A COMPARISON OF DIFFERENT ATMOSPHERIC TURBULENCE SIMULATION METHODS FOR IMAGE RESTORATION

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ABSTRACT

Atmospheric turbulence deteriorates the quality of images captured by long-range imaging systems by introducing blur and geometric distortions to the captured scene. This leads to a drastic drop in performance when computer vision algorithms like object/facerecognition and detection are performed on these images. In recent years, various deep learning-based atmospheric turbulence mitigation methods have been proposed in the literature. These methods are often trained using synthetically generated images and tested on real-world images. Hence, the performance of these restoration methods depends on the type of simulation used for training the network. In this paper, we systematically evaluate the effectiveness of various turbulence simulation methods on image restoration. In particular, we evaluate the performance of two state-of-the-art restoration networks using six simulations method on a real-world LRFID dataset consisting of face images degraded by turbulence. This paper will provide guidance to the researchers and practitioners working in this field to choose the suitable data generation models for training deep models for turbulence mitigation. The implementation codes for the simulation methods, source codes for the networks and the pre-trained models are available at https://github.com/Nithin-GK/Turbulence-Simulations

Index Terms — Atmospheric turbulence mitigation, deep learning, face verification, deblurring.

1. INTRODUCTION

The problem of recognizing a person appearing in an image taken by a long-range imaging system is important in many biometrics and surveillance applications [1, 2, 3]. Atmospheric turbulence adversely degrades the quality of images captured by long-range imaging systems by causing spatially varying blurring effects on each pixel in the captured image. Since most existing face verification algorithms perform best when used on clean images [4, 5], face verification on such images is performed by first removing the distortions caused due to atmospheric turbulence and then performing verification on the restored images. Recently some deep learning-based models [1, 6, 3, 7, 2] have been proposed to tackle this problem of atmospheric turbulence mitigation. These networks are trained using synthetically generated data modelling the turbulence distortion [8, 2].

Although multiple works have previously attempted to model the phenomenon of atmospheric turbulence, there is no detailed analysis of the performance of deep networks trained using these turbulence modeling techniques to restore real-world face images. Multiple techniques have been proposed in the literature for modelling atmospheric turbulence [9, 10, 11, 12, 8, 13]. Hardie et al. [9] proposed a numerical wave propagation method for modeling turbulence distortion of a scene under anisoplanatic condition. This method uses an array of Point Spread Functions (PSFs) to perform a spatially varying weighted sum operation on a clean image to generate the turbulence distorted image. Potvin et al. [10] proposed a simple physical model based on first-order Rytov theory for propagation through turbulence. The method uses two scalar fields derived using a Gaussian and non-isoplanatic PSFs. These scalar fields are further used to model blur and geometric deformations. Bos et al. [14] utilizes a simplified form of the split-step wave propagation method. Essentially this method employs a series of uniformly spaced phase screens to simulate turbulence distortions. Schmidt et al. [13] describes a set of wave optics algorithms to simulate atmospheric turbulence. Recently Mao et al. [11], and Chimitt et al. [12] have proposed fast turbulence generation algorithms based on computing the tilt and aberration coefficients using Zernike basis functions. Chak et al. [8] decomposes the turbulence mitigation problem into a blurring and geometric distortion problem and model both of these independently. Schwartzman et al. [15] utilizes the physics behind turbulence and generates distortion fields according to the empirical turbulence model. [2] uses elastic deformation operation to model the geometric deformation and Gaussian blur model for the blurring operator. In this paper, we focus on the works by [11, 12, 2, 8, 15] since they are computationally inexpensive and are suitable for generating data for training deep networks.

The problem of atmospheric turbulence mitigation has also been extensively studied in the literature. Essentially there are two main approaches for mitigating atmospheric turbulence – adaptive optics-based [16, 17, 18] and image processing-based [19, 20, 21, 22, 1]. Adaptive optics-based techniques require expensive and complex hardware, hence image processing methods are often preferred. Most image processing techniques are designed for mitigating atmospheric turbulence effects in videos. They [21, 23, 19] often proceed by combining the complementary clear regions across frames by the lucky fusion process and further performing deconvolution on this fused frame to get the restored output. With the success of deep networks in fast and accurate image reconstruction, a few deep learning techniques have also been proposed for atmospheric turbulence mitigation [7, 3, 24, 25]. All of these methods focus on restoring facial images degraded by atmospheric turbulence. The methods [7, 3, 25] have been proposed for single image turbulence mitigation and the method [6] is for turbulence mitigation in videos. The performance of deep image restoration networks depends on
the type of simulation method used for training the network. In order to gain further insight and also to compare the effectiveness of various simulation methods, in this paper, we study the performance of two state-of-the-art image restoration networks when trained by various turbulence simulation methods. The performance is evaluated on the real-world LRFD data consisting of face images degraded by turbulence. We present detailed analysis and comparison of different methods.

2. RECENT OPEN-SOURCE SIMULATION TECHNIQUES

2.1. Method from Chak et al. [8]

Inspired by the turbulence formulation in [22, 26], Chak et al. [8] use the following mathematical model to simulate the degradation caused by turbulence.

\[ T = D(H(I)) + n, \]

where \( T \) is the distorted image, \( I \) is the clean image, \( n \) is additive noise, \( D \) is a deformation operator which deforms the image randomly, and \( H \) is a blurring operator. The deformation operator \( D \) is created using the following process. From the given image \( I \), \( K \) pixels are selected. For each of these pixels at locations \((x, y)\), a random motion vector \( M^{(x,y)} \) of size \( S \times S \) is created according to, \( M^{(x,y)} = \eta(G_\sigma \ast N_1, G_\sigma \ast N_2) \) (2)

where \( G_\sigma \) is a Gaussian kernel with standard deviation \( \sigma \), \( \eta \) is the strength of the deformation and \( N_1 \) and \( N_2 \) are sampled from a standard Gaussian distribution. The deformation operation \( D(x) \) and the overall motion vector field over all \( K \) points is given by

\[ M = \sum_{i=1}^{K} M^{(x,y)}, \quad D(x) = M \oplus x, \]

where \( \oplus \) is the warping operation, the blurring operator \( H \) is a Gaussian blur kernel. Table 1 contains the values of hyperparameters used for our experiments.

2.2. Method from Schwartzman et al. [15]

Schwartzman et al. [15] follows a physics-based approach of turbulence modeling. The method introduces an efficient way to render 2D image distortions from physics-based distortion vector fields. The key idea in this method is derived from an empirical model of atmospheric turbulence. Empirically, the distortion motion vectors at two pixels \( p \) and \( p + v \) are related and their autocorrelation is given by,

\[ C(v) = E[e(p)^T e(p + v)], \]

where \( e \) denotes the distortion motion vector function. Now, according to Belen et al. [27], the function \( C(v) \) follows a particular form for turbulence based distortions. This idea is used to traceback to the distortion motion vectors \( e(p) \) for all pixels \( p \) in the image plane. Once the distortion motion vector function \( e \) is obtained, each pixel in the image is warped using this function to create the turbulence distorted image. Table 2 contains the camera and atmospheric parameter settings used in our experiments.

2.3. Method from Chimitt et al. [12]

Similar to Schwartzman et al. [15], Chimitt et al. [12] also follow a physics-based formulation of turbulence. The basis for this work is derived by establishing the equivalence between the angle-of-arrival correlation in Basu et al. [30], and the multi-aperture correlation by Chan [31]. Essentially, Chimitt et al. [12] first decomposes the geometric distortions (tilts) and blurring effect (aberrations) by utilizing Zernike decomposition. The Zernike coefficients are derived according to the correlation matrix defining the angle of arrival correlations. The tilts are derived from spatial correlation matrix and the blurring effect is drawn from the inter-mode covariance matrix. The overall flow of the simulator is as follows. First, the image is partitioned into blocks and a spatially varying blur estimated using the Zernike coefficients is applied. Then the image is warped according to tilts drawn by utilizing the correlation matrix. These tilts represent the geometric distortion at different pixels in the image. Table 4 contains the values of hyperparameters used for our experiments.

2.4. Method from Mao et al. [11]

This paper is inspired from the work from Chimitt et al. [12]. As can be seen from Chimitt et al. [12], estimating the blurring or the aberration operator from the basis of Zernike coefficients is a computationally expensive task compared to the tilt coefficients. To simplify this process, Mao et al. [11] proposed a method to bypass the expensive PSF formation process by learning the mapping between the Zernike coefficients that represents the phase domain to the spatial domain. For this, a simple neural network is utilized to learn this mapping. Overall the method first reformulates the spatially varying convolution as a set of invariant convolutions and then learns the basis functions for these invariant convolutions using known turbulence.
Table 3: Quantitative results for different ranges in real world turbulence distorted face image dataset (LRFID [28]). The networks AT-Net [3] and MPRNet [29] are trained using synthetic images generated using the five simulation techniques and tested on LRFID dataset. Green colour highlights the best value over all the simulation methods for the individual networks. \(↑\) represents higher the better.

| Metric     | Chak [8] | Schwartzman [15] | Mao [11] | Chimitt [12] | Mei [2] | Chak [8] | Schwartzman [15] | Mao [11] | Chimitt [12] | Mei [2] |
|------------|----------|------------------|----------|---------------|---------|----------|------------------|----------|---------------|---------|
| Top-1      | 22.47    | 5.61             | 14.60    | 24.71         | 21.35   | 21.34    | 17.97           | 15.37    | 20.22         | 21.78   |
| Top-3      | 35.95    | 13.48            | 24.71    | 44.94         | 31.46   | 31.46    | 25.84           | 35.95    | 37.07         | 36.63   |
| Top-5      | 42.69    | 26.96            | 30.33    | 55.05         | 46.06   | 41.57    | 34.83           | 42.69    | 38.20         | 46.53   |
| NIQE       | 5.26     | 6.584            | 6.530    | 6.152         | 6.768   | 6.064    | 6.186           | 6.150    | 6.248         | 6.601   |

300m dataset

| Top-1      | 0        | 3.33             | 3.33     | 6.67          | 3.33    | 3.33     | 3.33            | 10.00    | 13.33         | 20.00   |
| Top-3      | 10.0     | 13.33            | 10.00    | 16.67         | 16.67   | 16.67    | 16.67           | 10.00    | 20.00         | 20.00   |
| Top-5      | 6.458    | 13.33            | 16.67    | 26.67         | 26.67   | 30.00    | 23.33           | 23.33    | 30.00         | 20.00   |
| NIQE       | 51.50    | 65.97            | 51.28    | 48.52         | 55.52   | 58.08    | 70.27           | 63.99    | 57.32         | 59.32   |

650m dataset

| Top-1      | 0        | 0                | 6.67     | 6.67          | 6.67    | 13.33    | 13.33           | 20.00    | 6.667         | 13.33   |
| Top-3      | 26.67    | 6.67             | 13.33    | 26.67         | 26.67   | 20.00    | 33.33           | 33.33    | 33.33         | 26.66   |
| Top-5      | 40.00    | 20.00            | 40.00    | 46.67         | 46.67   | 46.67    | 46.67           | 33.33    | 40.00         | 33.33   |
| NIQE       | 5.647    | 6.677            | 6.375    | 6.329         | 6.652   | 6.533    | 7.434           | 6.639    | 6.018         | 6.250   |
| BRISQUE    | 52.38    | 60.05            | 64.46    | 51.62         | 54.92   | 57.40    | 68.57           | 64.54    | 55.50         | 58.25   |

1000m dataset

| Top-1      | 0        | 0                | 6.67     | 6.67          | 6.67    | 13.33    | 13.33           | 20.00    | 6.667         | 13.33   |
| Top-3      | 26.67    | 6.67             | 13.33    | 26.67         | 26.67   | 20.00    | 33.33           | 33.33    | 33.33         | 26.66   |
| Top-5      | 40.00    | 20.00            | 40.00    | 46.67         | 46.67   | 46.67    | 46.67           | 33.33    | 40.00         | 33.33   |
| NIQE       | 5.647    | 6.677            | 6.375    | 6.329         | 6.652   | 6.533    | 7.434           | 6.639    | 6.018         | 6.250   |
| BRISQUE    | 52.38    | 60.05            | 64.46    | 51.62         | 54.92   | 57.40    | 68.57           | 64.54    | 55.50         | 58.25   |

Table 4: Parameters of Chimit et al. [12].

| Aperture Diameter | 0.2034 m |
| Wavelength        | 525 nm   |
| Refractive index parameter \((C_n^2)\) | \(10^{-14}\) |
| Focal length      | 1.2 m    |
| Propagation Length | [300,650,1000] m |

Table 5: Parameters of Mao et al. [12].

| Aperture Diameter | 0.1 m |
| Fried parameter   | 0.02  |
| Wavelength        | 500 nm |
| Propagation Length | [300,650,1000] m |
| Distortion strength | 5 |

2.5. Method from Mei and Patel [2]

Recently, Mei and Patel [2] proposed a method that can model higher-order distortions due to turbulence using a simple method, called ElasticAug. The mathematical model for this method is the same as that in Equation 1. This method uses Gaussian blur as the blurring operator and uses the elastic transformation [32] as the deformation operator. The elastic transformation displaces pixels using random motion vectors. Table 6 contains the parameters used for the blur and elastic transformations in our experiments.

Table 6: Parameters of ElasticAug.

| Blur Kernel Size | 41 |
| Blur Kernel Types | [Isotropic, Anisotropic] |
| Blur \(\sigma\) Range | [1 to 25] |
| Down-sample Range | \([\frac{1}{8} to 1]\) |
| Elastic \(\alpha\) Range | [0 to 50] |
| Elastic \(\sigma\) Range | [4 to 5] |

3. IMAGE RESTORATION NETWORKS

We evaluate the effectiveness of the simulation methods using two state-of-the-art deep networks [3, 29].

Turbulence Distortion Removal Network (AT-Net) [3]. The first network that we use is the state-of-the-art network for single-image turbulence mitigation. AT-Net [3] first captures the regions that are hard to restore using epistemic uncertainty which are estimated based on Monte Carlo simulations. A restoration network is then guided using the estimated uncertainty maps to obtain the restored...
image. For all the simulation techniques, we re-train AT-Net with the following parameters. The number of Monte-Carlo simulations \( S = 10 \), Learning rate \( = 2 \times 10^{-4} \), batch size \( b = 2 \), number of epochs \( = 32 \) and we use Adam optimizer[33].

Multi-Stage Progressive Image Restoration (MPRNet) [29]. The second network we use is the state-of-the-art network for general image restoration. MPRNet [29] progressively learns restoration functions for degraded images through a multi-scale architecture. For the lower scales, contextualized features are learned using encoder-decoder architectures, which are later fused with higher resolutions. At each scale a pixel-wise attention mechanism is used to re-weight the features. The parameters used for MPRNet are: batchsize\( = 2 \), learning rate \( = 2 \times 10^{-4} \). We use Adam optimizer[33] for the training process.

4. EXPERIMENTAL RESULTS

In this section, we present the performance of AT-Net [3] and MPRNet [29] trained using different simulation methods. We train both networks by augmenting distortions produced by different simulation methods on 10,000 randomly selected images from the FFHQ dataset [34]. We use images of size \( 256 \times 256 \) obtained by re-scaling clean images from the FFHQ dataset for training. Both networks are trained using their default loss functions, as mentioned in their respective papers. We first re-train both networks using synthetic images generated using the simulation methods and test the performance of these trained networks on the LRFID dataset [28].

Evaluation dataset. The LRFID dataset [28] consists of real-world turbulence distorted images of 100 individuals in 6 different poses. These images are captured at different ranges – 300 meters, 650 meters, and 1000 meters. The atmospheric properties of the background conditions in the captured images can be seen in Table 7. Sample turbulence distorted images can be found in the third row of Fig.1. The LRFID dataset doesn’t have paired ground truth images in the same setting; rather, it contains a gallery set of the same 100 individuals in indoor conditions. As we can see from Fig. 1, the distortion level is quite high for the 1000m range. This holds true for most of the images at ranges 650 meters also. Hence only a very few images are present in the testing dataset prepared for evaluation.

Metrics. Since the corresponding clean target images in the LRFID dataset [28] are not available, the performance of the simulation methods are evaluated using the facial recognition scores obtained on the restored images. Specifically, we use the Top-1, Top-3, and Top-5 facial recognition scores. The Top-K score refers to the actual identity being present in the K nearest matches from the gallery set. For obtaining the recognition scores, we use Arcface [4] facial recognition algorithm by using the clean images of the people in the LRFID dataset [28] in the indoor conditions as the gallery set. For fair evaluations, all images are converted to grayscale before estimating the recognition scores. We also evaluate the methods using no-reference image quality metrics such as natural image quality evaluator (NIQE) [35] scores and blind/reference less image spatial quality evaluator (BRISQUE) scores [36]. NIQE and BRISQUE scores represent the naturalness of the images. Smaller scores represent better perceptual quality of the images.

Results. The quantitative results are presented in Table 3 and the corresponding qualitative results can be found in Fig. 2. In the case of 300m, as can be seen from Table 7, all turbulence simulation methods perform well. The best facial recognition scores for AT-Net are obtained by using Chimitt et al. [12] as the simulation method for generating synthetic training data. For MPRNet, Chimitt et al. [12] gives the best results for Top-3 recognition score, NIQE, and BRISQUE scores, while the best Top-1 and Top-5 recognition scores are obtained by using the simulation technique from Mei and Patel [2]. From the qualitative results in Fig. 2, we can see that the networks when trained using Chimitt et al. [12], produce the most visually pleasing results for the images at 300m. Although the method from Mao et al. [11] is a more recent technique for simulating atmospheric turbulence, the blurring aberrations in Mao et al.[11] are computed using the blurring aberrations derived in the method by Chimitt et al. [12]. Hence being an approximation of Chimitt et al. [12]. This is the main reason why the performance of the simulation method from Mao et al. [11] is lower for almost all evaluations when compared to the method from Chimitt et al. [12]. For the method from Schwartzman et al. [15], as we can see from Fig. 1, the tilt model is good, but the aberration model doesn’t match with that of the real-world turbulence images resulting in low recognition scores as can be seen in Fig. 2. Hence an effective simulation method for preparing training data to train deep networks for turbulence mitigation in grayscale images would be the method from Chimitt et al. [12], and for color images would be the method from Mei and Patel [2].

As can be seen from Eq. 1, turbulence mitigation is an ill-posed problem. Thus, restoring the exact facial identity is difficult when much of the salient facial features are not present in the distorted image. Hence, restoring images at higher ranges is very difficult while accurately reconstructing the facial features. This is the reason why the Top-1 recognition scores for the simulation methods are low for the higher ranges, which can be seen in Table 3. For AT-Net[3], for both 650m and 1000m, the method from Chimitt et al. [12] gives the best facial recognition and BRISQUE scores. One drawback of the method from Chimitt et al. [12] is that it is only defined for grayscale images. For color images, we have found that the method from Mei and Patel [2] utilizing elastic augmentations works the best for 650m range. While the method from Chak et al. [8] performs the best for 1000m range. One key observation from Table 3 is that the quantitative evaluation metrics from all simulation methods are very close for ranges 650m and 1000m. This is because the test set size is quite small and also the amount of distortion present in these images is quite high. Hence for the higher ranges, judging from the quantitative values in Table3, the turbulence phenomenon is best modelled by Chimitt et al. for grayscale images. In the case of colour images, since the values are very close, any one of the simulation methods from Chak et al.[8], Mao et al.[11] or Mei and Patel[2] could be used.

5. CONCLUSION

In this paper, we have studied the effectiveness of five recent atmospheric turbulence simulation methods on image restoration. Two state-of-the-art image restoration networks were utilized in our study. Based on facial recognition scores and no-reference image quality methods, we observe that the method from Chimitt et al. [12] gives the best possible simulated images in the case of grayscale images, and the technique from Mei and Patel [2] gives the best possible images in the case of RGB images.
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