map is upsampled to the original resolution. (Shu-Juan et al., 2021), proposes a method for real-time video dehazing which suppresses the visual artifacts by using incremental learning of transmission and spatial-temporal coherent regularization. A boundary limited dark channel model is provided to initialize the transmission map. Then, assuming a specific point on the scene produces highly correlated transmission values between the consecutive frames, a temporally coherent term is imposed for both maintaining the temporal consistency of the frame transmission values and continuously deriving an gradual transmission map to adapt the scene depth changes between the frames. In order to represent the scene depth, the study in (Zhu et al., 2015) builds a linear model and uses the color attenuation beforehand. This method prevents color distortion in the sky region, but the related dehazing results still contain some amount of visual distortions.

The study in (Chen et al., 2016) explores a gradient residual reduction approach for specifically eliminating any visual artifacts while concurrently recovering the haze-free image. Although this technique has successfully balanced haze removal with the reduction of visual artifacts, it frequently fails to maintain the image's fine details. The study in (Kim et al., 2013) attempts to make transmission values temporally consistent in the video sequence in an effort to decrease the visual contrast in a single frame and lessen flickering artifacts. Despite the fact that this method may generate outstanding dehazing results, it frequently results in oversaturated and blocking artifacts.

In this paper, the estimation of air light is automated on a deep model to get rid of the large amount of time spent for it. ALS model is then applied with the estimated air light and transmission map. By this way the processing time is reduced and near real-time dehazing is achieved. The rest of this paper is in section for proposed method is introduced in detail and in section 5 detail implementation results in terms of the obtained visual results and processing rates are presented. Finally, in the conclusion section a short summary of the proposed method and future studies are included.

4. Proposed Method

As stated in preliminary study part, the most amount time of dehazing with DCP (Park et al., 2014) is spent during the air light estimation. Therefore, in this study a deep CNN based estimation of air light is proposed. Firstly, RESIDE Indoor dataset (Boyi et al., 2017) is chosen to train the network. For each hazy image in RESIDE, QuadTree decomposition method in (Park et al., 2014) is employed and the corresponding air light values are handled. There are 13,990 hazy-clear image pairs in this dataset which is needed and sufficient to train a CNN model properly. The designed CNN model is shown in Figure 3 where the input is the hazy images and the output is the estimated air light by (Park et al., 2014). The shape of each of the convolutional, pooling and dense layers are shown on the figure. Also, the ratio of drop out layers are given. Drop out layers are very effective on preventing the overfitting problem which is mostly faced in the training of deep models. Figure 3 is plotted by using *Visualkeras* library (VisualKeras Library, 2023).

Batch size and learning rate are set to 32 and .0001, respectively. Number of epochs is set as 100. Input data is split in to training and validation sets with a ratio of 0.85 and 0.15. The training loss based on mean square error (MSE) for training and validation data is shown in Figure 4. It can be observed from the figure, training is very accurate. There is no overfitting and the amount of MSE is in the order of 10^{-4}. Training is done on a computer with windows operating system, 8GB RAM, 11th Gen Intel(R) Core(TM) i7-1165G7 2.80 GHz processor and GeForce RTX 3060 model graphic card. Following acquiring the trained model, the real-time design of the proposed method is shown in Figure 5.

In this study we employ the proposed real-time dehazing model on a computer with windows operating system. As the air light and transmission is estimated ALS model is used to reconstruct the dehazed image.

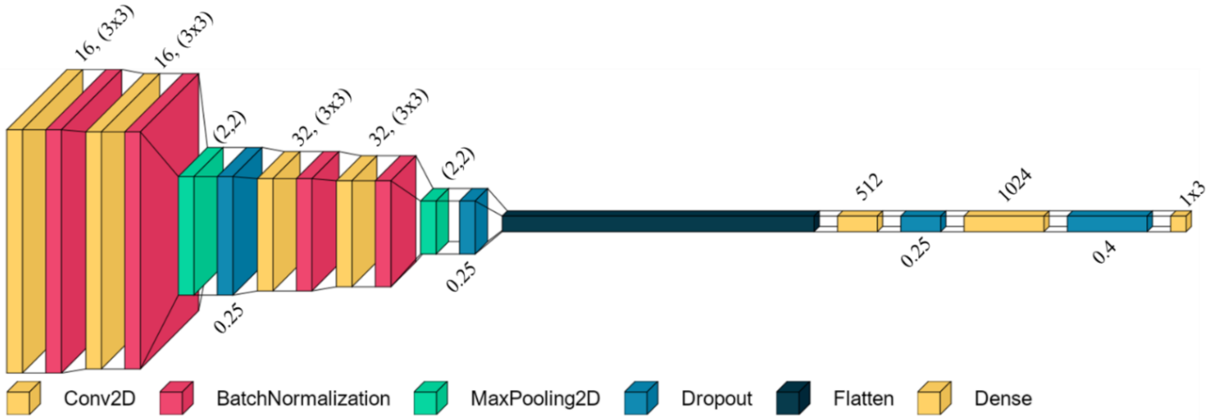

Figure 3. Proposed CNN model constructed with convolutional, normalization, pooling, dropout (ratio: 0.25) and dense layers.

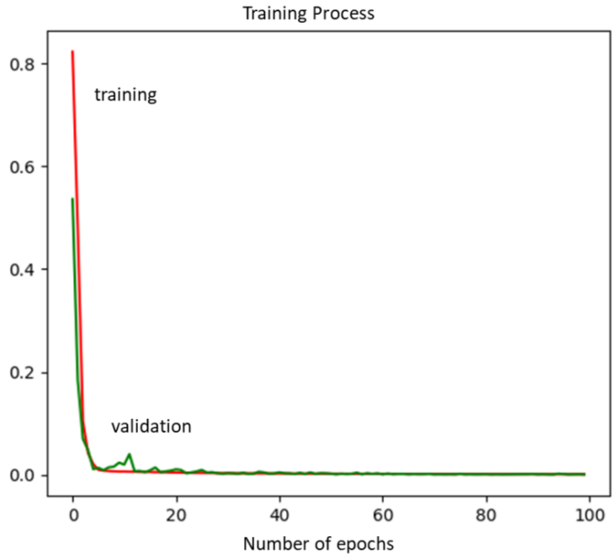

Figure 4. Training and validation loss.

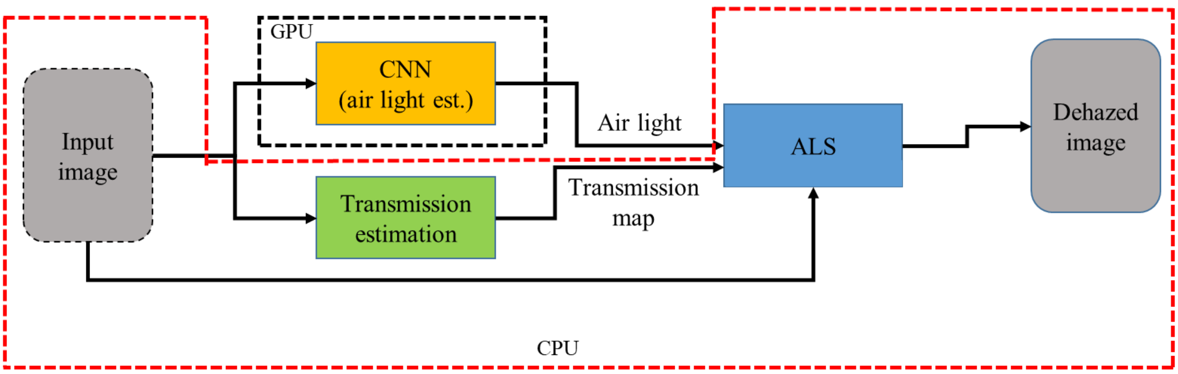

Figure 5. Proposed hybrid dehazing system.B

5. Results

In the application of (Park et al., 2014) the most time-consuming part of the dehazing process is the air light estimation. Instead of using the technique (Park et al., 2014) for air light estimation in this study a CNN is proposed. To measure the success of the proposed method, the system is run on a Windows PC. The time spent for air light estimation is given for three different resolutions: (640x480), (1280x720) and (1920x1080). By using the proposed deep model, air light estimation time is reduced for significant amount for each resolution as shown in Table 2. The time gain ratios for air light estimation are 65.1%, 84.3%, and 88.3% which is very promising.

Table 3 shows the overall dehazing time. This time is the summation of the time spent for air light, transmission and the solution of ALS model. Therefore it is higher than the values given in Table 2.

From Table 3, the frame processing time changes from 0.151 to 0.066, 0.442 to 0.126 and 0.972 to 0.336 s. for 480p, 720p and HD (High Definition) images, respectively. Therefore, approximately, 15.08, 7.89 and 2.97 frame rate is achieved. Frame rate reduces as the resolution increases. Since the air light is estimated by using a CNN running on GPU, due to the insufficient GPU memory, a 4K image could not be tested. The real-time performance of this study is compared with the results of the state of the art studies in Table 4.

Table 2. Air light estimation time on Windows PC

Resolution	Processing Time (ms.) with (Park et al., 2014)	Processing Time (ms.) (proposed method)	Time gain (%)
640x480	130	45.3	65.1
1280x720	373	58.3	84.3
1920x1080 (HD)	720	84.2	88.3

Table 3. Dehazing speed on Windows PC

Resolution	Method (Park et al., 2014)		Proposed Method	
	Tot. Proc. Time (ms)	Frame per Second	Tot. Proc. Time (ms)	Frame per second
640x480 (480p)	151	6.62	66.3	15.08
1280x720	442	2.26	126.7	7.89
1920x1080 (HD)	972	1.02	336.2	2.97

Table 4. Benchmark results for per frame processing time (ms)

Studies	(1920x1080)	(1280x720)	(640x480)
(Vazquez et al., 2020) with GPU	NA	88.3	NA
(Cheng et al., 2020) with Par. GPU	1	NA	NA
(Lu and Dong, 2019)	40.1	NA	NA
(Zhu et al., 2015)	7093.5	3609	1471.2
(Kim et al., 2013)	904.0	410.1	125.1
(Shu-Juan et al., 2021)	709.3	304.6	91.02
Proposed Method	336.2	126.7	66.3

It can be understood from the benchmark table, for HD imagery, except the ones with DSP device and parallel GPU system, proposed method is the best. Similarly, for 480p imagery, proposed method is the best and for 1280x720 image, proposed method is the second best. The most important contribution and innovation of the proposed method is to provide near real-time image dehazing with traditional computers with a single GPU, as it has 15.08 and 2.97 fps for 480p and HD image. To provide the dehazing quality of the proposed method, dehazing results on different hazy samples from various datasets are also presented. In Figure 6, from top to down, the test results belong to Reside, CHIC, Dense-Haze, I-haze, O-haze datasets are shown. From left to right, clear image (ground truth), hazy image, dehazed image with (Park et al., 2014) and dehazed image with proposed method are given. It can be observed that, for the proposed method, the visual quality of the dehazed image is kept well while increasing the frame rate.

Another important point is that the trained model performs a good generalization capacity. Although it was only trained on RESIDE hazy images, it can also perform well on estimation of the air light of other hazy images from different datasets. This is due to the fact that, the designed CNN structure is proper, dataset is rich and qualified, and there is only one parameter to be estimated which is the air light. Therefore, the proposed method is a kind of hybrid dehazing method based on traditional and deep learning based approaches which gets use of both approaches well.

Figure 6. Image dehazing results. Top to down: Samples from Reside, CHIC, Dense-Haze, I-haze, O-haze. Left to right: clear, hazy, Dehazed with DCP, Dehazed with Proposed Method.

6. Discussion and Conclusion

In this study, a deep learning based approach is proposed for the estimation of air light in ALS model on the hazy images. Since, the most amount of the processing time for dehazing is spent during air light estimation in (Park et al., 2014), this approach is crucial to reduce the estimation time, so overall dehazing time. The generalization performance of an end to end dehazing method based on deep learning is generally low when the model is tested on a different dataset which is different from the dataset used for training. For this reason, in this study an end-to-end dehazing model is not chosen instead the air light which can be estimated more properly independent of the dataset is estimated by using a pre-trained deep CNN model on GPU. By using a hybrid approach, then, air light and transmission map are used with ALS model for dehazing on CPU. Results show that proposed approach are superior or on par with the other state-of-the-art real-time dehazing applications. It reduces the time spent for air light estimation from 976 ms. to 336.2 ms. and increases the frame rate from 1.02 to 2.97 for HD imagery, which is very promising for real-time and/or near real-time dehazing applications on a traditional PC with a single GPU. Furthermore, while frame rate is increased, dehazed image quality is still kept which is the tradeoff in real-time and/or near real-time image dehazing applications. In the future this approach will be improved and the system will be applied on an FPGA hardware. This will be a challenging task due to the fact that it is hard to deploy a CNN model on FPGA hardware.

Author Contributions

The percentage of the author contributions is presented below. The author reviewed and approved the final version of the manuscript.

	Y.Ç.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

Acknowledgements

This study is supported by The Scientific and Technological Research Council of Türkiye (TUBITAK) within the Project number: 122E333.

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