Towards Metamerism via Foveated Style Transfer

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Abstract

Given the recent successes of deep learning applied to style transfer and texture synthesis, we propose a new theoretical framework to construct visual metamers: a family of perceptually identical, yet physically different images. We review work both in neuroscience related to metameric stimuli, as well as computer vision research in style transfer. We propose our NeuroFovea metamer model that is based on a mixture of peripheral representations and style transfer forward-pass algorithms for any image from the recent work of Adaptive Instance Normalization (Huang & Belongie). Our model is parametrized by a VGG-Net versus a set of joint statistics of complex wavelet coefficients which allows us to encode images in high dimensional space and interpolate between the content and texture information. We empirically show that human observers discriminate our metamers at a similar rate as the metamers of Freeman & Simoncelli (FS) In addition, our NeuroFovea metamer model gives us the benefit of near real-time generation which presents a \times 1000 speed-up compared to previous work. Critically, psychophysical studies show that both the FS and NeuroFovea metamers are discriminable from the original images highlighting an important limitation of current metamer generation methods.

1 Introduction

The history of metamers originally started through color matching theory, where two light sources were used to match another wavelength test, until both light sources are indistinguishable from each other producing what is called a color metamer. This leads us to define the general concept of metameric stimulus: two physically different stimuli that are perceptually equivalent. Freeman and Simoncelli were the first to create such metameric stimuli through texture matching algorithms that tile the entire visual field locally given log-polar pooling regions that simulate the V1 and V2 receptive field sizes, as well as having global image statistics that match the metamer with the original image. The essence of their algorithm is to use gradient descent to match the global and tiled local texture statistics of an image (Portilla & Simoncelli) given a fixation point with the original image until convergence. The computational complexity of their metamer synthesis algorithm is $O(MN)$, where M is the number of pooling regions, and N is the number of gradient descent steps per pooling region. See Figure 1 for an example of the metamers conditioned on point of fixation created by Freeman and Simoncelli.

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Despite the high quality metameric outputs, there are two current issues regarding metamer rendering. The first is that there exists a family of metamers that satisfy our previous definition such that there is no unique solution. Consider the trivial examples of having an image $I$ and its metamer $Q$ where all pixel values are identical except for one which is set to zero (making this difference unnoticeable), or the case where the metamer response has an imperceptible equal perturbation across all pixels \[ |Q_i - I_i| < \epsilon \], ∀ pixels $i$ (similar to the concept of Just Noticeable Differences [26, 5]).

However, like the work of Freeman and Simoncelli and Rosenholtz et al. [19, 30, 2], we are interested in creating point-of-fixation driven metamers (or mongrels), which create images that preserve information in the fovea, yet lose spatial information in the periphery (through scrambling) such that this information is unnoticeable at a given fixation (Figure 1). The second issue is that the current state of the art for a complete field of view rendering of a $512\times512$ px metamer is 6 hours for a grayscale image and roughly a day for a color image. Moreover, the previous method produces errors when the image matrix is non-invertible (consider a black patch of all zeros).

From a theoretical standpoint, understanding how metamers can be created through deep models (VGG-Net) [33], may enable better understanding of what is encoded in the human visual system. Moreover, metameric visualizations may allow us to understand peripheral processing: what is the role of peripheral processing [29]? Can the peripheral nature of the human visual system give advantages to computer vision [6]? Constructing such models may also be used to emulate improved models of visual search [6, 30] and saliency [20, 4].

From a practical perspective, creating alternative metamers that are quick to compute may lead to the creation of rich neuroscience-driven experiments that require metameric stimuli such as gaze-contingent displays, or metameric videos for fMRI, EEG, MEG or Eye-Tracking [30] studies.

2 Previous Work

Recent work in texture synthesis through CNN’s by Gatys et al. [10, 11] has lead to the development of a new popular subfield in the computer vision community called Style Transfer [34, 17, 15]: where an application of the texture synthesis algorithm can be used to transfer such textures onto the content of an image, hence ‘transferring artistic style’. This parametric model uses per-layer Gram matrices that are computed with feature map activations pre-trained on ImageNet [32] when performing a forward pass of a texture. The idea is that the VGG-Net [33] which has been pre-trained for object classification can roughly represent the entire human visual stream simulated through the network, since it has hierarchically encoded object information in its layers [10, 11].

Despite the excellent texture synthesis results of Gatys et al., their $O(N)$ algorithm is still limited by the $N$ gradient descent steps that it must perform similar to the work of Portilla & Simoncelli [28], except that the features are driven by a VGG-Net CNN rather than a set of statistical parameters extracted from a steerable pyramid decomposition with the goal of fully describing the texture under the Julesz conjecture [18]. The latter proposing that any texture can be described by matching its $n$-th order statistics. This $O(N)$ performance bottleneck was solved through feed forward models.
Figure 2: Interpolating between an image’s intrinsic content and texture via a convex combination in the output of the VGG-Net Encoder \[33, 15\]. Here we are treating the patch as a single pooling region. In our model, this interpolation given Eq. 1 is done for every pooling region in the visual field.

(Ulyanov et al; Johnson et al.) \[34, 17\] which can synthesize textures and perform style transfer in \(O(1)\) time with high quality results. Their approach: rather than fixing the network and learning the image \[10, 11\], these feedforward models fix the image and essentially learn the texture and style parameters in the network through supervised training with texture and perceptual loss functions. However both models are limited to a single texture or style. The most recent work of Ming et al. \[24\] can also adapt feed forward synthesis and style transfer to a gamma of textures with a single network through a texture controller module, but can not adapt to unseen styles or textures. However the network is able to effortlessly blend multiple textures it has been trained on.

Gatys et al. \[12\] recently introduced guidance channels to control for perceptual style factors such as spatial control, color control and scale control. Their mathematical formulation is both applicable for Neural Style Transfer \[11\] (parametric matching through gradient descent) and Fast Neural Style Transfer \[17\] (feed-forward networks), however the network is constrained to only one style, and would have to be re-trained for any new style unseen in training.

Ideally, we would want a complete and flexible framework where a single network can encode any style and texture without the need to re-train, and with the power of producing style transfer with a single forward pass, thus enabling real-time applications. Furthermore, we would want such a framework to also control for spatial and scale factors \[12\] which is critical in metameric rendering given the underlying peripheral architecture \[2, 7, 6, 19\]. The very recent work of Huang and Belongie \[15\], enables such power through adaptive instance normalization(AdaIN), where an image is stylized by adjusting the mean and standard deviation of the \(relu1_1, relu2_1, relu3_1, relu4_1\) activations of the content image to match those of the style. Their framework also allows for spatial control \[12\]. However their model is currently adapted to a single binary window for spatial control of foreground vs background style transfer. Extending style transfer algorithms to work with \(M\) windows has been explored in Deep Photo Style Transfer \[25\] where Luan et al. have successfully created incredible photorealistic style transfer by mixing \(S\) different styles with \(M\) windows, however they reduce any sort of texture transfer by constraining the optimization with a ‘photorealism’ regularizer which avoids texturized distortions through an affine color transformation \[24\].

Other related work is of Deza & Eckstein \[6\] where they stack V1 peripheral architectures on top of dense clutter representations to produce foveated cluttered models \[31, 37, 27\]. They show that such foveated versions predict target detectability better than dense versions, under forced fixation experiments. Along the same lines, we stack a V2 peripheral architecture \[39, 8\] on top of style transfer models (in their feature space through spatial control) \[12\] to create a foveated style transfer model. We show that a family of metamers can be produced through foveated style transfer. At the time of submission this is the first type of foveated style transfer model currently available (See Discussion, for parallel work). Technical aspects of our model will be discussed in the next Section.

3 Constructing the NeuroFovea metamer

To construct our metamer we propose the following statement: A metamer \(Q\) can be rendered by transferring \(M\) localized styles over a content image \(I\), controlled by a set of style-to-content ratios \(\alpha_i\) for every pooling region \(i\). Every stylized location matches a pooling region as a function of eccentricity and receptive field size. We pick our receptive field sizes that match V2 \[7\] since it is strongly suggested that the size of such receptive fields encodes texture information \[8, 39\].

More formally: An input image \(I \in \mathbb{R}^L\) is fed through a VGG-Net encoder \[33\] \(V(\cdot) : \mathbb{R}^L \rightarrow \mathbb{R}^D\) which is both the content and the style image, to produce the content feature \(C \in \mathbb{R}^D\), as shown in Figure 3. A noise patch \(\mathcal{N} \sim (\mu_\perp, \sigma_\perp^2) \in \mathbb{R}^L\) is also fed through the same VGG-Net encoder producing the noise
Additional specifications of our model: we use (and interpolated) feature vector through the Meta VGG-Net Decoder.

The computational cost of our algorithm is $O(M)$, yet computing each metamer takes less than one second. Creating a single feed-forward neural architecture with engrained $M$-window spatial control is not the focus of our work. Note that such pipeline would be impressive since it would enable $O(1)$ metameric rendering via our framework. However, having an $O(M)$ model that is still reasonable to compute in less than a second gives us the flexibility of simulating multiple points of fixation, given that adjusting the point of fixation results in changing the location of the $M$ pooling windows.

Additional specifications of our model: we use $M = M_p + M_f = 126$ spatial control windows, $M_p = 125$ pooling regions and $M_f = 1$ fovea (at an approximate 2 deg radius). Details regarding the decoder network architecture and training can be seen in Huang et al. [15]. Constructions of biologically-tuned peripheral representations are explained in detail in [7,16]. Our pix2pix Super-Resolution module took 3 days to train on a Titan X GPU, and was trained with 64 crops (256×256) per image for 100 images, including horizontally mirrored versions. We ran 200 training epochs of these 12800 images.

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1Also see Henaff & Simoncelli [14] for a similar idea of interpolating between two images along a geodesic.
on the U-Net architecture proposed by Isola et al. [16] which preserves local image structure as much as possible given an adversarial and L2 loss.

4 Methods

In the following Section we describe the experiments to assess whether our proposed technique generates metameric samples.

Six undergraduate observers (3 female) with 20/20 natural and corrected vision participated in all our experiments. All experiments were done with at a viewing distance of 52cm, and a 800 × 600px resolution monitor, where each 512 × 512 image subtended 26deg × 26deg, as in the original experiments of Freeman and Simoncelli [7]. We used a BARCO monitor that was linearly calibrated to a mean luminance of 55.6 cd/m². An SR-Research EyeLink 1000 Tower Mount with a refresh rate of 250 Hz was used to collect data for each experiment. Every observer went through a 9-point calibration before each session. Each condition in Experiment 1 was completed in roughly 2 hours on average, while Experiment 2 was completed in 3 hours. Both conditions in Experiment 1 had 1400 trials with 50 different images, while both conditions in Experiment 2 had 1800 trials with 100 different images. PsychToolbox for MATLAB was used to conduct our psychophysical experiments.

All our experiments were ABX tasks under a Forced-Fixation viewing condition at the center of the screen (observers are not allowed to move their eyes), and trials were discarded when observers broke center fixation. Figure 4 shows the schematic of an ABX task: Observers are shown two images: Image 1 and Image 2, each one masked after the other. Then a third image is shown: Image 3, and observers must guess if Image 3 is Image 1 or Image 2. Observers pressed the ‘a’ key to select Image 1, and the ‘l’ key to select Image 2. Experiment 1 had inter-stimulus masks, while Experiment 2 had inter-stimuli white noise masks to penalize small spatial distortions. They had unlimited time for response, but they all responded roughly in less than a second. If observers can’t discriminate between both images, their behavioural response will be at chance (50%), thus providing metameric evidence between both stimuli under forced fixation [7][6]. Also see Wallis et al. [36] for alternative tests of local metamerism through an odd-ball paradigm.
5 Experiments

What is the maximum amount of distortion that is allowed in the visual periphery before an observer will notice? To address this question we look for a set of $\alpha$ values that will limit the amount of global structure loss vs texture loss for human observers (See Eq. 1). This is the main parameter for our model, vs the Freeman & Simoncelli model that varied a receptive field scaling factor ($s$), and also computed a closed-form expression psychometric function that would model such behavioural response parametrized by $s$. We will fix the scale ($s = 0.5$), to match the receptive field sizes of V2, and instead modify $\alpha$. Note that finding the optimal $\alpha$ is non-trivial, as we do not know a priori the shape of the function $\alpha_i = \gamma_i(x)$, that will control how much noise (given our model parameters) is maximally allowed at each eccentricity $x$ for the fully rendered image to be metameric with the original.

For both our experiments we use the same 6 participants to engage in a series of ABX tasks where we randomly counterbalance two conditions:

1. Discriminating between Synthesized images (Synth vs Synth) which has been done in the original study of Freeman & Simoncelli. While this test does not guarantee metamersim (Original vs Synth), it is the evaluation the previous authors used for their experiments.

   2. Discriminating between the Original and Synthesized images (Original vs Synth). This metamersism test, was not reported in previous works [7, 36].

These two conditions are similar to those proposed by Wallis et al. [36], however their study focused on discriminating local regions placed at multiple eccentricities within an image that have been replaced by purely synthesized textures without any global (image) constraints; i.e. texture-to-image [36] discrimination vs metamer-to-image discrimination (our study).

5.1 Experiment 1: Maximum Noise Estimation via Eccentricity Control

In our first experiment, we are interested in estimating what is the maximum amount of global loss that can be tolerated at multiple eccentricities in the periphery, with the hope of estimating these values independently, to consequently render a metamer with these different $\alpha_i$ values. An advantage of this method is that one can remain agnostic to the underlying $\gamma(\cdot)$ function that determines each $\alpha$ value for every eccentricity. The disadvantage of this method, is that one must do an exhaustive search of multiple $\alpha$ values per eccentricity to fully capture the point of subject equality. But most importantly: a theoretical drawback of this noise estimation process is that there is no guarantee that calculating eccentricity-driven $\alpha$ values will also be metameric when all metameric rings are stitched together; i.e., it could be the case that the whole is other than the sum of its parts [21].

Nevertheless, any boundary estimation of $\alpha$ values will be useful when trying to compute global metamersism. We render metameric rings at one of four possible noise values: $\alpha =$
We create a family of metameric stimuli rendered with multiple values to test discrimination tolerance at the fovea. The metamer observers can discriminate minimal distortions given the invertibility of the AdaIN pipeline [15], as image (including Super-Resolution and Contrast Normalization), without any noise, to test how well in the visual field [22]. The Synth vs Synth task shows that the bounds of the first eccentricity ring is: \( \alpha = 0.375 \), and the second-to-largest in the periphery: \( \alpha = 0.875 \). The rendered stimuli in this experiment did not use the Super-Resolution module, which suggests that even small artifacts can give away peripheral distortions. The significant difference in performance (p<0.05) across all eccentricities including the fovea, also suggests that testing for metamerism in a Synth vs Synth task is a necessary but not sufficient condition for true metamerism [36].

5.2 Experiment 2: Maximum Noise Estimation via Global Control

In our second experiment we will evaluate global metamerism against synthetic image pairs, and against the original image. We explore this task for two main reasons: the first is to extend the results of Wallis et al. regarding the difficulty of discriminating original vs metameric stimuli – which consequently leads to explore if indeed true tests of metamerism via Synth vs Synth tasks are a necessary and sufficient condition. The second reason is to test the original metamers proposed by Freeman and Simoncelli [7] in a more rigorous environment (vs the original stimuli). If the results of the latter experiments are not at chance (i.e. there is some discriminability), this would imply that the Freeman & Simoncelli model does not hold for true metamerism [36].

We create a family of metameric stimuli rendered with multiple \( \gamma(\cdot) \) curves. It would be naive to assume that metamers can only be produced by equally spaced \( \alpha \) values along a linear function \( \alpha_i = \gamma(x) \) as a function of eccentricity. Indeed, we do not know the shape of this function, which also depends on our choice of our image to texture interpolation as introduced in Eq. We did not explore these mathematical constraints. Instead we render 6 families of metamers that obey either a linear function, or an exponential function, with 3 different parameters each. We build off the results of Experiment 1 to roughly estimate reasonable \( \alpha \)-noise boundaries. In our first case: \( \alpha_i = \gamma(x) = mx + b \), and in the second case: \( \alpha_i = \gamma(x) = a \exp(bx) \); where \( x \) is the eccentricity of the center of the \( i \)-th pooling regions in degrees of visual angle. All pooling regions that lie in the same ring, have the same \( \alpha \) value. We call each curve \( \text{Linear}_1, \text{Linear}_2, \text{Linear}_3 \) and \( \text{Exp}_1, \text{Exp}_2, \text{Exp}_3 \) respectively, depending on their parameters as shown in Figure [6].

In addition, we have a base case condition (Base_Case) which is comparing the Meta Decoded image (including Super-Resolution and Contrast Normalization), without any noise, to test how well observers can discriminate minimal distortions given the invertibility of the AdaIN pipeline [15], as
Results: The results from our second experiment (Figure 7) show that all our NeuroFovea functions produce similar behavioral responses to the metamers of Freeman and Simoncelli, with \( \text{Exp}_3 \) and \( \text{Linear}_3 \) showing a small comparative advantage. There was only one statistically significant advantage for the NeuroFovea for one observer. Four out of 6 observers showed significantly \((p < 0.05)\) less discriminability between the \text{Base Case} and the \text{FS_model}. This result seems to suggest that there might be more than one set of parameters that may achieve global metamerism \((\text{VGG-Net} [33] \text{ vs Steerable Pyramid derived statistics} [28])\).

Discussion
The main difference of our method and that of Freeman & Simoncelli is that Freeman & Simoncelli used gradient descent to match local image appearance as well as texture statistics locally and globally for the image. Our method is performing an interpolation in VGG-Net space between the original image and the texturized version of the image (stylized noise in our model). Parallel work has investigated the use of different noise initializations such as matching power spectrum [9]. In addition, parallel and complementary to our work: Wallis et al. have developed metameric images using gradient descent methods from the original NeuralSynth by Gatys et al.. However this model does not achieve metamerism between the original and synthetic images for all tested images \([35]\) (only a subset). We have not tested if it the case that our model produces some group of metameric images given that we do not do our evaluations on a per image basis, but rather in the aggregate. However, it might be the case as our observers do not achieve near perfect discriminability in our original vs synth condition. See for example the performance of each observer in our \text{Exp}_3 and \text{Base Case} metamers, which fluctuates between 60% and 85% – an indication that observers are in fact confusing our metamers with the original images, but we have not evaluated if this is systematic for all observers. Moreover, each observer only evaluates each scene twice: once per condition (original vs synth, and synth vs synth).

![Figure 7](image-url)
A current limitation of each model is also the number of images they are evaluated with. The study of Freeman & Simoncelli use 4 images with an ABX task. The study of Wallis et al. [35] evaluates their set of images under an oddity paradigm [36], and our study uses 100 images under an ABX task with interstimuli white noise masks. Thus, metamerism should be tested on a wide variety of scenes that uniformly sample the scene manifold – as well as a wide variety of testing paradigms. Testing metamerism on a wide variety of scenes is of utmost importance given that metamerism for certain images that are heavily textured or uniform is easier to produce than a-periodic images or heavily cluttered [6] ones. Finding a subset of sufficient statistics [28, 33] that work for such images need not to apply for more complex scenes with less periodicity or clutter, which are still equally likely to appear in the real world.

Arguably, the most surprising finding of Experiment 2 is that neither the baseline (Base Case) of our NeuroFovea model nor the Freeman & Simoncelli [7] model can generate images that are indistinguishable from the original images. This points to a severe limitation in all current methods. However the central idea of our work and that of Freeman & Simoncelli [7], and recently Wallis et al. [35] remains: true metamerism may derive from capturing near-perfect image and texture statistics and interpolating (or matching [7, 35]) between them in a high dimensional feature space.

Future work in this direction may also explore the role of different layers of the VGG-Net for texture encoding: What layers are critical for metamerism and which ones are not? What is the minimum number of layers need to achieve metamerism through our pipeline? What network architectures are efficient towards encoding metamerism [13]? The parallel work of Funke et al. [9] has explored the role of texture matching via VGG-Net texture synthesis a la Gatys et al. (gradient descent), and has found that the third layer in a VGG-Net architecture is the minimal hierarchy for texture encoding in the periphery. This later finding supporting the use of our VGG-Net Decoder and Encoder architecture which includes layers up to relu4_1.

Indeed, generating metamers is still an open problem because of various contraints like human sentivity to contrast levels and edges, statistical convergence of gradient descent rendering-based methods [11], and image rendering time. We have proposed a possible solution to this last problem via feed-forward style transfer techniques in our aproach. Moreover, it is still not known what is the minimum set of parameters that both encode image content and texture across the entire visual field such that any small perturbation in these parameters will remove metamerism as first explored and mentioned by Freeman and Simoncelli.

7 Conclusion

In this paper we provide an innovative approach to utilize new methods in deep learning to try to generate metameric images in real time. The proposed method based on style transfer (NeuroFovea model) matches that of Freeman & Simoncelli in the degree at which humans can discriminate between two synthetic images and also between the synthetic images and the original image. One advantage of the proposed method is that the metamers can be generated in near real time. Our psychophysical studies also point to a limitation of the two methods: humans can discriminate the rendered synthetic images from the originals. As style transfer research continues to move forward, we are confident that the core ideas of our model will be building blocks in constructing true visual metamers (original vs synthetic) that lie in the perceptual boundary of human discriminability.
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Eccentricity in degrees away from fovea

(a) Top: $g_{\eta}(\varepsilon)$ function. Bottom: $h_\eta(\theta)$ function.
(b) Peripheral Architecture.

Figure 8: Construction of a Peripheral Architecture *a la* Freeman & Simoncelli [7] using the functions described in this section are shown in Fig. 8(a). The blue region in the center of Fig. 8(b) represents the fovea where all information is preserved. Outer regions (in red), represent different parts of the periphery at multiple eccentricities. Original figure from Deza & Eckstein [6].

### 8 Supplementary Material

#### 8.1 Creation of Peripheral Architecture

In our work we use a V2 peripheral architecture which presents a scaling factor $s$ of $(s = 0.5)$ as proposed in Freeman & Simoncelli which is the maximum scaling factor used for metamerism given Portilla & Simoncelli texture parameters. The V1 peripheral architecture model [6, 7] which pools over lower level features such as Feature Congestion [31] is set to a scaling factor of $s = 0.25$. The scaling factor controls the rate of growth of the pooling regions in the visual field, which in return will control how much scrambling or crowding occurs per pooling region.

More specifically: $w_\theta = s/2$ and $N_\theta = 2\pi/w_\theta$. Equations 2-4 fully describe these log-polar regions (Fig. 8).

\[
\begin{align*}
  f(x) &= \begin{cases} 
  \cos^2\left(\frac{x}{2} \frac{(x-(t_0-1)/2)}{t_0} \right); & (1 + t_0)/2 < x \leq (t_0 - 1)/2 \\
  1; & (t_0-1)/2 < x \leq (1 - t_0)/2 \\
  -\cos^2\left(\frac{x}{2} \frac{(x+(1-t_0)/2}{t_0} \right) + 1; & (1 - t_0)/2 < x \leq (1 + t_0)/2 
  \end{cases} \\

  h_\eta(\theta) &= f\left(\frac{\theta - (w_\theta n + \frac{w_\theta(1-t_0)}{2})}{w_\theta}\right); \frac{2\pi}{N_\theta}; n = 0, ..., N_\theta - 1 \tag{3} \\

  g_{\eta}(\varepsilon) &= f\left(\frac{\left(\log(\varepsilon) - \left[\log(e_0) + w_\varepsilon(n + 1)\right]\right)}{w_\varepsilon}\right); \frac{\log(e_\varepsilon) - \log(e_0)}{N_\varepsilon}; n = 0, ..., N_\varepsilon - 1 \tag{4}
\end{align*}
\]

#### 8.2 Example Stimuli in Experiments

Figures [9] and [10] show some of the stimuli used in our experiments, where better comparisons can be made between the different original image and our Metameric outputs (Exp_1, Exp_2, Exp_3, Linear_1, Linear_2, Linear_3, Base_Case), as well as the NeuroFovea. Scrambling in the outer periphery is quite noticeable for Exp_1 and Linear_1, while Exp_3 and Linear_3, show smoother transitions of image-to-texture interpolation across the visual field. The Base_Case inversion can also be observed, where indeed a very close approximation to the original image is achieved, yet even under this baseline condition human observers are quite susceptible to small distortions, local contrast differences, or possibly the loss of high-spatial frequency information of the image.

What also remains to be evaluated in experiments regarding visual metamers is the role of attention when evaluating across images. Freeman and Simoncelli evaluated to control for such factors by extending stimuli presentation time, as well as endogenous cues that signal the area of greatest difference between synthesized examples [7]. How do landmarks affect metamerism perception? How can we classify a priori, both semantically and computationally what makes an image difficult to metamerase? What attentional strategies do observers use to improve their discriminability of the images in the ABX task, or is this due purely to perceptual variance across subjects? These are all important questions that should be addressed in future work regarding metamerism and attention.
Figure 9: Five of the 100 images and their respective metamer used in our experiments. Images and distortions best viewed when zoomed in. Original stimuli were rendered at 512×512 px and 26×26 deg.
Figure 10: Five of the 100 images and their respective metamers used in our experiments. Images and distortions best viewed when zoomed in. Original stimuli were rendered at $512 \times 512$ px and $26 \times 26$ deg.