Assessing the Effect of Atmospheric Turbulence on Long-Range Face Recognition Accuracy

Muskan Jain

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Assessing the Effect of Atmospheric Turbulence on Long-Range Face Recognition Accuracy

by

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Computer Science
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submitted to the College of Engineering and Science of Florida Institute of Technology
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Assessing the Effect of Atmospheric Turbulence on Long-Range Face Recognition
Accuracy

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ABSTRACT

Title:
Assessing the Effect of Atmospheric Turbulence on Long-Range Face Recognition Accuracy

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Recent investigations have demonstrated that it might be challenging to identify faces in the images taken using a long-distance camera. A face seems blurry in these images because of the presence of atmospheric turbulence. To examine how atmospheric turbulence impacts face biometrics, we establish a simulated environment that exhibits different degrees of turbulence. We employed the Rytov Variance, which relies on the distance and refractive index, $C_n^2$, to get various turbulence levels. We used the LRFID dataset to carry out the study, which is a collection of photos and videos taken in the field and in a controlled setting. Using the metadata extracted from the LRFID dataset, we were able to determine the three extreme $C_n^2$ values and their accompanying Rytov values for different levels of turbulence while labeling them as weak, moderate, and strong for two different distances of 300m and 500m. With the simulated dataset, we see how atmospheric turbulence affects biometrics using two biometric software, one open-source algorithm, ArcFace, and another commercial matcher.
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Dedication

I credit my success to my parents, who have been my staunchest supporters throughout this process and have never wavered in their desire to see my goals fulfilled.

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Chapter 1

Introduction

The rapid advancement in science and technology has driven the idea of using biometric technology for identification purposes. In high-security areas, long-range cameras or drones are used to capture faces from a distance. Because of the unrestricted environment conditions, the photographs are frequently hampered during capture by distortion, blurriness, poor illumination, or atmospheric turbulence. Face verification, person re-identification, and gait-based analysis are approaches used to recognize a person in an uncontrolled setting.

In this study, we focus on face identification, a method used to compare a face from a database to check whether the face belongs to the database. An example of this can be a frontal posed face taken from a driver’s license document to compare to a profile face pose captured in an uncontrolled setting. Depending on several components, like the time of day, location, amount of sunshine, weather, or the distance between the camera and the person being photographed, atmospheric turbulence in the images may differ from picture to picture for the same person.
Therefore, before considering removing turbulence, it is necessary to know the degree of atmospheric turbulence present to understand how blurred the picture is. Nair et al. [1] provide a comparison of the different simulation methods used for atmospheric turbulence developed recently for restoring images.

Rytov variance, a typical measure of the strength of turbulence variations, is used to comprehend and assess the degree of atmospheric turbulence. Using the Rytov value, we develop a simulated environment that creates varied amounts of blur in a photograph. The Rytov value is determined by the focal apertures of the camera used to take the picture, the refractive index structure parameter, $C_n^2$, and the distance from which the picture is taken. We estimated the Rytov value by varying the $C_n^2$ value for various distances and thereby producing blur.

Using existing face biometric tools, we investigated how atmospheric turbulence affects recognizing a person from a distance. We also use face verification to investigate how blur impacts face biometrics in a controlled vs. uncontrolled situation. This study makes use of the LRFID dataset, with a subset of 100 people having pristine photos in a controlled and uncontrolled setting with frontal and profile facial poses.

The aim and motivation behind this study are to provide an experiment-based result for face detection and identification performance using two algorithms: first, an open-source algorithm, ArcFace, with a Resnet-50 architecture, and second, a commercial off-the-shelf algorithm (COTS-A). Based on Rytov variance, we see how an image captured using long-range cameras containing atmospheric turbu-
lence affects face recognition as the level of turbulence increases. Further, we provide the background information in the next section, which explains what atmospheric turbulence is and how we calculate it. In Chapter 2, we provide a literature review, which highlights knowledge gaps and possible contributions from earlier efforts. In chapters 3 and 4, the experimental setup and implementation are then thoroughly explained. Chapter 5 presents the findings and associated analysis. The investigation is wrapped with a Conclusion.
1.1 Background

This section aims to provide an overview of the concepts underlying the topic of this thesis. We explain what atmospheric turbulence is, how the Rylov value is calculated, and its dependencies.

The refractive index structure parameter, $C_n^2$ (variations in the air, depending on the wind and temperature), is used to calculate the Rylov value. Later, we check the turbulent intensity at different ranges using the Rylov value to see how the atmosphere affects face recognition. We later explain how biometrics can be used to recognize a person from a distance.

1.1.1 Atmospheric Turbulence

It is an imaging phenomenon [2] brought on by the unpredictable and erratically moving air in the atmosphere, which also changes the air pressure, temperature, and wind speed. This ultimately results in blur and distortion, which degrade picture clarity and might make target capture less effective. The interaction of air with irregular topography, such as mountains and structures, as well as thermal effects and wind shear, may also result in atmospheric turbulence. When pictures are taken using long-range imaging systems like drones, atmospheric turbulence can significantly affect the efficacy of facial identification systems, as the distortions and blurring in the image can make it challenging for algorithms to recognize and match faces correctly.

Atmospheric turbulence [3] [4] plays an important role as the impact of the movement and mixing of heat, moisture, and pollutants in the atmosphere also results in weather predictions and climate modeling. Therefore, it is crucial to
comprehend and analyze atmospheric turbulence in many academic disciplines, such as fluid dynamics, atmospheric science, and weather.

1.1.2 RYTOV

Based on $C_n^2$, the Rytov index is a measure of the intensity of atmospheric turbulence. In the area of free-space optical transmission, the Rytov parameter is crucial because it establishes the degree of signal fading brought on by air turbulence. In pictures with faces, the Rytov value can also be used to determine how turbulent the atmosphere is. In this situation, the amount of distortion and blurring brought on by air disturbance in facial pictures can be determined using the Rytov measure.

Zhang et al. [5] calculated the Rytov variance to check the turbulence intensity under weak conditions while looking at its effect on the performance of free-space optical communication links. When the link range in optical communication approaches 1 km, they note a rise in the error rate for the received signals caused by scintillation (a shift in the optical signal’s intensity that occurs while it is being transmitted through the atmosphere.) So, they measure the atmospheric turbulence in a controlled environment using an indoor atmospheric chamber. The effects of turbulence on the radiated beam are characterized using Rytov variance $\sigma_R^2$, which uses the refractive index structure parameter $C_n^2$ to calculate the strength of atmospheric turbulence.

The Rytov variance is calculated using the following formula:

$$\sigma_R^2 = 1.23C_n^2K^{7/6}L^{11/6},$$

(1.1)
where, $C_n^2 = \text{turbulence structure constant,}$

\[ K = \text{wavenumber (2}\pi/\lambda), \]

\[ L = \text{distance} \]

In our work, we use equation 1.1 to see the effect of the Rytov variance while performing facial recognition. To calculate the Rytov variance, $C_n^2$ is taken from the LRFID [6] [7] metadata sheet.

The graph below depicts the $C_n^2$ value with the changing time of the day for the LRFID dataset, containing about 247 users who had their pictures taken at different times of the day.

![Figure 1.1: $C_n^2$ with time of the day](image)

To calculate the wavenumber,

\[ K = 2\pi/\lambda \]

where, $\lambda$ = 0.55e - 6 m
And distance $L$ can be varied depending on the range at which the image is taken,

with Distance, $L = 300\text{m}, 500\text{m}, 1000\text{m}$

Based on the equation, 1.1, the graphs below depict the Rytov value with the changing time of the day at various ranges.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{RytovVarianceVsTime.png}
\caption{Rytov variance($\sigma^2_R$) with time of the day}
\end{figure}

From figure 1.2 we obtained three strength categories,

Weak: $\sigma^2_R \sim 0.1$

Moderate: $\sigma^2_R \sim 1$

Strong: $\sigma^2_R \sim 10$
1.1.3 Biometrics

Biometric verification is the automated identification of a person based on biometric traits obtained from physiological and behavioral characteristics. A biometrics system collects biometric data from individuals, extracts feature sets, and compares them to a template set in a database. A biometric verification system may identify between a *mated* and *non-mated* more reliably than traditional systems that employ a card or a password. The present biometric systems include but are not limited to fingerprinting, iris detection, gait, face analysis, and palm prints [8].

![Building block of a biometrics system](image)

Figure 1.3: Building block of a biometrics system

1.1.4 Biometrics from a Distance

Some approaches used in face biometrics to recognize a person from a distance include face verification, face identification, person re-identification, and gait-based analysis. These techniques can assist in recognizing the individual by comparing pictures/videos taken from the uncontrolled setting to a government database, including images from the driver’s license document or any other identification papers.
The first approach, face verification, compares two faces to check whether the faces belong to the same person. It is also frequently known as one-to-one matching (1:1). Face verification in an uncontrolled context can be problematic owing to differences in viewpoint, such as comparing a frontal posed face to a profile face pose. Another reason for obtaining a false match can be low resolution or occlusion [9] [10].

Face identification is the process of verifying a person’s identity by matching their facial characteristics with a pre-existing database of known identities. Face identification problems can be divided into two categories: closed identification problems and open identification problems. In a closed identification problem, the algorithm is given a set of known identities and needs to determine which face matches the input face. In contrast, an open identification problem does not have a pre-existing database of known identities, and the algorithm needs to determine the identity of the input face from scratch. As the subject’s face is compared with N faces from either known identities or a collection of unknown faces in the database, it is also known as one-to-N matching (1:N) [8] [10].

Figure 1.4: Face Verification (1:1) and Face Identification (1:N)
In cases where it is challenging to perform face verification, person re-identification and gait-based analysis are used. In the person re-identification (Re-ID) [11], it is checked if the same person has appeared at a different location or at another time from an extra camera to obtain the person with a change in their pose or a different lightning setting [12]. Gait analysis identifies people based on their posture and mobility [13]. Nalty et al. [14] provide an overview of these approaches used to recognize humans from a distance.

Figure 1.5: Face Re-identification (Re-ID)
Chapter 2

Literature Review

We provide a literature review on the impact of atmospheric turbulence on facial recognition.

The images captured by long-range surveillance and security camera systems are used to recognize the identity of the person if suspicious [15] [16] [17] [1]. But, due to long distances, spatially varied blurring effects are created on each pixel of the acquired image, thus resulting in atmospheric turbulence. It negatively affects the quality of images captured by long-range imaging devices [18]. To get better results with the latest face verification algorithms, the distortions brought on by air turbulence are first eliminated from these blurred images, then verification is performed on the obtained images. Therefore it is paramount to measure the atmospheric turbulence and remove the distortions.
2.1 Methods to Measure Atmospheric Turbulence:

2.1.1 The Gill Propeller Anemometer

According to the specification document [19], the propeller is a self-powered low-threshold precision air velocity sensor. It measures airflow from any direction, but the propeller only responds to the airflow component parallel to the axis of its rotation. Off-axis response closely approximates a cosine curve with appropriate polarity. When the angles of the propeller change, improvements can be seen as it improves symmetry.

![Figure 2.1: The Gill propeller anemometer](image)

2.1.2 The K-Gill

Atakturk and Katsaros [20] introduced a new design in twin propeller-vane anemometers that measure atmospheric turbulence during moderate to high wind speed in
the presence of rain and sea spray. This instrument consists of two Gill anemometers mounted on a vane. The propeller shafts make an angle of $45^\circ$ with the horizontal to give symmetry while also managing tilt corrections so that updraft and downdraft winds are measured identically when determined by calibration. They also state that as far as the calibration of the sensors is known, the airflow distortion can be corrected.

![Figure 2.2: The K-Gill propeller-vane anemometer](image)

### 2.1.3 Optical Triangulation Method

De Oliveira et al. [21], in their Free Space Optical (FSO) applications, face atmospheric turbulence during communication using an air channel. The atmospheric
turbulence is created due to the temperature change in the air, producing a variety of refractive index, further influencing the propagation of the optical beam. Thus, they use a simple and low-cost device based on the optical triangulation method [22]. To measure the atmospheric turbulence, it performs the statistical analysis by tracking the FSO systems using a beam hotspot on the receiver plane and comparing it with the distance between the hotspot and the origin of the Cartesian plane $r_c$ and the Refractive Index Structure Constant, $C_n^2$.

2.1.4 2-μm Doppler Lidar

As turbulence energy dissipation rate (TEDR), a turbulent characteristic of the atmospheric, is a significant factor influencing the aircraft wake vortices, Smalikho et al. [23] use 2-μm pulsed Doppler lidar [24] for TEDR estimation. They experimented with the velocity structure function (VSF method) and the Doppler spectrum width (DSW method) to perform the estimation for different turbulent conditions. They verified their numerical results with theory to conclude that the VSF method is more feasible for measuring low atmospheric turbulence. In contrast, the accuracy of TEDR estimation from the DSW method for moderate and high turbulence levels is double the VSF method.

Figure 2.3: The Doppler lidar
2.1.5 Vortex Beam

Due to the effects arising from the turbulence inducing random phase modulation of the optical field, Gu and Gbur [25] use vortex beam propagation to measure atmospheric turbulence. It is calculated using the radius of a ring dislocation of a vortex beam, which helps estimate the turbulent strength $C_n^2$, verified using numerical and theoretical examples.

Using numerical analysis, they demonstrated that the refractive index could be calculated at any turbulence level by correctly choosing the beam and propagation parameters and managing the saturation, thus resulting in high spatial coherence when dealing with strong turbulence [25].

2.1.6 Ultrasonic Anemometers and the Calibration Processes

Nosov et al. [26] introduce a new algorithm based on the Kolmogorov–Obukhov law [27] to measure parameters of atmospheric turbulence with the development of a new autonomous meteorological complex (AMK-03-4), differing from others due to the presence of four identical ultrasonic anemometers. Compared to the old algorithms based on a similar law, this algorithm gives significant error rate differences while calculating the structural characteristics of turbulent properties. Their work showed that using this algorithm, they get an error of not more than 10%. Due to how it is built, statistical properties of turbulent fluctuations’ spatial derivatives can be registered.
2.1.7 Rylov Variance

In the past, Rylov variance was used to calculate atmospheric turbulence in space optics for communication and underwater laser radar systems.

Potvin [28] presents a numerical algorithm while generalizing the Rylov approximation by dividing the refractive index into large and small components, thus making it flexible for use with modeling imaging systems. He then investigated how the Rylov approximation for expressing log amplitude and phase variations of a wave traveling through weak uniform turbulence can be generalized to the case of large-scale non-uniform turbulence.

Wang et al. [29] summarise using Rylov theory for optical wave propagation theory while looking at both Kolmogorov (i.e., turbulence in Earth’s atmosphere in the boundary layer) [27] and non-Kolmogorov [30] (i.e., turbulence in the free atmosphere and the stratosphere) atmospheric turbulence. The scintillation index, covariance function of irradiance, and beam wander for a Gaussian-beam wave have all been calculated using the Rylov method. While beam wandsers for a Gaussian-beam wave were developed in weak irradiance fluctuation regimes, the temporal
spectrum of irradiance for plane waves was investigated with strong variations.

Milonni et al. [31] provide some essential findings from the theories of photon statistics and radiation propagation in turbulent atmospheres. They compare data for horizontal atmospheric propagation pathways with predictions of photon counting distributions, using the Kolmogorov model with the refractive-index structure constant $C_n^2$.

Arockia Brazil Raj et al. [32] represents a low-cost customized system for continually measuring the local meteorological data while estimating the atmospheric turbulence strength $C_n^2$.

This thesis focuses on measuring atmospheric turbulence using the Rytov variance of an image [33].
2.2 Effects of Atmospheric Turbulence

Due to variations in the spatial dimensions and turbulence wavelengths, pictures of space and pictures with faces of people are affected by atmospheric turbulence in different ways.

When viewing space [2] [34], atmospheric turbulence happens at very long wavelengths—typically tens to hundreds of centimeters—and over vast spatial scales—typically several kilometers [35]. Images may look fuzzy and warped due to large-scale distortions and wavefront aberrations in light traveling through the atmosphere. These distortions can significantly impact the sharpness and contrast of celestial pictures, making it challenging to study minute features in far-off objects.

HST (Hubble Space Telescope) is a 2.4m optical, ultraviolet, and near IR that orbits 600km above the Earth. while the Subaru telescope (optical-infrared telescope) is at 8m on Mauna Kea (summit of Maunakea, Hawaii)
When imaging faces [36] [37], atmospheric turbulence usually happens over much smaller spatial dimensions, between a few millimeters and a few centimeters, and at much shorter wavelengths. It may be more challenging for facial recognition systems to correctly identify features due to these small-scale distortions, which can result in subtle changes to the form and texture of the face. Further complicating the identification process is an atmospheric disturbance, which can alter illumination and cast reflections on the face.

![Figure 2.6: Effects of Atmospheric Turbulence- Face](image)

(a) No Turbulence  
(b) Turbulence

The impacts of air turbulence can be reduced by using a variety of techniques, such as optical flow technology [38], deep learning-based approach [39], and the GAN inversion method [16]. However, the application and the intensity of the disturbance are what determine the particular strategy to be used.
2.3 Methods to Remove Atmospheric Turbulence Distortions

Wu and Su [38] presented a method to eliminate atmospheric turbulence using optical flow technology to suppress geometric deformation. A temporal filter was used to obtain a single blurred image. Further, they used Laplacian graph regularization for the final clear picture to construct the cost function while maintaining the image details, thus improving image quality.

Yasarla and Patel [39] proposed a deep learning-based approach with both synthetic and natural images of faces to obtain an image after removing distortions. They employed epistemic uncertainty based on Monte Carlo dropouts to identify areas in the image where the network is having trouble recovering. The estimated uncertainty maps then direct the network to produce the restored image.

LTT-GAN, a method introduced by Mei and Patel [16], uses the GAN inversion method to incorporate visual priors. The model learns to maintain the identity of restored images on a spatial periodic contextual distance based on the visual priors. In the network, they also built hierarchical pseudo connections, which adds more appearance variation without changing identity.

To eliminate the geometric distortion and space-time varying blur in a given turbulence-degraded sequence, Xie et al. [40] suggested a technique based on total hybrid variation and deformation-guided kernel regression.
2.4 Impact of Atmospheric Turbulence on Facial Recognition

However, the above approaches presented in the past may help eliminate atmospheric turbulence. Still, they do not guarantee that the details and textures required by biometric applications to detect and recognize the face in the picture remain.

Sikkema [41] used a model based on Zernike coefficients [42] to evaluate the face recognition performance affected by air turbulence. The results demonstrated that atmospheric turbulence could significantly impair facial recognition performance at mid- to extended ranges.

The performance of automatic facial recognition software is examined by Leonard et al. [43] about the impacts of image deterioration due to turbulence. They also studied the viability of long-range facial recognition in poor imaging environments.
Chapter 3

Experimental Design

This chapter discusses the dataset needed to carry out the experiment design as well as the process for generating the desired dataset.

3.1 LRFID Dataset

The Long-Range Facial Identification Dataset, abbreviated LRFID, is a collection of videos/pictures featuring human faces at long-range. The dataset contains a minimum of 200+ subjects at ranges up to 1 km. This is the first long-range collection of faces acquired under operational settings with fully defined turbulence. The recruitment of the subjects was unconstrained based on gender, race, hair color, eye color, and age. The mugshot-style pristine images at a distance of 2m were captured using 11 different pose variations, including one frontal, ten distinct profile poses, and two different obscuration conditions, consisting of upper and lower face coverings. For the range collection, the ranges were: 300m, 650m, and 1000m, with each subject being photographed with 11 poses and two obscuration
conditions. This collection was collected with multiple bands simultaneously to provide researchers with a database for infrared or cross-spectral FR development.

Table 3.1: Sample of LRFID dataset

<table>
<thead>
<tr>
<th>Indoor Image</th>
<th>Outdoor Image</th>
<th>Turbulent Image</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.jpg" alt="Image" /></td>
<td><img src="image2.jpg" alt="Image" /></td>
<td><img src="image3.jpg" alt="Image" /></td>
</tr>
<tr>
<td><img src="image4.jpg" alt="Image" /></td>
<td><img src="image5.jpg" alt="Image" /></td>
<td><img src="image6.jpg" alt="Image" /></td>
</tr>
<tr>
<td><img src="image7.jpg" alt="Image" /></td>
<td><img src="image8.jpg" alt="Image" /></td>
<td><img src="image9.jpg" alt="Image" /></td>
</tr>
<tr>
<td><img src="image10.jpg" alt="Image" /></td>
<td><img src="image11.jpg" alt="Image" /></td>
<td><img src="image12.jpg" alt="Image" /></td>
</tr>
<tr>
<td><img src="image13.jpg" alt="Image" /></td>
<td><img src="image14.jpg" alt="Image" /></td>
<td><img src="image15.jpg" alt="Image" /></td>
</tr>
<tr>
<td><img src="image16.jpg" alt="Image" /></td>
<td><img src="image17.jpg" alt="Image" /></td>
<td><img src="image18.jpg" alt="Image" /></td>
</tr>
</tbody>
</table>

Note: The turbulent image is the frame extracted from the video sequence.
3.1.1 Occluded/Obscured Images

This section highlights the part of the dataset not used in this research. Still, it acknowledges its importance and relevance to the changes it can make while recognizing faces in a controlled and uncontrolled environment.

While detecting faces in a controlled setting for occluded or non-occluded images may not make a significant difference because the environment is constant, it significantly impacts detection in an uncontrolled environment as nature changes. It can modify the background, add shadow, or even cause the person to close their eyes due to the sunlight. Consequently, occlusion combined with the constant change of nature can conceal some crucial aspects of the face required to recognize a person. Although this occluded subset of the entire dataset was not used, it is nevertheless a comprehensive study of the chosen topic.
Figure 3.1: Obscured data

Figure 3.1 provides an example of obscured data comprised of photographs with either upper face coverings such as sunglasses (25%), sunglasses + hat (50%), or lower face coverings such as scarves with nose exposed (25%), or bandana with nose covered (50%). It provides an additional factor for face detection while performing facial recognition. This is because ArcFace creates a digital facial representation containing the most crucial discriminating information needed for person recog-
nition. As a result, these coverings can alter the cosine distance value, resulting in a different score. However, it can be interesting to see how, if at all, coverings change the match score as the turbulence is increased.

Thus, the images without any obscuration condition, i.e., the pristine images, were exclusively considered in the outcomes of this research.

3.1.2 Data Collection Methods

The final subset of the LRFID dataset selected for the study now contains 100 users in two environmental conditions: controlled (indoor) and uncontrolled (outdoor), with 11 face poses for each user. The face poses are shown in figure 3.2, where the pose name represents the pose of the face relative to the camera. For instance, PC00C00 represents the face in the center with 0-degree angle. For other pose names (P as the pose), C stands for the center, L stands for left, R stands for right, U stands for up, and D stands for down. We have 2107 photos, with 1100 for the controlled environment and 1007 for the uncontrolled environment.
Figure 3.2: Different poses
Chapter 4

Implementation

This chapter covers the necessary experimental procedures and the approach taken to conduct the study. The acquired results are validated using a commonly used open-source face recognition algorithm and a commercial off-the-shelf algorithm.

4.1 Data Pre-processing

To get the desired dataset for the study, we use images containing all the poses as shown in figure 3.2 for both controlled and uncontrolled environments. Then, we create a simulated environment [33] with Kolmogorov turbulence spectrum using diffraction limited (DL) modulation transfer function (MTF) for obtaining the images with different levels of turbulence based on the equation of the Rytov Variance as explained in 1.1. It is dependent on the Distance, L, and atmospheric turbulence strength, $C_n^2$ value.

The following $C_n^2$ value has been chosen for the turbulence levels:
Weak Turbulence,
\[ C_n^2 = 1.2 \times 10^{-14} \] (4.1)

Moderate Turbulence,
\[ C_n^2 = 1.2 \times 10^{-13} \] (4.2)

Strong Turbulence,
\[ C_n^2 = 1.2 \times 10^{-12} \] (4.3)

Table 4.1 and 4.2 below show the indoor and outdoor simulated dataset for the three turbulence levels: Weak, Moderate, and Strong for 5 Distances.
Table 4.1: Indoor Images with different turbulence at various ranges:

<table>
<thead>
<tr>
<th>Range</th>
<th>Weak Turbulence</th>
<th>Moderate Turbulence</th>
<th>Strong Turbulence</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 m</td>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
<td><img src="image3" alt="Image" /></td>
</tr>
<tr>
<td>300 m</td>
<td><img src="image4" alt="Image" /></td>
<td><img src="image5" alt="Image" /></td>
<td><img src="image6" alt="Image" /></td>
</tr>
<tr>
<td>500 m</td>
<td><img src="image7" alt="Image" /></td>
<td><img src="image8" alt="Image" /></td>
<td><img src="image9" alt="Image" /></td>
</tr>
<tr>
<td>650 m</td>
<td><img src="image10" alt="Image" /></td>
<td><img src="image11" alt="Image" /></td>
<td><img src="image12" alt="Image" /></td>
</tr>
<tr>
<td>1000 m</td>
<td><img src="image13" alt="Image" /></td>
<td><img src="image14" alt="Image" /></td>
<td><img src="image15" alt="Image" /></td>
</tr>
</tbody>
</table>
Table 4.2: Outdoor Images with different turbulence at various ranges:

<table>
<thead>
<tr>
<th>Range</th>
<th>Pristine Input</th>
<th>Weak Turbulence</th>
<th>Moderate Turbulence</th>
<th>Strong Turbulence</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 m</td>
<td><img src="image1" alt="Pristine" /></td>
<td><img src="image2" alt="Weak" /></td>
<td><img src="image3" alt="Moderate" /></td>
<td><img src="image4" alt="Strong" /></td>
</tr>
<tr>
<td>300 m</td>
<td><img src="image5" alt="Pristine" /></td>
<td><img src="image6" alt="Weak" /></td>
<td><img src="image7" alt="Moderate" /></td>
<td><img src="image8" alt="Strong" /></td>
</tr>
<tr>
<td>500 m</td>
<td><img src="image9" alt="Pristine" /></td>
<td><img src="image10" alt="Weak" /></td>
<td><img src="image11" alt="Moderate" /></td>
<td><img src="image12" alt="Strong" /></td>
</tr>
<tr>
<td>650 m</td>
<td><img src="image13" alt="Pristine" /></td>
<td><img src="image14" alt="Weak" /></td>
<td><img src="image15" alt="Moderate" /></td>
<td><img src="image16" alt="Strong" /></td>
</tr>
<tr>
<td>1000 m</td>
<td><img src="image17" alt="Pristine" /></td>
<td><img src="image18" alt="Weak" /></td>
<td><img src="image19" alt="Moderate" /></td>
<td><img src="image20" alt="Strong" /></td>
</tr>
</tbody>
</table>
The Rytov value changes for each turbulence level based on the Distance $L$. As a result, using the following parameters in the equation 1.1 to compute the Rytov value:

With Distance, $L = 300m$, and

$$K = \frac{2\pi}{\lambda}$$

where, $\lambda = 0.55e^{-6}m$

For weak turbulence, taking $C_n^2$ from equation 4.1, Rylov variance will be

$$\sigma_R^2 = 0.08802283$$

Similarly, for moderate turbulence, with equation 4.2,

$$\sigma_R^2 = 0.8802283, \text{ and}$$

For strong turbulence, with equation 4.3,

$$\sigma_R^2 = 8.802283$$

For this study, we created a set of weak, moderate, and strong turbulence for controlled and uncontrolled environments over distances of 300m and 500m.
4.2 Face Recognition Algorithm

Face recognition algorithms are commonly implemented in all biometric systems for individual identification and verification. This work makes use of two face identification software, one COTS-A; due to a confidentiality agreement, we are not permitted to share information regarding that and another ArcFace.

ArcFace [44], a well-known deep-learning face matcher and one of the most extensively used algorithms with a cutting-edge accuracy of 98 percent in face recognition. Using the Additive Angular Margin Loss function, ArcFace [44] optimizes feature embedding to ensure higher similarity for intra-class samples and diversity for inter-class samples.

Our research uses the pre-trained ArcFace model using the buffaloJ model, downloaded from the ArcFace GitHub [45] repository, which contains images of 600K individuals. The ArcFace models have a ResNet50-based architecture [46] [47] (i.e., a neural network architecture containing a stack of 50 convolution and pooling layers to reduce computational memory utilization while getting deep insight into the features in picture samples, thus enhancing accuracy.)
With the pre-trained model across all demographics, we construct a digital representation of the face using 512-d features from the last but one layer of ResNet50 architecture. As shown in Figure 4.1, the feature set, in the form of a .npy file, retrieved from each gallery comprises of only the most essential discriminatory
information required for person recognition. We compare these properties using
the cosine distance function to create a match score from each gallery’s input im-
age. The match score includes both mated and non-mated scores. If the cosine
distance value between the match scores is on the higher side of the -1 to 1 scale,
it is regarded as the same individual, also known as a mated score, otherwise an
imposter score. We can then construct the score distribution, ROC curve, CMC
curve, and even bar-whisker plots using the imposter and genuine scores.

The experiment analyzed the generated mated score to check the involvement
of atmospheric turbulence when the individual’s identity is still preserved with
facial features.
Chapter 5

Results

This chapter gives a detailed description of the significant points analyzed from the conducted study.

First, we present results for images in a controlled environment. Then, we document the results for images in an uncontrolled environment. By obtaining these results, we try to see at what level of turbulence the face detection and recognition start deteriorating and if distance affects the same. The scores have been produced using an open-source Face Recognition system, ArcFace, and a commercial off-the-shelf algorithm (COTS-A).

The analysis is broken down in accordance with the four groups based on the turbulence level with the two sets of LRFID dataset, indoor (controlled) and outdoor (uncontrolled): no turbulence (pristine image), and the simulated images with weak turbulence, moderate turbulence, and strong turbulence. The simulated images have been generated for distances 300m and 500m. For each set of images, indoor and outdoor, we provide results in three forms:
1. Mated score distribution based on the eleven different face poses, as shown in figure 3.2 against the frontal pose PC00C00 (from section 3.1.2) individually. For instance, consider the mated distribution of PC00C00 (figure 3.2, e) image of the first user with profile pose, PC00U30 (figure 3.2, b) of the same person. The findings are displayed as a bar and whisker plot, with the box plots depicting the mated scores for each posture in the gallery when compared to the frontal pose, PC00C00, as the probe. In every figure, one graph depicts results for ArcFace with orange box plots, while the other presents COTS-A results with blue box plots.

2. Mated score distribution of the frontal posture vs. photographs of all stances combined. The results are shown as a bar and whisker plot, with the plots representing the true scores for all the postures in the gallery when compared to the frontal stance, PC00C00, as the probe. In each figure, one graph presents ArcFace results with orange box plots, while the other provides COTS-A findings with blue box plots.

3. Comparison of the mated scores of the pristine image with the turbulent images for both data of 1. and 2..
5.1 Analysis for Images in Controlled Environment

We begin our analysis with pristine images. For the pristine images, we compare the frontal pose, PC00C00 (from section 3.1.2), with all the other face poses one by one. Therefore, to obtain the mated scores for all the users, the frontal image of a user is compared with ten posed images of the same person present in the gallery to see how profile images affect face recognition. Along the horizontal axis, the poses are presented, and along the vertical axis, the match score values are mentioned in figure 5.1.

Two bar and whisker plots generated with ArcFace and COTS-A are shown in figure 5.1. These figures clearly show that the scores for COTS-A are more biased towards high scores, spanning between 0.74 and 1 with a few outliers, but the scores for ArcFace are spread over a larger range, with maximum scores ranging between 0.4 and 0.95. PR90C00 and PL90C00 (from section 3.1.2) had the lowest scores, with a median score of approximately 0.6 with ArcFace and 0.87 with COTS-A.

There is a noticeable difference in the score range between postures PC00D30 and PC00U30, with PC00U30 generating superior results for both ArcFace and COTS-A. The results demonstrate that the scores for the left side of the face are marginally better than the scores for the right side of the face. Also, whether the left (yaw: +45 degree) or right (yaw: -45 degree) side of the face is visible, pitch: +30 degrees (face facing upwards) always performs better.

Also, while ArcFace fails to describe the failure to detect faces, COTS-A provides a list of images where it failed to detect faces, with a total of 10 images failing
(a) ArcFace

(b) COTS-A

Figure 5.1: Bar & whisker plot for the indoor pristine images

to detect faces which contains six PL90C00, two PC00U30, one PL45U30, and one PR45U30 posed images.

Similarly, we present findings for simulated pictures with $\sigma^2_R = 0.08802283$ (weak turbulence). We compare the pristine frontal posture, PC00C00 (from section 3.1.2), with all the photographs of angles of the face exhibiting weak turbulence one by one. To achieve mated scores for all users, the pristine image with a frontal pose of a user is compared to turbulent photographs of the same person’s frontal as well as posed face existing in the gallery to evaluate how turbulence impacts facial recognition. The match score values are provided along the vertical axis,
while the postures are indicated along the horizontal axis.

Figure 5.2 shows four bar and whisker plots created using ArcFace and COTS-A for simulated pictures with weak turbulence at two different distances: 300m and 500m.

The graphs simply illustrate that the scores for COTS-A are more biased towards high scores, i.e., generally ranging between 0.6 and 1. In contrast, the scores derived using ArcFace are dispersed over a larger range, with the majority of scores ranging between 0.4 and 1. The stances PR90C00 and PL90C00 had the lowest scores across all four plots, with PR90C00 somewhat better. ArcFace’s median score for both positions is approximately 0.59 for 300m and 0.56 for 500m,
whereas for COTS-A, it’s approximately 0.86 for 300m and 500m.

For the photos with weak turbulence, the distance has little effect on the scores; although the top whisker remains at the same score value, the range of the bottom whisker increases by 0.02. We can also observe that the outliers in the ArcFace plots are comparably dispersed over the range of values, with the lowest score being 0.3, whereas the lowest score for COTS-A is 0.57. The frontal posture \( \text{RC00C00} \) of photos with weak turbulence had the highest similarity, with scores ranging from 0.95 to 0.98 for both ArcFace and COTS-A. When compared to the scores derived from figure 5.1, the results show no significant difference. Moreover, COTS-A produced 12 failures to detect cases at 500m, compared to 9 at 300m with maximum error for the pose \( \text{PL90C00} \).

Furthermore, we report results for simulated images with \( \sigma^2_R = 0.8802283 \) (moderate turbulence). We compare the clean frontal posture, \( \text{PC00C00} \), with each snapshot of a face angle with mild turbulence one by one. To acquire mated scores for all users, a user’s immaculate image with a frontal posture is compared to turbulent images of the same person’s frontal as well as posed face in the gallery to assess how turbulence affects facial recognition. The match score values are presented along the vertical axis, while the postures are displayed along the horizontal axis in figure 5.3.

Four bar and Whisker plots were constructed using ArcFace and COTS-A for simulated images with moderate turbulence at two different distances: 300m and 500m. The plots are shown in figure 5.3. It demonstrates that the standard deviation (variation), regardless of the poses, rises as we compare the scores at 300m with that of 500m for the same level of turbulence. The poses \( \text{PR90C00} \) and
Figure 5.3: Bar & whisker plot for the indoor moderate turbulent images for distances- 300m (a,b) and 500m (c,d)

**PL90C00** continue to have the lowest scores, as seen for pristine and weak images.

Overall, it can be determined that when compared to weak turbulence photos for a distance of 300m, the median of the scores for all positions decreased by 0.05 with ArcFace and 0.02 with COTS-A. Using ArcFace, the median scores for poses **PL90C00** and **PR90C00** display a trend comparable to other poses, while there is a 0.6-point decline with COTS-A. Also, about 21 images gave an error for failure to detect, with the highest number of photos (10 error) with pose **PL90C00**.

Although the stances **PR90C00** and **PL90C00** have the lowest scores for 500m, there is one outlier for pose **PC00U30** with the lowest score of 0.02. The largest number of errors were found in photographs with the posture **PR90C00** (63 errors), followed by **PL90C00** (41 errors) and **PL45U30** (20 errors). We notice 153 more...
images producing an error for failing to identify at a distance of 500m, which as compared to that of 300m, is nearly 7 times.

Moreover, we report results for simulated images with $\sigma^2_R = 8.802283$ (strong turbulence). We compare the pristine frontal posture, PC00C00, to each snapshot of a face angle with strong turbulence. To acquire mated scores for all users, a pristine image of a user in a frontal stance is compared to turbulent images of the same person’s frontal as well as posed face in the gallery to assess how turbulence affects facial recognition. The postures are shown on the horizontal axis, while the match score values are on the vertical axis in figure 5.4.

![Bar & whisker plot for the indoor strong turbulent images for distances- 300m (a,b) and 500m (c)](image)

**Figure 5.4:** Bar & whisker plot for the indoor strong turbulent images for distances- 300m (a,b) and 500m (c)

The plots in 5.4 show the bar and whisker plots created with ArcFace and
COTS-A for simulated pictures with strong turbulence at two different distances: 300m and 500m. While the charts in 5.1, 5.2, and 5.3 show the lowest score for PL90C00 and PR90C00, the scores for strong turbulence reveal a different picture. We were unable to construct a bar and whisker plot for COTS-A over a distance of 500m due to the maximum failure to recognize faces, resulting in insufficient data received from COTS-A.

The best score we obtained with ArcFace for 300m is 0.61 with the frontal stance, which is the same as the probe, but with turbulence. The frontal stance has the greatest median score of 0.36, followed by poses PL45C00 and PR45C00, which have the lowest median score of 0.31. Pose PC00C00, PL45C00, PL45D30, PR45C00, and PR45D30 all had a comparable median score of 0.61 with COTS-A. The ArcFace result for 500m reveals that the values are closer to the least match score, i.e., 0, with all scores falling between -0.1 and 0.2. At 300m, we failed to find faces in 414 photographs, including 96 PR90C00 and 92 PL90C00 images, while at 500m, we only saw results for 14 images.
We now give the findings for the mated score distribution of the frontal posture versus photos, including all of the stances combined.

Figure 5.5: Bar & whisker plot for the indoor pristine images

The plots above demonstrate the mated scores for the pristine photographs when comparing the pristine frontal position, PC00C00, to all of the images in the gallery with facial angles. The box plot for COTS-A is rather short, indicating that the total scores are very close. The highest scores obtained from ArcFace range from 0.52 to 0.94, whereas most COTS-A scores range from 0.85 to 0.98. The lowest COTS-A score (an outlier) is 0.46, while the lowest ArcFace score is
0.35, which is comparatively closer than most of the scores.

The charts above compare the results for the $\sigma_R^2 = 0.08802283$ (weak simulated pictures) over two distances of 300m and 500m. PC00C00, the clean frontal position, is contrasted with a gallery of photos with little turbulence. As we increased the distance using ArcFace, the maximum score decreased from 0.99 to 0.97. While COTS-A failed to recognize faces in three additional photographs at 500m instead of 300m, we didn’t observe a change in scores since the top score remained constant. With increasing distance, there is no major noticeable change as the values alter slightly.

Figure 5.6: Bar & whisker plot for the indoor weak turbulent images for distances- 300m (a,b) and 500m (c,d)
Figure 5.7: Bar & whisker plot for the indoor moderate turbulent images for distances- 300m (a,b) and 500m (c,d)

The graphs above depict the results of two face recognition models when the pristine frontal position, PC00C00, is compared to a gallery of photos with $\sigma^2_R = 0.8802283$ (moderate turbulence) at two distances, 300m, and 500m. The turbulence shows a significant influence on the scores, followed by a precipitous reduction as the distance increases. The COTS-A scores are still closer to one, but the ArcFace values are contrary. While the ArcFace’s performance deteriorates, COTS-A reports 252 failed to identify face errors for a distance of 500m.
Figure 5.8: Bar & whisker plot for the indoor strong turbulent images for distances- 300m (a,b) and 500m (c,d)

The plots above show the scores for the $\sigma^2_R = 8.802283$ (strong simulated images) while comparing two distances, 300m, and 500m. The pristine frontal position, PC00C00, is compared with a gallery containing images with strong turbulence. With a distance of 500m, COTS-A detected faces for only 14 images, because of which we could not generate the plot for the same. With ArcFace, the minimum score obtained with a distance of 300 is 0, while with 500m, it is close to -0.1.
To show a comparison between the mated scores of the pristine image with that of the turbulent images, we present tables with the maximum and minimum scores for each category.

Table 5.1: Comparison of pristine and simulated images for controlled data at 300m

<table>
<thead>
<tr>
<th>Category</th>
<th>Minimum</th>
<th>Maximum</th>
<th>FTE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PRISTINE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.52</td>
<td>0.94</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.85</td>
<td>0.98</td>
<td>10</td>
</tr>
<tr>
<td><strong>WEAK</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.53</td>
<td>0.99</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.86</td>
<td>0.99</td>
<td>9</td>
</tr>
<tr>
<td><strong>MODERATE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.43</td>
<td>0.96</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.81</td>
<td>0.98</td>
<td>21</td>
</tr>
<tr>
<td><strong>STRONG</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.002</td>
<td>0.53</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.39</td>
<td>0.79</td>
<td>414</td>
</tr>
</tbody>
</table>

Note: The max. and min. scores are based on the box plot, ignoring the outliers.

The table 5.1 comprises the values acquired from ArcFace and COTS-A for the distance 300m using both pristine and simulated data. The values are derived from the total scores, regardless of the postures. It also shows the number of Failures to Enroll instances for COTS-A and N/A, which stands for Not Applicable for ArcFace.
The table 5.2 comprises the values acquired from ArcFace and COTS-A for the distance 500m using both pristine and simulated data. The values are derived from the total scores, regardless of the postures. It also shows the number of Failures to Enroll instances for COTS-A and N/A, which stands for Not Applicable for ArcFace. For the strong turbulence, the scores are highly impacted as they show negative scores.
5.2 Analysis for Images in Uncontrolled Environment

We begin our analysis with pristine images for the images photographed outdoors. For the pristine images, we compare the frontal pose, PC00C00, with all the other face poses one by one. Therefore, to obtain the mated scores for all the users, the frontal image of a user is compared with ten posed images of the same person present in the gallery to see how profile images affect face recognition. Along the horizontal axis, the poses are presented, and along the vertical axis, the match score values are mentioned.

The plots generated using ArcFace and COTS-A are shown in figure 5.9. These figures show that the scores obtained from COTS-A are more biased towards high scores for some poses, while for others, they are widely spread. Also, for pose PL135C00, the distribution is positively skewed because the whisker and half-box are longer on the bottom side of the median than on the top side. Also, the images from the uncontrolled environment contain poses that focus more on the left profile.

The lowest score obtained from COTS-A is for the pose PL135C00, but results from ArcFace show that PL90U30 performed the worst out of all. We do see some outliers present for the pose PL135C00 from ArcFace, with similarity scores really low, while the rest are in the range of 0.62 to 0.93. Also, while ArcFace fails to describe the failure to detect faces, COTS-A provides a list of images where it failed to detect faces, with a total of 140 images failing to detect faces.
Similarly, we present findings for simulated pictures with $\sigma^2_R = 0.08802283$ (low turbulence) in Figure 5.10. We compare the pristine frontal posture, PC00C00, with all the photographs of angles of the face exhibiting weak turbulence one by one. To achieve mated scores for all users, the pristine image with a frontal pose of a user is compared to turbulent photographs of the same person’s frontal as well as posed face existing in the gallery to evaluate how turbulence impacts facial recognition. The match score values are provided along the vertical axis, while the postures are indicated along the horizontal axis. These match scores obtained using ArcFace and COTS-A are then presented using four bar and whisker plots at two different distances: 300m and 500m.
Figure 5.10: Bar & whisker plot for the outdoor weak turbulent images with poses for distances- 300m (a,b) and 500m (c,d)

The graphs simply illustrate that the scores for COTS-A are more toward high scores, i.e., generally ranging between 0.35 to 1. In contrast, the scores derived using ArcFace are dispersed over a more extensive range (i.e., -0.1 to 1.)

For the photos with weak turbulence, the distance has little effect on the scores; The scores are downgraded by 0.2 for ArcFace, while for COTS-A, the highest scores somewhat remain the same, but the range of score increases. For pose PL135C00, the scores are spread all over from 0 to 1 for the distance 300m, while the scores for 500m decreases and move towards negative scoring, meaning that the face cannot be recognized. Moreover, COTS-A produced 143 failures to detect faces at 300m and 211 face errors at 500m.
Furthermore, we report results for simulated images with $\sigma_R^2 = 0.8802283$ (moderate turbulence). We compare the clean frontal posture, PC00C00, with each snapshot of a face angle with mild turbulence one by one. To acquire mated scores for all users, a user’s perfect image with a frontal posture is compared to turbulent photos of the same person’s frontal and posed face in the gallery to assess how turbulence affects facial recognition. The match score values are presented along the vertical axis, while the postures are displayed along the horizontal axis.

Figure 5.11: Bar & whisker plot for the outdoor moderate turbulent images with poses for distances- 300m (a,b) and 500m (c,d)

Four bar and whisker plots were constructed using ArcFace and COTS-A for simulated images with moderate turbulence at two different distances: 300m and 500m. The plots are shown in figure 5.11. It demonstrates that the standard deviation (variation), regardless of the poses, rises as we compare the scores at 300
with that of 500m for the same level of turbulence. The pose PL135C00 continues to have the lowest scores, as we have seen for pristine and weak images.

We notice 343 images giving an error for failing to identify for a distance of 300m, while for a distance of 500m, it gives 843 errors. It means that the plot only shows scores for about 150 images; therefore, it doesn’t help us prove that the plot shown is correct. Although the scores are limited, they still show really low scores, which clearly shows that it is difficult for images with moderate turbulence to find faces with images taken from a distance of 500m.

Moreover, with the images containing $\sigma_R^2 = 8.802283$ (strong turbulence), we compared the pristine frontal posture, PC00C00, to each snapshot of a face angle with strong turbulence. Unfortunately, we failed to identify any face in any images for 300m and 500m.
We present results for the mated score distribution of the frontal pose against images with all the poses together.

![Mated Score Distribution: Outdoor Pristine Images](image1)

(a) ArcFace

![Mated Score Distribution: Outdoor Pristine Images](image2)

(b) COTS-A

Figure 5.12: Bar & whisker plot for the outdoor pristine images

The plots above demonstrate the mated scores for the pristine photographs when comparing the pristine frontal position, PC00C00, to all of the images in the gallery with facial angles in an uncontrolled environment. The box plot for COTS-A is rather short, indicating that the total scores are very close. The highest scores obtained from ArcFace range from 0.29 to 0.94, whereas most COTS-A scores range from 0.70 to 0.98. The lowest COTS-A score (an outlier) is 0.45, while
the lowest ArcFace score is 0.01, which means that ArcFace failed to detect face while comparing an image for the same person.

![Mated Score Distribution: Outdoor Weak Simulated Images](a) ArcFace

![Mated Score Distribution: Outdoor Weak Simulated Images](b) COTS-A

![Mated Score Distribution: Outdoor Weak Simulated Images](c) ArcFace

![Mated Score Distribution: Outdoor Weak Simulated Images](d) COTS-A

Figure 5.13: Bar & whisker plot for the outdoor weak turbulent images for distances- 300m (a,b) and 500m (c,d)

The charts above compare the results for the $\sigma^2_R = 0.08802283$ (weak simulated pictures) over 300m and 500m. PC00C00, the clean frontal position, is contrasted with a gallery of photos with little turbulence. As we increased the distance using ArcFace, the maximum score observed decreased by 0.1 from 300m to 500m, while, for COTS-A, the number of failures to recognize faces increased. Although the maximum score for COTS-A remains the same when we increase the distance,
an obvious difference can be noticed in the other scores.

Figure 5.14: Bar & whisker plot for the outdoor moderate turbulent images for distances- 300m (a,b) and 500m (c,d)

The figure above depicts the results of two face recognition models when the pristine frontal position, PC00C00, is compared to a gallery of photos with $\sigma_R^2 = 0.8802283$ (moderate turbulence) at two distances, 300m, and 500m. The turbulence shows a significant influence on the scores, followed by a sharp reduction as the distance increases. The COTS-A scores are still closer to one, but the ArcFace values are contrary. ArcFace performance deteriorates as the scores obtained are closer to zero than one, which means ArcFace could not find similarity in the faces.
even though it was the same user. The COTS-A reports 843 failed to identify face errors for a distance of 500m, which says that most faces were unrecognized. In other words, The box plot obtained from COTS-A does not even consider about one-fourth of the scores.

ArcFace couldn’t provide evaluations for any of the images with $\sigma^2_R = 8.802283$ (high turbulence). On the other hand, COTS-A obtained four similarity scores for a distance of 300m but none for a distance of 500m. Therefore, with no data from ArcFace and insufficient data from COTS-A, we were unable to provide results.
We give tables with the maximum and minimum scores for each category to illustrate a comparison between the mated scores of the pristine image as opposed to the turbulent images.

Table 5.3: Comparison of pristine and simulated images for uncontrolled data at 300m

<table>
<thead>
<tr>
<th>Category</th>
<th>Minimum</th>
<th>Maximum</th>
<th>FTE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRISTINE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.29</td>
<td>0.94</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.70</td>
<td>0.98</td>
<td>140</td>
</tr>
<tr>
<td>WEAK</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.25</td>
<td>0.97</td>
<td>N/A</td>
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<tr>
<td>COTS-A</td>
<td>0.66</td>
<td>0.99</td>
<td>143</td>
</tr>
<tr>
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<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>0.018</td>
<td>0.74</td>
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</tr>
<tr>
<td>COTS-A</td>
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<td>0.91</td>
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<tr>
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<tr>
<td>ArcFace</td>
<td>N/A</td>
<td>N/A</td>
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</tr>
<tr>
<td>COTS-A</td>
<td>N/A</td>
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Note: The max. and min. scores are based on the box plot, ignoring the outliers.

Table 5.3 comprises the values acquired from ArcFace and COTS-A for the distance of 300m using both pristine and simulated data. The values are derived from the total scores, regardless of the postures. It also shows the number of Failures to Enroll instances for COTS-A and N/A, which stands for Not Applicable. ArcFace failed to provide any scores with strong turbulence, while COTS-A provided only five scores. Thus it was not appropriate to count the least score out of the five values as the minimum score, as most faces were undetected. N/A in the category minimum and maximum expresses that no scores were present.
Table 5.4: Comparison of pristine and simulated images for uncontrolled data at 500m

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>FTE</th>
</tr>
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<tbody>
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<td></td>
<td></td>
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</tr>
<tr>
<td>ArcFace</td>
<td>0.29</td>
<td>0.94</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.70</td>
<td>0.98</td>
<td>140</td>
</tr>
<tr>
<td><strong>WEAK</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
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<td>0.8</td>
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<td>0.97</td>
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</tr>
<tr>
<td><strong>MODERATE</strong></td>
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<td></td>
</tr>
<tr>
<td>ArcFace</td>
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<td>0.27</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>0.34</td>
<td>0.69</td>
<td>843</td>
</tr>
<tr>
<td><strong>STRONG</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>ArcFace</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>COTS-A</td>
<td>N/A</td>
<td>N/A</td>
<td>1008</td>
</tr>
</tbody>
</table>

Note: The max. and min. scores are based on the box plot, ignoring the outliers.

The table 5.4 comprises the values acquired from ArcFace and COTS-A for the distance 500m using both pristine and simulated data. The values are derived from the total scores, regardless of the postures. It also shows the number of Failures to Enroll instances for COTS-A and N/A, which stands for Not Applicable for ArcFace. For the strong turbulence, the scores are highly impacted as they show negative scores. For the distance of 500m, both ArcFace and COTS-A failed to provide any score. N/A in the category minimum and maximum expresses that no scores were present.
5.3 Comparison of Controlled and Uncontrolled Environment

The plots below sum up the similarity scores for the mated comparison for each of the four groups: pristine (original) images and simulated images- weak, moderate, and strong turbulent images for both controlled and uncontrolled environments at a distance 300m and 500m.

The figures (5.15, 5.16, 5.17, and 5.18) below show that COTS-A depicts better scores in all cases. For the pristine set (figure 5.15), the maximum scores lie between 0.87 and 1 for indoors and 0.7 and 1 for outdoors. While these scores are almost the same for images with $\sigma_R^2 = 0.08802283$ (figure 5.16) with a distance of 300m, it shifted slightly for a distance of 500m for images in the controlled environment. For images in an uncontrolled environment, the distance impacted the scores. With an increase in distance, the scores decreased from 0.7-1 to 0.49-0.97, with the same turbulence. We see only 1% more Failure to Enroll cases with indoor images and about 10% more with outdoor images when weak turbulence is added. Also, for controlled data, the number of failure to enroll decreases by one as we move from pristine to weak turbulent images as COTS-A added three new errors in the weak set while finding faces in the four images that produce errors for the pristine set.
The scores for photos with moderate turbulence (figure 5.17) begin to decline, and the number of failed face detections rises. While the number of failures to recognize faces increased from 21 to 253 for controlled data as the distance increased from 300m to 500m, it increased from 343 to 843 for outdoor images. Thus, we conclude that photographs with $\sigma_R^2 = 0.8802283$ (figure 5.17) photographed in a controlled environment at 300m do not require atmospheric correction, but correction is needed as the distance increases.
With images having $\sigma_R^2 = 8.802283$ (figure 5.18), are hard to recognize, containing the maximum failure to detect cases, we observed that for indoor images for a distance of 300m, we obtained about 414 errors, but for 500m, we could only detect 14 faces. Moreover, outdoor images could only show five detections at 300m while none at 500m. This clearly states that atmospheric correction must be applied before detecting faces.
Chapter 6

Conclusion and Future Work

The goal of this study is to: (1) determine whether images are detected for the different Rytov values with atmospheric turbulence, (2) the impact of distance on the Rytov value with turbulence, and (3) at what Rytov value the biometrics degrades.

To provide an experiment-based result for biometric performance, we used a curated version of the LRFID dataset containing a collection of images in controlled and uncontrolled environments. Our study used one commercial facial matcher, COTS-A, and one open-source algorithm, ArcFace. The Rytov value is calculated using the obtained $C_n^2$ values from the metadata of the dataset. To obtain different turbulence levels, we created a simulated environment and used the three extreme $C_n^2$ values obtained from various times of the day and categorized the turbulence as weak, moderate, and strong. For each $C_n^2$ value, a corresponding Rytov value is calculated. The Rytov value is also dependent on the distance. So, to conduct this study, we chose two distances of 300m and 500m, and it also gave us an insight into how distance affects the Rytov value with turbulence.
Now, based on the Rytov variance, we see how an image captured using long-range cameras containing atmospheric turbulence affects face recognition as the level of turbulence increases. The results show us that COTS-A gives better similarity scores at all times. For the images with $\sigma^2_R = 0.08802283$ at 300m, while that with a distance of 500m, the change is non-noticeable for pictures in the controlled environment. The distance impacted the scores for images in an uncontrolled environment. The scores decreased by 34% for the same turbulence level.

Similarly, for $\sigma^2_R = 0.8802283$ at 300m having moderate turbulence, the similarity scores for the controlled environment decreased by 37%, which is about the same as we got for images with weak turbulence taken in an uncontrolled environment. With photos containing moderate turbulence, taken in an uncontrolled environment, we notice an increase of 145% in failure to enroll images while seeing a 20% decrease in the highest score. Moreover, with $\sigma^2_R = 8.802283$, we can hardly recognize a face if no atmospheric correction is applied.

As we in this study used a simulated environment to introduce atmospheric turbulence, future work can involve using images or videos taken from long-range cameras or drones in an uncontrolled environment and comparing both analyses to see how Rytov values affect those images with turbulence. Also, we can see how atmospheric correction methods can be added for each turbulence level to improve detection and recognition. Moreover, future work can involve adding obscured images to see how, if at all, coverings change the match score as the turbulence is increased.

Finally, with this study, we conclude that if we apply atmospheric correction in images with a higher level of turbulence, i.e., with $\sigma^2_R = 0.8802283$ or up, it can
help detect a person’s face. This is because the face recognition software failed to detect and recognize faces in the images with \( \sigma^2_{\mathcal{R}} = 0.8802283 \). Also, detecting the face depends on the environment in which the picture is taken and the distance of the person from the camera. To our knowledge, no previous studies use Rytov variance to measure atmospheric turbulence in images with faces to see how turbulence affects face recognition software.
Bibliography


[11] Person Re-identification Technology That Matches People Even If They Are Facing Away or Their Bodies Are Hidden.


