Fourier Spectrum Discrepancies in Deep Network Generated Images

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Abstract

Advancements in deep generative models such as generative adversarial networks and variational autoencoders have resulted in the ability to generate realistic images that are visually indistinguishable from real images. In this paper, we present an analysis of the high-frequency Fourier modes of real and deep network generated images and the effects of resolution and image compression on these modes. Using this, we propose a detection method based on the frequency spectrum of the images which is able to achieve an accuracy of up to 99.2% in classifying real, Style-GAN generated, and VQ-VAE2 generated images on a dataset of 2000 images with less than 10% training data. Furthermore, we suggest a method for modifying the high-frequency attributes of deep network generated images to mimic real images.

1 Introduction

In recent years, advances in deep generative models for image synthesis have caused widespread concern regarding their potential malicious uses. Current state-of-the-art models can generate hyper-realistic images that are visually indistinguishable from real images, as shown in Fig. 1. These models can be used for illegal purposes, such as falsifying news, fabricating evidence, or attacking biometric security systems, and as a result, recent research efforts have been focused on developing methods for detecting such images [1][2]. Various detection strategies have been employed, from traditional image forensics methods such as analyzing encoding or acquisition fingerprints to, more recently, machine learning based approaches such as statistical modeling for disparities in color components, textures, or features [3][4][5][6][7]. Boulkenafet et al. developed a method for face spoofing detection by analyzing the statistical distributions of the image spectra in other color spaces such as HSV and YCbCr [4]. Li et al. expanded upon this method to detect images generated by generative adversarial networks [5]. Marra et al. showed that generative adversarial networks leave unique artificial fingerprints in the noise of their generated images that are dependent on the network architecture which can be used to detect if an image was generated by a particular network [6]. Although these methods have shown promise in terms of accuracy with minimal user input, they require large amounts of data to train, something which may not be feasible in many applications. As such, there is a need for detection methodologies that can obtain similar levels of accuracy with minimal training data.

In this work, we propose a simple detection method for deep network generated images based on their high-frequency characteristics. We compare real images to images generated by two deep generative models: Style-GAN [8], a generative adversarial network, and VQ-VAE2 [9], a variational autoencoder [10][11]. Based on a reduced-order model of the high-frequency spectrum of the images, we show that the relative magnitude and the decay rate of the high-frequency spectrum is clearly distinguishable between the three types of images. Furthermore, we show that at higher resolutions,
these differences are more easily observed, and we consider the impact of compression methods which can significantly affect the high-frequency spectra, causing difficulties in detecting deep network generated images. We also show the results of binary classification experiments of images at different resolutions and compression levels from datasets such as Flickr-Faces-HQ (FFHQ), ThisPersonDoesNotExist.com, and the works of Razavi et al. and Zhang et al. [8, 9, 12]. Finally, we present a method for modifying the spectra of deep network generated images to mimic the high-frequency characteristics of real images as a way of deceiving such classifiers.

2 Methodology

2.1 Fourier spectrum analysis

To analyze the characteristics of real and deep network generated images in the frequency domain, a Fourier transform is required. For a discrete two-dimensional signal \( f(p, q) \) representing individual color channels of an image of size \( m \times n \), the discrete Fourier transform \( F(k_x, k_y) \) is defined as

\[
F(k_x, k_y) = \frac{1}{mn} \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} f(p, q) e^{-i2\pi(k_x p/m + k_y q/n)},
\]

(1)

which is of the same dimension as the input signal. To construct a scale and rotation invariant threshold for the highest frequencies, a transform in wavenumber space can be performed from Cartesian coordinates \( k_x, k_y \) to normalized polar coordinates \( k_r \in [0, 1] \) and \( \theta \in [0, 2\pi) \).

\[
F(k_r, \theta) = F(k_x, k_y) : k_r = \sqrt{\frac{k_x^2 + k_y^2}{4(m^2 + n^2)}}, \theta = \text{atan2}(k_y, k_x).
\]

(2)

Furthermore, the dimensionality can be reduced without significant loss in information by azimuthally averaging the magnitude of the Fourier coefficients to obtain the reduced spectrum \( c(k_r) \), a quantitative representation of the strength of the signal with respect to the radial wavenumber \( k_r \).

\[
c(k_r) = \frac{1}{2\pi} \int_0^{2\pi} |F(k_r, \theta)| \ d\theta.
\]

(3)

In practice, this averaging is approximated with binning along the radial direction to smooth the large fluctuations in the Fourier spectrum at high frequencies. Although a classifier can be trained on the reduced spectrum, a simpler and more robust classifier can be built by fitting a decay function to the reduced spectrum and classifying using the parameters of this function. In this work, performing classification on an exponential decay function is considered, modeled as

\[
c(k_r) \approx b_1 e^{b_2 k_r/k_T}, \quad k_r \in [k_T, 1],
\]

(4)

where the parameter \( k_T \) denotes a threshold wavenumber above which the fitting is performed. With this approximate form, the high-frequency spectrum is represented by two independent parameters: \( b_1 \), which represents the magnitude of the high-frequency content, and \( b_2 \), which represents the decay rate of the high-frequency spectrum. These parameters, along with the reduced spectra, are used to highlight differences in the high-frequency characteristics of real and deep network generated images.
2.2 Image compression and resolution

In order to minimize storage and bandwidth requirements, deep network generated images are typically resized and/or compressed, procedures which can change the characteristics of the image spectra. The image resolution dictates the maximum frequency in the frequency domain, and higher resolutions yield more information at the highest frequencies. Compression may particularly affect the high-frequency spectrum of an image since the high-frequency components of an image correspond to the small scale features whereas the low-frequency components correspond to the large features. Therefore, compression algorithms generally tolerate losses in the high-frequency components as they have less impact on the way an image is seen compared to the low-frequency components [13]. Common compression methods such as quantization and subsampling can spuriously introduce or reduce high-frequency content, respectively [14].

Images with varying resolutions and compression levels were analyzed in this work. Datasets of different resolutions were used in the experiments, and compression levels were varied using lossy JPEG compression with Python Imaging Library (Pillow). A quality metric is given to indicate the amount of compression with 100% indicating minimal compression, although not lossless. Two additional compression levels were chosen corresponding to high quality (95%) and medium quality (85%) compression. The latter was chosen qualitatively based on the visually noticeable presence of compression artifacts while the former was chosen as it is a default setting in many applications.

2.3 Classification

A binary classification task was performed between various real and deep network generated images. Image samples were taken from real, Style-GAN generated, and VQ-VAE2 generated image datasets, and a support vector machine with a cubic polynomial kernel was used for classification between real and deep network generated images with respect to the decay parameters \((b_1, b_2)\) of the grayscale component of the images. Negligible differences in training classification accuracy were obtained with higher-order polynomial kernels as the data was easily separable in many cases. Since the classification was performed with respect to only two parameters, minimal training data was required, in some cases as few as 8 images, and the computational cost of training and classifying was insignificant. Classification accuracy was determined by the ability of the classifier to predict if an image was real or fake, and no weight was placed on discerning between Style-GAN and VQ-VAE2 generated images. However, overall classification accuracy was calculated as the mean classification accuracy between the three image types. The pipeline for the classification task was as follows:

1. Perform the discrete Fourier transform of the image.
2. Transform from Cartesian coordinates to normalized polar coordinates in the frequency domain.
3. Bin the magnitudes of the Fourier coefficients along the radial direction and average azimuthally to obtain the reduced spectrum.
4. Fit the decay parameters \(b_1, b_2\) to the reduced spectrum above some threshold wavenumber \(k_T\).
5. Train/apply the binary classifier to the decay parameters of the image to predict if the image is real or fake.

3 Experiments and results

In this section, the reduced spectrum for the sample images in Fig. 1 is shown as well as the effects of resolution and compression on the spectra. Additionally, experimental settings and results for a classification task between real, Style-GAN, and VQ-VAE2 images at different resolutions and compression qualities are presented.

3.1 Reduced spectrum

A comparison of the reduced spectrum of the grayscale-converted 1024\(^2\) pixel images in Fig. 1 is shown in Fig. 2 using a threshold wavenumber \(k_T = 0.75\). At the threshold wavenumber, the real image shows a decay initially proportional to approximately \(k^{-4}\) before leveling off near the end of
the spectrum. In contrast, the Style-GAN and VQ-VAE2 generated images do not show such decay, exhibiting decay exponents of less than 1. When the spectra were normalized by the DC gain, the Style-GAN generated image exhibited slightly more high-frequency content than the real image, whereas the VQ-VAE2 generated image showed significantly less. Similar results were observed with the spectra of the individual color channels as with the grayscale-converted images.

The disparities in the decay of high-frequency content in the real and deep network generated images can be attributed to the fact that deep generative networks are not incentivised to learn the high-frequency components (i.e. noise) of their input data to discourage overfitting. As a result, the high-frequency components of the generated images behave as random (white) noise which has constant power density similar to Fig. 2. However, the reason for the notable decrease of high-frequency content in VQ-VAE2 images compared to real images is not as evident. It is hypothesized that VAEs tend to distribute probability mass diffusely over the data space, and thus their generated images tend to be blurry [15, 16, 17]. Although this is not visually noticeable, it is noticeable in the frequency domain as the high-frequency content associated with sharp edges is dramatically reduced.

3.1.1 Resolution

The reduced spectrum was computed for $256^2$ pixel images sampled from TheseCatsDoNotExist.com and the works of Zhang et al. and Razavi et al. [12, 9]. These spectra were compared to the $1024^2$ pixel image spectra from Fig. 2. In comparison to the high-resolution images, the high-frequency spectra at lower resolutions behaved similarly, although they had significantly more fluctuations, as shown in Fig. 3. The disparities in the decay rates between real and deep network generated images were not as evident at lower resolutions, and the spectra were not as distinct. As the resolution was lowered, it became more difficult to distinguish between the real and deep network generated image spectra as the maximum frequency was reduced.

Figure 2: Reduced spectrum normalized by cutoff frequency magnitude (left) and DC gain (right).

Figure 3: Reduced spectrum for $1024^2$ pixel (left) and $256^2$ pixel (right) images.
3.1.2 Compression

The effects of image compression on the reduced spectrum of the $1024^2$ pixel images in Fig. 1 is shown in Fig. 4 for compression qualities of 100%, 95%, and 85%. For the 100% quality images, the original provided images were used, consisting of either lossless PNG or 100% quality JPEG images. Although the latter is not considered lossless, negligible differences in the reduced spectra between the two image formats were seen, and therefore both of these are referred to as uncompressed in this work.

Even at a small compression ratio (95%), the high-frequency reduced spectrum of the Style-GAN image was significantly modified, and its decay rate converged to the decay rate of the real image. At 85% compression, the Style-GAN and real image spectra were indistinguishable, with only slightly lower decay rates than the uncompressed real image. In contrast, the reduced spectrum of the VQ-VAE2 image was largely unaffected by the compression resulting in a clearly distinguishable spectrum even for compression qualities as low as 60%. This can be attributed to the low amount of high-frequency content in VQ-VAE2 images mentioned previously, which cannot be reduced significantly more with compression. Therefore, the spectrum is not greatly affected. This is contrast to Style-GAN images, where the relatively large amount of high-frequency content can be reduced using lossy compression methods whose effects are proportional to the frequency and effectively modify the decay rate.

![Figure 4: Reduced spectrum for compression qualities of 100% (left), 95% (middle), and 85% (right).](image)

These observations indicate that compression, even in small amounts, acts to homogenize the spectral content of Style-GAN images. In a model-unaware scenario where the classifier does not know if the images are compressed, it would not be able to distinguish between uncompressed real images, compressed real images, and compressed Style-GAN images, but would be able to easily distinguish uncompressed Style-GAN images. However, VQ-VAE2 images would remain easily distinguishable regardless of compression as their spectra’s decay rates are unaffected, and a different method for mimicking the spectrum of real images is needed.

3.2 Classification

3.2.1 Datasets

In the classification experiments, a cubic SVM classifier was trained and tested on various datasets of real, Style-GAN generated, and VQ-VAE2 generated images at compression qualities of 100%, 95%, and 85%, shown in Table 1. For the high-resolution ($1024^2$) experiments, images of faces were used. 1000 images from Flickr-Faces-HQ (FFHQ) and ThisPersonDoesNotExist.com were used for the real ($R_{1024}$) and Style-GAN generated ($G_{1024}$) datasets, respectively, and 10% of the images were used for training while the remaining 90% were used for testing since the classifier did not require large amounts of training data [8]. For the VQ-VAE2 dataset ($V_{1024}$), only a small number of high-resolution images were presented in the work by Razavi et al., and therefore only 8 images were available for training and 9 for testing [9]. These images were duplicated to match the size of the other high-resolution datasets to give equal weight to the training and testing metrics.

For the low-resolution ($256^2$) experiments, images of cats and other animals were used for classification. As with the high-resolution datasets, 1000 images split into 10% training and 90% testing data were used for the real ($R_{256}$) image dataset, provided by Zhang et al., and the Style-GAN generated ($G_{256}$) dataset, taken from TheseCatsDoNotExist.com [12]. For the VQ-VAE2 dataset ($V_{256}$), a larger amount of low-resolution images were provided in the work by Razavi et al. 100 of the 364 images
provided were used for training while the remaining were used for testing, and the same duplication method was used as with the high-resolution images.

### Table 1: Experimental datasets

| Dataset | Origin          | Dataset Type | Resolution | Compression Quality | Training Samples | Testing Samples |
|---------|-----------------|--------------|------------|---------------------|------------------|-----------------|
| R_{1024} | FFHQ Faces      | 1024         | [100, 95, 85] | 100                 | 900              |                 |
| G_{1024} | ThisPersonDoesNotExist Faces | 1024         | [100, 95, 85] | 100                 | 900              |                 |
| V_{1024} | Razavi et al. [9] Faces | 1024         | [100, 95, 85] | 8                   | 9                |                 |
| R_{256}  | Zhang et al. [12] Cats | 256          | [100, 95, 85] | 100                 | 900              |                 |
| G_{256}  | TheseCatsDoNotExist Cats | 256          | [100, 95, 85] | 100                 | 900              |                 |
| V_{256}  | Razavi et al. [9] Animals | 256          | [100, 95, 85] | 100                 | 264              |                 |

#### 3.2.2 Results

The results of the cubic SVM classifier for image resolutions of $1024^2$ and $256^2$ with compression qualities of 100% (uncompressed), 95%, and 85% are shown in Table 2. For the uncompressed $1024^2$ images, the classifier was able to obtain a 99.2% accuracy with the support vector boundary shown in Fig. 5a. The distribution of the data along the $b_1 - b_2$ axes shows three distinct regions corresponding to the three image types. Real images exhibited large high-frequency content ($b_1$) as well as high decay rates ($-b_2$). Both Style-GAN and VQ-VAE2 generated images had significantly smaller decay rates than the real images, but the high-frequency content was only noticeably lower with the VQ-VAE2 images. However, as the images were compressed, the distribution of the decay rates of the real and Style-GAN generated images converged and the regions were indistinguishable at 85% compression quality, shown in Fig. 5c, where the classification accuracy was reduced to 79.8%. The effects of compression on the VQ-VAE2 images were minimal due to their small high-frequency content, and as such, the VQ-VAE2 images were correctly classified regardless of compression quality. Nevertheless, omitting the VQ-VAE2 images from the $1024^2$ experiments would result in even higher classification accuracies with lower-order SVMs as the Style-GAN and real image distributions were more easily separable than the VQ-VAE2 and real image distributions, as shown in Fig. 5a and 5b.

### Table 2: Classification experiments and results

| Experiment | Resolution | Compression Quality | Average Class. Acc. | Real Class. Acc. | Style-GAN Class. Acc. | VQ-VAE2 Class. Acc. |
|------------|------------|---------------------|---------------------|------------------|-----------------------|---------------------|
| A          | $1024^2$   | 100                 | 99.2%               | 97.9%            | 99.6%                 | 100%                |
| B          | $1024^2$   | 95                  | 95.4%               | 95.3%            | 90.8%                 | 100%                |
| C          | $1024^2$   | 85                  | 79.8%               | 84.8%            | 54.7%                 | 100%                |
| D          | $256^2$    | 100                 | 89.7%               | 79.7%            | 89.5%                 | 100%                |
| E          | $256^2$    | 95                  | 89.9%               | 74.5%            | 89.1%                 | 100%                |
| F          | $256^2$    | 85                  | 86.6%               | 69.6%            | 93.1%                 | 97.3%               |

![Figure 5: Experiments A-C at $1024^2$ resolution. Training points: ○ Testing points: ·](image)
When the classifier was tested on the $256^2$ images (experiments D-F), the classification accuracy was significantly lower. Even for the uncompressed images, the data was not as clearly separable as with the $1024^2$ images, and the classifier was only able to obtain an 89.7% classification accuracy. However, the overall distribution trend along the $b_1 - b_2$ axes of the three image types was similar at both resolutions as shown in Fig. 5a and Fig. 6a. Compression did not have as large of an effect on the $256^2$ images, and thus the classifier performed only slightly worse at 85% compression quality than on the uncompressed images. In contrast to the $1024^2$ experiments, the images that were primarily affected by the compression were the real images, not the Style-GAN images, and the effects of compression were primarily to decrease the high-frequency content than to decrease the decay rates, although these effects were minimal.

Figure 6: Experiments D-F at $256^2$ resolution. Training points: ○ Testing points: ·

4 Spectrum Synthesis

To disguise deep network generated images to classifiers based on high-frequency spectrum characteristics, a method for modifying the spectra of the deep network generated images to behave as real image spectra is proposed. Given the spectrum of a real image as a target, the high-frequency components of a deep network generated image were scaled to match the real image to produce a spoofed spectrum $\hat{F}(k_r, \theta)$, which was then transformed back to a spoofed image.

$$\hat{F}(k_r, \theta) = F(k_r, \theta) \Gamma(k_r)$$

(5)

The scaling factor $\Gamma(k_r)$ was defined as the ratio of the fitted decay functions of the target (real) and source (deep network generated) images.

$$\Gamma(k_r) = \begin{cases} 1, & k_r < k_T, \\ \frac{b_1}{b_1} k_r \exp \left( \frac{b_2, t - b_2, s}{k_T} k_r \right), & k_r \geq k_T. \end{cases}$$

A sharp cutoff below the threshold wavenumber $k_T$ was used to leave the low-frequency components of the image unaffected, but a smooth blending function for the scaling factor would, in theory, give better results.

The effects of the spectrum synthesis method on the reduced spectra of the example Style-GAN and VQ-VAE2 images are shown in Fig. 7 and 8, respectively. Using the real image in Fig. 1 as the target, the spoofed spectra matched the real image spectrum very closely in both decay and magnitude. The spoofed images were also visually indistinguishable from the original images. For the Style-GAN generated image, where compression can act as an effective spoofing method, the spoofed image was of noticeably higher quality than the compressed image as the spectrum synthesis method did not introduce compression artifacts. For the VQ-VAE2 generated image, spectrum synthesis effectively disguised the image to the classifier whereas compression could not. The effects of spoofing on the classification of the images is shown in Fig. 9. The spoofed images fell well within the classification boundary for real images.

5 Conclusion

In this work, we presented an analysis of the high-frequency content of real images and images generated by generative adversarial networks and variational autoencoders. We showed that for
deep network generated images, the Fourier coefficients at the highest frequencies did not decay as seen in real images, but instead stayed approximately constant. By modeling the decay of the Fourier spectrum at high frequencies, we observed that the high-frequency spectra of the three image types had distinct characteristics: real images showed high magnitudes and large decay rates, GAN generated images showed high magnitudes and small decay rates, and VAE generated images showed low magnitudes and small decay rates. These differences were more noticeable at higher resolutions, but lossy image compression algorithms modified the high-frequency spectra and reduced those differences. Highly compressed GAN generated images were indistinguishable from real images in the frequency domain, but VAE generated images were not affected by compression due to their low levels of high-frequency content.
We proposed a detection method for identifying deep network generated images based on their high-frequency characteristics and performed binary classification experiments on images of faces and animals from real, Style-GAN generated, and VQ-VAE2 generated image datasets. This detection method achieved an accuracy of 99.2% on uncompressed, high-resolution images with minimal training data, but the accuracy was notably lower with compressed and/or low-resolution images. Finally, we presented a method for modifying the high-frequency spectra of a deep network generated image to mimic the spectra of real images, effectively deceiving the classifier without any visually noticeable changes in the image itself. In the future, this detection and synthesis method will be applied to videos manipulated by deep generative models (i.e. deep fakes) to evaluate their effectiveness.

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