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FOGGY DEGRADED IMAGES: A RESTORATION APPROACH UTILIZING NEURAL NETWORK

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ABSTRACT

Atmospheric problems such as fog or dust reduce visibility on roads. Car cameras with a suitable image restoration technique can be used to enhance automotive vision in a misty (foggy) weather. Foggy images can be restored by using a suitable filter (de-noise filter) to reconstruct a clear image from its degraded version. Accordingly, this paper aims to find a fog filter to restore foggy images in real time (as a step toward the development of automotive vision in foggy weather). Supervised neural network (SNN) is used as a technique to restore a foggy image to its original version. Although training SNN is time consuming (during training phase), the process of applying the generated fog filter on a foggy image (for restoration) is a rapid operation. For generating a fog filter, SNN is trained offline through mapping between a foggy scene and its corresponding original scene. The weight matrix, which is obtained from training the SNN, represents a fog filter. In this paper, seven approaches utilizing different feature sets are proposed. Each approach presents different neural network (NN) architecture. Image features are extracted from spatial and transformed domains using discrete cosine transform (DCT). DCT is applied locally to suppress noise components while preserving the useful image content. The seven fog filters (resulting from training the seven NNs) are evaluated empirically, using Peak signal-to-noise ratio (PSNR), and perceptually (based on judgment of expert persons). Their performances are compared to specify the effective fog filter and to determine the feature set that best suits the NN technique for restoring foggy images. The recommended approach has demonstrated its efficiency and usefulness in restoring moderately foggy images in real time.

Keywords: *Image restoration, Artificial Neural Network, Discrete Cosine Transform, Foggy Image Filter*

1. INTRODUCTION

Outdoor scene images often suffer from various atmospheric degradations resulting from haze, fog, or other types of degradation. Under such weather conditions, atmospheric particles absorb and scatter light when traveling from the scene points to the observer, causing blurred vision (image degradation). Image restoration is used to recover the original scene (image) from the degraded one by using previous knowledge about the degradation phenomena. This approach is considered as an inverse process that uses the prior knowledge of degradation (as input) and produces real image (as an output) [1-3]. Image restoration is applied on astronomical imaging, medical imaging, and other fields [4]. Image restoration deals with images corrupted by noise. Noise can be caused by sensors, loss of focus, object camera relative motion, and random atmospheric turbulence (fog, haze, smoke, and so on). Noise sources in images are characterized by Gaussian-like distributions [4]. The noise should be modeled and removed without eliminating the high-frequency components of the image (original image components).

Image restoration is a problem where suitable solutions cannot be easily obtained. Mathematically, renovating an image degraded by fog is an ill-posed problem. Numerous effective methods, such as inverse filter, Wiener filter, moving-average filter, parametric Weiner filter, mean-squared error filter, discrete wavelet transform (DWT), and DCT have been proposed to reduce image degradation [5, 6]. In this paper, we are interested in using DCT, which exhibits the advantages of acceptable computational complexity (fast implementation especially when applied locally on small windows) and reduction of block artifact in the image with visual boundaries between its sub-images [2, 7, 8]. Application of DCT locally approximates the Karhunen–Loeve de-correlating transform, which enables effective suppression of noise components while preserving

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the useful image content (texture, edges, and details) [7-9].

Zhai and Zhang [10] showed that the degraded image E can be expressed by equation (1)

$$E = WR + (1 - W)I_{\infty} \quad \textbf{(1)}$$

where E denotes the degraded image matrix, R is the clear scene image matrix, $I\infty$ is brightness, and W is the weight coefficient matrix. The degraded image matrix E is known because the sky brightness $I\infty$ can be measured by selecting a region of the sky. Thus, the process of restoring the clear scene (matrix R) has been reduced to the process of computing the weight coefficient vector W. As seen from (1), Back-propagation neural network (BPNN) is suitable for finding weight coefficient vector W when trained using both foggy image and its corresponding original clear image. However, few attempts have been made using artificial neural network (ANN) to restore images blurred by fog, smoke, dust, and others. Moreover, limited attempts were conducted to use DCT combined with ANN to restore foggy images. No attempt has been made to specify the best features that suit foggy image restoration when SNN is used with local DCT. This paper aims to combine local DCT (using sliding window) with SNN approach to generate a suitable fog-filter used for image de-fogging in real time, which is considered as the first step toward the development of automotive vision in foggy weather. In this paper, seven approaches utilizing different feature sets are proposed. Their performances are compared to specify the feature set that best suits the SNN technique for restoring foggy images. Finally, the time complexity of the suggested approach is discussed to confirm its suitability to real-time application.

The rest of this paper is organized in eight sections. Related works are discussed in section 2. Section 3 illustrates the contribution and objectives of this research. The proposed foggy image restoration model is described in section 4. In section 5, the seven approaches are explained. Experimental results are discussed and evaluated in section 6. We concluded in section 7. Limitations and future work are discussed in section 8.

2. RELATED WORKS

Foggy image restoration is one of the significant image processing problems, which benefits visual systems and improves traffic. Much research is concerned with enhancing foggy images to improve outdoor vision. In [11], authors summarized and experimentally compared different video and image defogging algorithms. They reviewed the detection and classification method of a foggy image in addition to current video defogging algorithms. The objective image quality assessment methods used for evaluating defogging algorithm performance were illustrated. They concluded that problems of video and image defogging need further study. In [12], authors studied number of image defogging algorithms. Approaches based on single- and multiple-image restoration were compared subjectively and objectively. The researchers discussed and summarized the performance of seven different algorithms and observed that the objective image quality assessments are sometimes unsuitable for subjective image quality assessment. Therefore, the authors suggested the use of new assessment methods based on deep learning algorithm and found that no single image defogging algorithm suits thin and dense fog. Most algorithms can handle thin or homogenous fog. They suggested combining several techniques to construct a defogging system that best handles the foggy image (homogeneous or dense fog). Authors in [13] proposed a solution to detect the free space area in foggy road scenes by using contrast restoration approach. The method simultaneously estimates the density of fog and the position of the horizon line in the image, which considerably improves the state of the art in this area. Authors in [14] explored the capability of Advance Driver Assistance System (ADAS) to recognize objects, especially traffic signs, under reduced visibility conditions (caused by fog). Accordingly, they proposed a database that contained artificial images of road signs (with and without fog). They studied the effect of reduced visibility from fog on a gradient-based geometrical model of traffic signs by using this database. In [15], authors proposed a novel method to enhance foggy degraded images. First, foggy image is converted to HIS (hue, intensity, saturation) component. The correct intensity is calculated to create new HIS. Finally, the new HIS is converted back. PSNR and mean squared error (MSE) show that the resulting images are increasingly clear. Park and Ko [16] proposed an approach to restore fog-degraded images by estimating depth, using the physical model for characterizing the RGB channel in a single monocular image. They removed fog effects by subtracting the estimated radiance, which is empirically related to the scene depth information obtained from the total irradiance received by the

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sensor. In [6] authors proposed various image-enhancing techniques to improve the contrast and visibility of foggy images. Five enhancing techniques, namely, high boost filtering, homomorphic filtering, Weiner filtering, DCT, and DWT, were tested and analyzed. Authors claimed that DWT outperforms other enhancement techniques. Caraffa and Tarel [17] proposed a new Markov random field (MRF) model for Bayesian defogging, with the de-fogging algorithm derived from this model by α-expansion optimization.

Enhanced solutions and results may emerge in image restoration using neural network (NN) because of its features, which are related to the parallel computing power and the plasticity of NN method. Owing to these two features, NNs are appropriate for applications in pattern recognition, signal processing, and other applications [1]. Castro and Silva [1] proposed the use of NNs in multi-scale image restoration. This approach uses a multi-layer perceptron (MLP) trained with artificially degraded images of gray level co-central circles. The space relations are taken from different scales; thereby providing correlated space data to the NN. The approach does not require a priori knowledge of the degradation causes. Quantitative analysis is performed using MSE and the Signal-to-noise ratio (SNR). In [18], NN approach is proposed, which is trained to estimate visibility distances under foggy weather. The proposed approach helps motorists adapt their car speed according to the estimated visibility range. A SNN is trained with hybrid global image features (Shannon entropy, and Fourier transform magnitude descriptor). Feature vector is reduced by using principal component analysis (PCA). The proposed approach was tested using a set of images under various foggy conditions. Authors claimed that the suggested approach outperforms the classical method of estimating the maximum distance at which a selected target can be seen. In [19], authors developed deep NN (DNN) to approximate fog mathematical model (find the corresponding fog function) that allegedly operates in real- time. In this approach, the foggy image is divided into N×N non-overlapping blocks. Each block is normalized to a range to optimize the learning process of the DNN. The DNN consists of 5-8 layers, each layer contains 16-128 nodes (specified empirically) with hyperbolic tangent transfer function, as activation function. Foggy Road Image Database (FRIDA) is used to check system performance. Experiments results show that the proposed technique can eliminate fog from the scene (using the approximated fog function), thus improving visibility. Although the proposed approach showed limited capability in replicating the original scene details for certain foggy images, the main details of the original scene are recognizable. In [20], authors proposed an effective algorithm with Cellular Neural Network (CNN) and contour matching for painting images, digital images, or video frames with a large noise ratio (41-55 dB). This approach achieved visually good result even with high percentage of defects in the pictures. In [21], a new restoration method based on minimizing the total variation under constraints using MLP was proposed. Artificial and real images were used for performance testing. ISNR (improvement of signal to noise ration) and NMSE (normalized mean square errors) were used for objective evaluation. In [22], CNN with edge detection and segmentation was developed to restore motion or static images that are damaged with high noise ratio. PSNR and logical MSE were used for evaluation.

3. CONTRIBUTION AND OBJECTIVS

Foggy image restoration is considered an ill-posed problem where suitable solutions cannot be easily obtained. Numerous effective methods have been proposed to enhance foggy degraded image. However, few attempts have been made using artificial neural network (ANN) to restore images blurred by fog, smoke, dust, and others [18, 19]. Most researches that utilize ANN [1, 20-22] attempt to restore images that are degraded by noise (such as Gaussian noise) addition. Moreover, limited attempts were conducted to utilize DCT to filter fogy images [5, 6]. No attempt has been made to train ANN with features extracted from local DCT (apply DCT on overlapped n×n windows). Also, no attempt is conducted to specify the best features (extracted from the local DCT window) that improve foggy image restoration when SNN is combined with DCT.

The main contribution of this research is to combine local DCT with SNN to generate a suitable fog filter for reconstructing a clear image from its degraded version in real time. A suitable SNN architecture will be constructed to generate a fog filter and restore foggy images. DCT is applied locally (using overlapped sliding window) to suppress noise components while preserving the useful image content. We will study the effect of using local DCT as pre-processing step in foggy image restoration. Therefore, image features are extracted from spatial domain)extract features from overlaped n×n sliding windows) and from transformed domains (extract features after applying DCT on overlaped n×n windows).

The constructed SNN (BPNN) is trained using features extracted from set of image pairs (foggy image and its corresponding clear image) to generate the final weight matrix W, which represents a fog filter. Seven different approaches are suggested to specify the recommended feature set that improves the foggy image restoration model when BPNN is used. Each of these seven approaches presents a different SNN architecture depending on type and number of used features. In this paper, the restoration process performance is measured empirically (using PSNR) and perceptually (using human judgment of 20 persons). Finally, the time complexity of the suggested approach is discussed to confirm its suitability to real-time application.

4. FOGGY IMAGE RESTORATION: THE PROPOSED MODEL

The proposed model is concerned with developing a foggy image restoration system using NN (FIRNN). Prior knowledge is needed (two images taken for the same scene, foggy image and non-foggy image) in this work. Figure (1) shows FIRNN phases in details. Seven different approaches are suggested for image restoration. Each approach presents its own NN architecture and feature set. The results are compared perceptually and empirically (using PSNR results). FIRNN consists of four phases (pre-processing and feature extraction phase, training phase, testing phase, and image reconstruction and post processing phase). In pre-processing and feature extraction phases, DCT is applied locally (using overlapped sliding window) to reduce noise [7-9]. Features are extracted from image transformed domain (using DCT). Application of DCT locally to enables effective suppression of noise components while preserving the useful image content (texture, edges, and details) [7-9].

4.1 Pre-processing and Feature Extraction Phase

The first step in FIRNN is to convert the image from true-color type to gray-scale. Feature extraction is the most important step in any image processing system. In this paper, features are extracted from the spatial and transformed domains. When spatial domain is used, each pixel value of the foggy image is mapped to the corresponding pixel value of the original image. Features are extracted from image transformed domain using DCT. In this case, either the DCT of each pixel in the image is taken as feature, or pixel feature is extracted from the surrounding window of size n×n. In this case, both images (foggy and original images) are partitioned into overlapped sub-images (windows) of size n×n, and features are extracted from each window. In this paper, different window sizes (n can be 3 or 5) are considered.

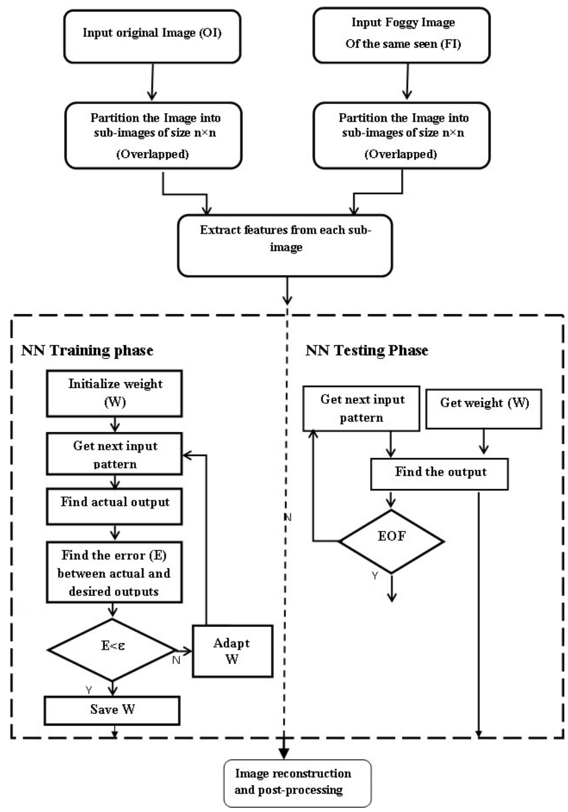

Figure 1. FIRNN Model

4.2 SNN Architecture

After the construction of sub-images (windows), image features are extracted from a transformed domain of each window. The extracted features represent the features of the center pixel. Different window sizes are tested to determine the best window size that suits the image restoration process. Window size affects the number of nodes in the NN input layer, which may also affect the number of nodes needed in the hidden layer. The number of nodes specified in the hidden layer depends on the number of nodes in both input and output layers, in addition to the nature of the training data.

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One of the main aspects that should be considered when using BPNN is specifying proper NN architecture, which includes the number of hidden layers and the number of nodes in each layer. No standard method is available for doing this step. Recently, most researchers used the verification phase to specify the most suitable NN architecture for their problems. The architecture with the best performance measurement (such as specificity, sensitivity, and misclassification rate) is selected as the recommended architecture. In this work, the general architecture of the recommended BPNN is composed of the following:

- ✓ *Number of layers:* The suggested NN consists of three layers (input, hidden, and output) because of the nonlinearity nature of the training data, which requires solving a certain sort of activation function. BPNN architecture without hidden layer(s) serves linear nature problems [23]. We select one hidden layer because most nonlinear problems do not need more than one hidden layer to be solved. BPNN with one hidden layer can approximate any function that performs a continuous mapping from one finite space to another [23, 24].

- ✓ *Number of nodes in each layer*: The network architecture substantially influenced the performance of the NN. No problem exists in specifying the number of nodes in the input and the output layers. The main problem involves how to specify the numbers of nodes in the hidden layer to improves the performance measure. A verification set (small random samples of the dataset) is used to specify the proper number of nodes in the hidden layer. Different networks with different numbers of neurons in the hidden layer are trained and tested for selecting the suitable number of hidden nodes. We start from the number of nodes equal to the mean of the input and output nodes and end with approximately triple the number of input nodes (which is empirically proven to include the best architecture) [24]. For every cycle, the network is trained and tested to capture the error rate. In this work, PSNR improvement is used as the performance measure. The network architecture with the best performance (in each testing approach) is selected. In general, the recommended BPNN architecture is composed of the following:

  1) *Input Layer*: specified according to type and number of used features in each approach.

  2) *Hidden Layers*: specified empirically as illustrated above.

  3) *Output Layer*: according to the approach used (can be 1 node, 9, or 25 nodes).

- ✓ *Neural Network parameters*: The hyperbolic tangent sigmoid function (tansig) is employed as the transfer function. MSE is used as the performance function. The learning rate was α=0.01(which is adapted to 0.1 after certain NN convergence) with a momentum term of μ=0.8.

After constructing the proper NN architecture for each approach, we start training each designed network until the network performance is stable. The dataset is first divided in two parts, namely, training and testing sets, more than once (in this work, three different sets are generated). This partitioning process will overcome the effect of sampling on the NN performance (reduce the effect of noise samples in training set only or testing set only). The training set is used for training the network, and the testing set identifies how well the NN performed. The NN should be trained using the training set, which consists of a set of foggy images and the corresponding set of their original scenes images, because BPNN is a SNN. For each image and its corresponding original scene, one of the approaches is applied to extract features from both foggy and original image. The corresponding NN is trained. The main steps of NN training are as follows:

Step-1: The following are repeated for all training feature sets.

1) The input feature set and the corresponding feature set (desired output) are obtained.

2) The training feature set is applied to the NN one by one, each with the corresponding desired output.

3) The weight matrix is adapted based on the error rate between the input and the output values.

Step-2: Step one is repeated until NN performance is stable or for a specific number of epochs. When the training process is finished, the resulting weight matrix will represents the target restoration filter.

To test the performance of the generated restoration filter:

Step-1: Features are extracted from testing foggy images (set of foggy images that differ from

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the training test).

Step-2: The resulting weight matrix is used to filter foggy images and produce output, which is either transformed value(s) (apply DCT^{-1} to obtain the restored pixel(s)) or spatial domain pixels.

Step-3: Finally, the filtered image is evaluated empirically and perceptually.

4.3 Post-processing Phase

The restored image is reconstructed after the generated fog restoration filter is applied on the foggy image. In case of spatial domain approach, the corresponding pixel value is determined, and the restored image is rebuilt by combining the pixels values. A median filter of 3×3 is applied on the restored images to improve and enhances these images. The tested median filter of 5×5 causes image blurring.

5. FIRNN APPROACHES

The NN architecture varies based on the number of extracted feature and feature type. In this work, seven approaches are suggested based on the number of extracted features and the domain from which the features are extracted. In all approaches, both image pairs (foggy and original) are first converted to gray-scale images, and then features are extracted. Table (1) summarizes the seven approaches.

5.1 First Approach: Features Are Extracted From Frequency Domain

✓ *Training phase*: DCT is applied on all image pixels for both original and foggy images. The NN is trained using all training image-transformed pixels from foggy images (input) with their corresponding transformed pixel from the original observed image (desired output). If image size is 256×256, then 2^{16} training pairs exist (for n image pairs, then $n×2^{16}$ iterations/epoch are needed to train the NN).

✓ *Testing Phase*: The testing foggy image is converted to gray-scale. DCT is applied on each image pixel. The image pixels are filtered using the generated restoration filter (weight matrix). DCT^{-1} is applied on each of the resulting values to generate the restored image pixels. The restored image is rebuilt (restored image size is the same as the foggy image size).

Table 1. The 7 suggested approaches with the corresponding BPNN architecture

Approach #	Window Size	Transfer Function	ANN input (foggy image)	ANN output (original image)	#nodes in hidden layers
1	1	DCT	1 Pixel	1 Pixel	26
2	3×3	DCT	1 Pixels (max DCT value)	1 Pixels (max DCT value)	26
3	3×3	DCT	9 Pixels (Full DCT window)	1 Pixel (DCT of centre Pixel)	26
4	1	spatial domain	1 Pixel	1 Pixel	26
5	3×3	DCT	9 Pixels (Full DCT window)	9 Pixels (Full DCT window)	26
6	5×5	DCT	25 Pixels (Full DCT window)	1 Pixels (max DCT value)	16
7	5×5	DCT	1 Pixels (max DCT value)	1 Pixels (max DCT value)	16

5.2 Second Approach (features are extracted from frequency domain).

✓ *Training phase*: The foggy and *corresponding* original images are partitioned to several overlapped windows of size 3×3. DCT is applied on each window (for both images), and the maximum DCT value is selected (because much of the signal energy lies at low frequencies; these appear in the upper left corner of the DCT window) [2]. The maximum DCT value of the foggy image window is used as input with the corresponding maximum DCT of the original image window (desired output) to train the NN. Let H be Image-height and W be Image-width. If image size is $H×W$, then there are $(H\text{-}2)×(W\text{-}2)$ training pairs (for n image pairs, $n×((H\text{-}2)×(W\text{-}2))$ iterations/epoch are needed to train the NN).

✓ *Testing phase:* The foggy testing image is partitioned into overlapped 3×3 windows. DCT is applied on each image window, and the maximum DCT value is obtained. Each value is filtered using the generated restoration filter (weight matrix) DCT^{-1} is applied on each restored values to generate the restored image pixels. The restored image is rebuilt. The restored image size is (H-2)×(W-2).

5.3 Third Approach: Features Are Extracted From Frequency Domain

- ✓ *Training phase:* Each image is partitioned to several overlapped windows of size 3×3. The windows of the foggy images are converted to DCT form (nine values are used as input). For the corresponding original image window, the middle pixel is obtained, and DCT is applied on the pixel (one desired output value). In this approach, we attempt to obtain the features of the middle pixel value from its surrounding eight-pixel values. The number of iterations/epochs is the same as the second approach.
- ✓ *Testing phase:* The foggy testing image is partitioned into overlapped 3×3 windows. DCT is applied on each window, and the 9-DCT values are obtained. Each window is filtered using the generated restoration filter (weight matrix). The desired output is the DCT value that represents the DCT value of window's middle pixel. DCT^{-1} is applied on each of the restored values to generate the restored image pixels. The restored image is rebuilt.

5.4 Fourth Approach: Features Are Extracted From Spatial Domain

- ✓ *Training phase:* Images pixel values of the foggy image (input) and the pixels of the corresponding original image are used to train the NN. The architecture of the BPNN is the same as that used in the first approach.
- ✓ *Testing phase:* Each pixel is filtered in the testing foggy image by using the restoration filter (weight matrix) generated from the training phase. The restored image is rebuilt. The restored image size is equal to the foggy image size.

5.5 Fifth Approach: Features Are Extracted From Frequency Domain

- ✓ *Training phase:* This phase is the same as training phase of the third approach, except that the desired output is fully transformed to the corresponding window of the original image (9-DCT values).
- ✓ *Testing phase:* This phase is the same as testing phase of the third approach , except that DCT^{-1} is applied on the resulting nine full values (window size) to restore nine pixels. The middle pixel value is used only when reconstructing the restored image.

5.6 Sixth Approach: Features Are Extracted From Frequency Domain

Training and testing phases are the same as those in the third approach, except window size is 5×5 (that is, input nodes = 25), and the desired output node is the maximum DCT value of the corresponding original image window. The restored image size is (H-4)×(W-4).

5.7 Seventh Approach: Features Are Extracted From Frequency Domain

The training and testing phases are the same as those in the second approach, except that the window size is 5×5 (that is, input nodes = 25). The restored image size is (H-4)×(W-4).

6. EXPERIMENT RESULT: ASSESSMENT

As previously mentioned, seven different approaches are suggested and must be tested and evaluated. Selection of the proper foggy image dataset that contains both clear (original) and foggy images of the same scene is crucial in evaluating the performance of the suggested FIRNN. Most recent researchers used FRIDA2 database, which was constructed by Jean–-Philippe Tarel et al. [25]. The database was established by multiple authors and used solely for research purposes. The database comprises a dataset of numerical images used to measure the performance of visibility and contrast restoration algorithms and containing 330 synthetic images of 66 different road scenes [26]. Each non-foggy image (clear) is associated with four foggy images and a depth map. In this paper, 40 images (with various fog densities) are used to evaluate the performance of the seven suggested approaches. Each approach is trained using 30 pairs of images and tested by using 10 images (testing set is different than the training set).

Figure (2) shows the 10 original scene images used in a testing phase for the seven approaches. The 10 testing images are classified as moderate to high-density foggy images. The 40 selected images show different fog density, so we can conclude to which degree each approach can restore images close to their original scene. The testing set contains images not used during the training operation.

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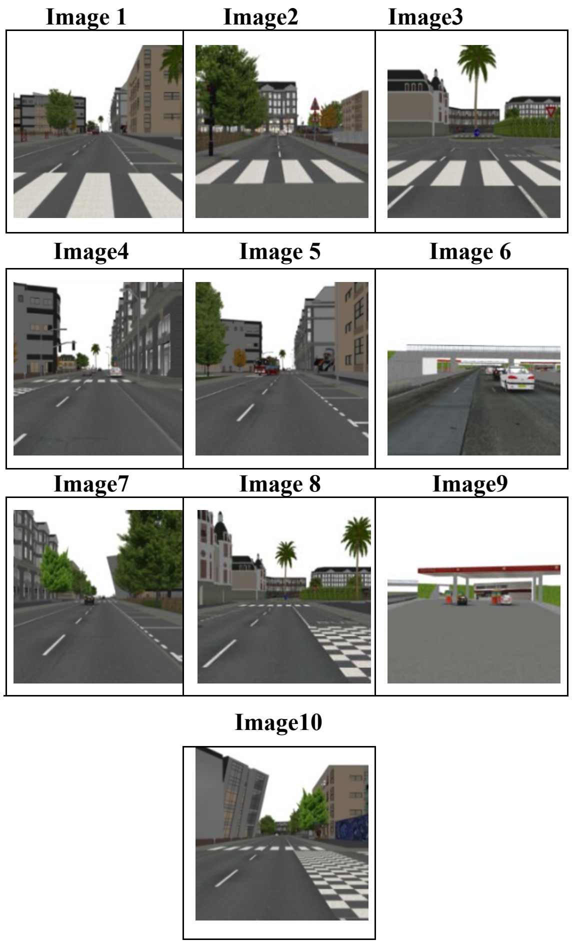

Figure 2. The 10 original images used in testing phase

NN is time consuming during training operation. However, once the NN is trained, the time complexity is O(n) during foggy image restoration, which suits real time applications. N is the total number of pixels in the restored image. Three-fold cross-validation (the 40 images are partitioned three times to 30 training images and 10 testing images) is used to evaluate the performance of the suggested FIRNN. Each approach is trained and tested three times. After applying the fog filters resulting from training the seven approaches on the 10 images, the PSNR value between each original scene image and its corresponding restored scene is computed. The average PSNR of the three folds for each testing image is used as an empirical distortion measure. Chart (1) shows the average of PSNR values of the three groups (threefold) for the 10 testing images. Chart (2) illustrates the average PSNR values for the seven approaches. The approach with the highest average PSNR value is selected as the best approach. The poorest approach is clearly the fifth approach because the training input and the output comprise a full window without removing high frequency, which can be noise (the noise of the surrounding pixels exerts a full effect on the center pixel value).

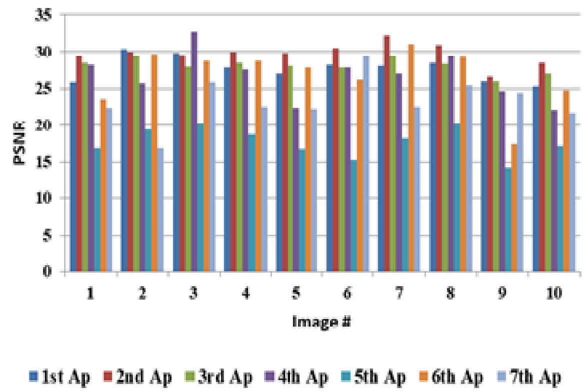

Chart 1.The PSNR values of the 10 restored images for the 7 approaches

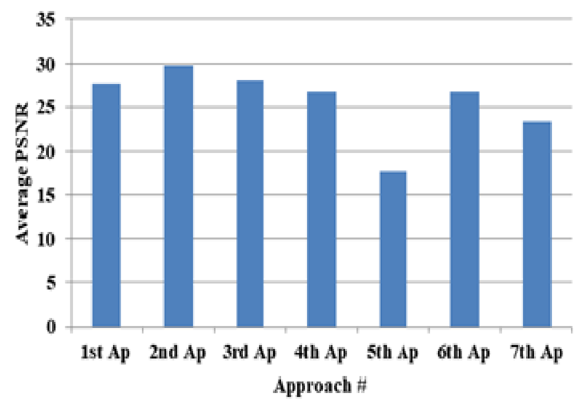

Chart 2. The average PSNR values of the 7 approaches

The sixth and the seventh approaches (windowed approaches as the second and the third) show low performance compared with the first three approaches. This degradation is caused by window size. In case of a noisy area (foggy area), the noise in the window center pixel increases because of the effect of more surrounding noisy pixels. The fourth approach shows degraded performance compared with the first approach because direct pixel values are used during the training phase (using DCT in the first approach reduces noise to a certain degree thereby improving the performance). The second approach shows the best performance because noise is reduced from the input foggy window and the output original window (DCT is applied, and only the maximum coefficient is obtained). Although the second approach exhibits a high PSNR value, the first, second, and third approaches show comparable and good results. In the three approaches, noise is reduced from the

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desired original image and foggy image. The PSNR criterion is insufficient to find the best approach to restore the foggy images [12]. Therefore, perceptual evaluation is used to approve the conclusion derived from the PSNR measure and suggest the final recommended approach. Chart (2) clearly shows that the best two approaches based on average PSNR values are the second and the third approaches. We will compare the restored images of the second and the third approaches perceptually from the perspective of clearness degree (the clearness of the image topographies).

Figure 3. The 10 Foggy scene (testing images)

Figure (3) shows the 10 testing foggy scene images (different that the training image set). Figure (4) shows a sample of three restored images (images 1,2,3 in figure 3) using second and third approaches. It is clearly seen that most objects (image details) that were hidden by fog appear and recognized in the restored image (check the red pointers on each restored image). Figure (5) shows the restored images after applying fog filters generated by the seven approaches on Image-1.

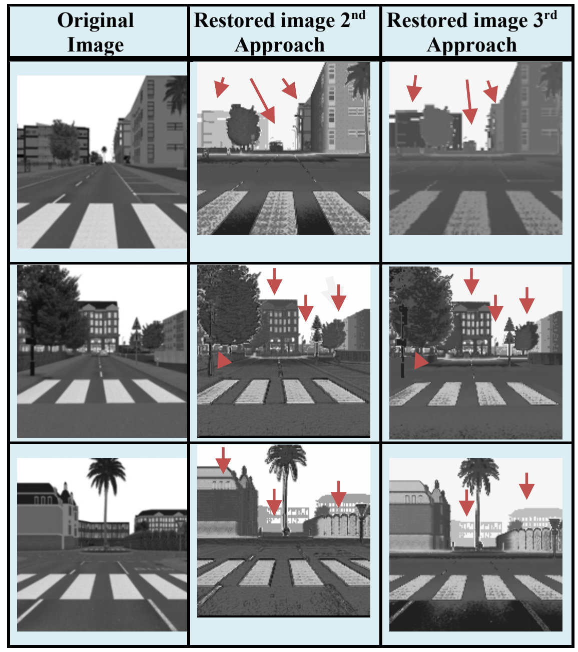

Figure 4. Samples of restored foggy images (images 1, 2, and 3 in figure 3) using 2nd and 3rd approaches

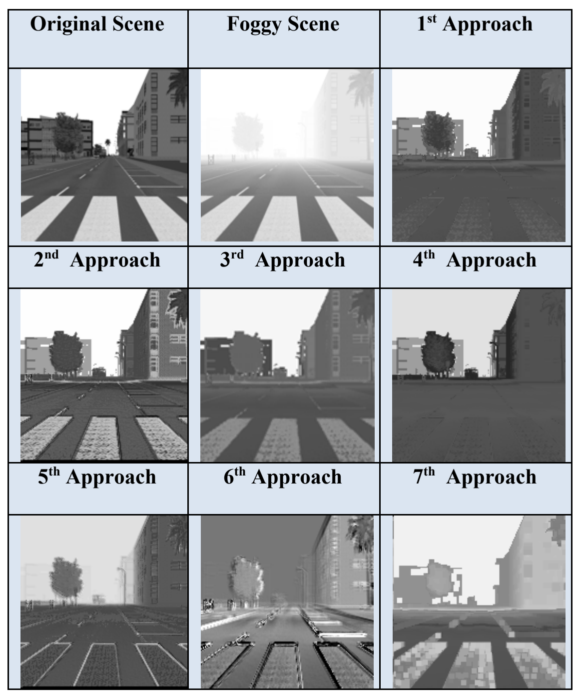

Figure 5.1st scene images restored using 7 approaches

On the basis of the restored images generated by applying the seven approaches (samples are shown in Figures (2–5)), the judges agreed that the images restored by the second and third approaches are the best images. According to the perceptual performance evaluation, which is based on the opinion of 20 persons to judge the clarity of the restored images, 75% of the judges agreed that the restored images resulted from applying the 2nd approach are clearer than those from the 3rd approach.

By comparing the proposed system performance perceptually with the NN approach in [19], foggy images restored by FIRNN are comparable to those restored by [19] taking in consideration, in FIRNN, one hidden layer is used; while in [19] six hidden layers are used. e choose to compare with [19] since FRIDA2 database (with the same testing images) are also used for system evaluation. On the other hand, by comparing the PSNR improvement with

To analyze the time complexity of the second approach (recommended approach), we should consider the steps needed to restore the foggy image based on the generated fog filter. In the first step, the time needed to partition the image into overlapped windows requires passing through all image pixels. The complexity of the used algorithm is O(n) (n is the total number of image pixels). The second step is the local application of DCT (on slide window of 3×3). The time complexity is n×O(9), which is equivalent to O(n) (actually O(9n), but constants are dropped with large O notation). Finally, as explained before, the time complexity of applying the fog filter on each image pixel is extremely small depending on the number of input nodes (x), hidden nodes (h), and output nodes (y) of the second approach NN. Time complexity equals h×O(x) + y×O(h) (that is, 26×O(1) + 1×O(25)=2×O(26), which is O(52)). For n pixels, the time complexity is n×O(52)= O(52n). By using the same concept of disregarding constant values, the complexity of applying a fog filter on a foggy image is O(n). For such an algorithm, the total time complexity equals the maximum time complexity of the three steps, that is, O(n). Given that image height and width are fixed (that is, n is fixed), the time needed for image restoration can be calculated based on CPU speed. Complexity analysis shows that the time required to restore foggy images is suitable for real-time application.

7. CONCLUSION

In this work, we develop a technique to restore foggy degraded images by using SNN. The suggested technique is based on mapping between a foggy scene and its corresponding original scene. The weight matrix resulted from training the NN represents the fog filter.

By testing different feature sets and different window sizes (1 pixel, 3×3 pixels, and 5×5 pixels), we can specify the effective feature set and the proper window size that suits NN technique for foggy image restoration. Testing results show that windows exceeding 5×5 provide poor results because fog features may dominate and lead to low performance. The empirical evaluation (PSNR) shows that the best feature set used to generate the fog filter is the maximum DCT value, which is extracted from a window of size of 3×3 (the second approach illustrated in Table (1)). Perceptually, the second approach is recommended because of its superior results. Extraction of features from small window sizes is reasonable especially with heavy fog images because the fog dominates when we attempt to extract features from large windows. The use of local DCT improves system performance because it separates the image into spectral sub-bands of differing importance, thereby reducing noise and preserving important image details. The use of the maximum DCT value reduces unimportant data and, thereby aiding the improvement of the restoration process. If the fog is extremely heavy (pixel value is totally white), the mapping process is virtually impossible. A comparison of the PSNR values of (original with foggy) and (original restored) images showed that the generated filter works properly, as shown by the nearly two fold improvement. This finding reveals that the approach succeeds in rebuilding the main details of the original scene and clarify the vision. Although some image details are lost but the important image details are preserved.

Finally, by analyzing the time complexity of the second approach (best approach), it is clearly seen that the time required to restore foggy images is suitable for real-time application.

8. LIMITATIONS AND FUTURE STUDIES

As missioned before, the proposed approaches need original clear scene and foggy scene to train the NN. Although this could be a limitation, but the need for the two scenes is only for training the NN to get the fog filter. After that, only the foggy scene is needed to be filtered. During testing phase, we apply the resulted fog-filter on a new scene, which is not used during training phase. The fog-filter is capable to clarify the image and rebuild the original scene (with most details). On the other hand, FRIDA2 database is used to evaluate the suggested system performance. This could be a limitation since FRIDA2 database contains steady synthesized image. It is better to

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evaluate the system performance using car cameras, especially in testing phase.

As future work, the proposed approach will be tested and evaluated using car cameras under various conditions of dust and misty (foggy) weather. We also are developing the FIRNN to reconstruct color image rather than gray scale images. This will enable us to develop an automotive vision system. Car speed should also be controlled to suit the restoration process under various foggy conditions.

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