Visually Synthesizing the Genotype-Phenotype Distinction in *Cannabis sativa*

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Abstract

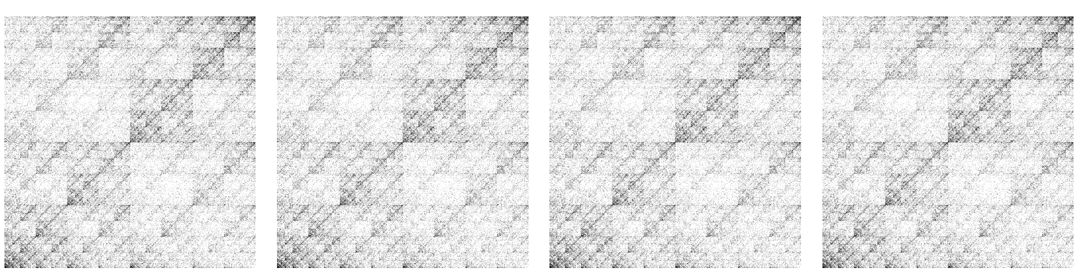
Presented are results of two numerical experiments: the whole chloroplast genome chaos game representation of *Cannabis sativa* and the comparison of two state-of-the-art neural network architectures applied to the neural style transfer problem. A brief explanation of the chaos game representation is given followed by results illustrating that the whole chloroplast genome has global structure. An explication of neural style transfer and the ResNet and FractalNet neural network architectures is then given followed by results when both networks are trained to learn the underlying feature representation of an image of *Cannabis sativa*. Finally, the artistic motivation of these numerical experiments is presented in the context of the genotype-phenotype distinction.

Chaos Game Representation

Chaos game representation (CGR) [4] is a method for visualizing global structure in DNA sequences by uniquely representing the sequence as a set of points on the unit square. The CGR of a sequence is given by plotting the set S computed using the following steps:

1. Associate each vertex $\{(0,0), (1,0), (1,1), (0,1)\}$ with the nucleotides $\{A, G, T, C\}$, respectively.
2. Initialize a set $S = \{(0,0)\}$.
3. Read off the sequence. For each element in the sequence, add to the set S the midpoint between the most previous point added to the set and the vertex associated with the current element.

Analysis of many sample sequences taken from several taxonomic subsets done by [6] demonstrated that the CGRs of DNA sequences have fractal, self-similar structure. However, the CGR of *Cannabis sativa* was not included in this analysis, as it did not fall under the taxonomic subsets of interest, and so is reported below. Figure 1 shows the CGR of four complete chloroplast genomes taken from *Cannabis sativa* [10, 11]. Prior work in using genomic information for algorithmic art can be found in [2, 8].



Dagestani, Russia | *Yoruba, Nigeria* | *Carmagnola, Italy* | *Cheungsam, Korea*

Figure 1: *Chaos game representations of Cannabis sativa from different regions around the world.*

Neural Style Transfer

The *neural style transfer* (NST) problem, popularized by the technique of [1], is an image processing task where neural networks are trained to learn the 'style' of a target image such that this style may be applied (i.e. 'transferred') to the 'content' of a source image in order to render an aesthetically similar result while preserving semantic content. Work done by [9] demonstrated that NST may be considered as a domain adaptation problem where the objective is to minimize the Maximum Mean Discrepancy. That is, NST may be thought of as learning the convolutional kernels such that the source image pixel distribution shifts towards the target image.

As in [5], a bottleneck (downsample, feature representation, upsampling) neural network was trained to approximate a solution to the problem presented in [1] by learning the feature representation of the target image and stylizing the source image by a feedforward pass. Feature layers encode the lower dimensional representation of the target image and thus it is of interest to compare style transfer results given either *ResNet* [3] or *FractalNet* [7] encoding. ResNet is a popular architecture introducing a skip connection between convolutions. Let R be a feature layer:

$$R(x) := \sigma\Big((f_C \circ \sigma \circ f_B \circ \sigma \circ f_A)(x) + x \Big)$$

where $\{A, B, C\}$ are learnable kernels for the convolution operator f, $\sigma(x) = \max(0, x)$ the rectified linear unit (ReLU) activation function applied element-wise, and x an (image) function $\mathbb{R}^2 \to \mathbb{R}^3$. FractalNet is an architecture based on the repeated application of an expansion rule to generate deep neural networks whose structure is a truncated fractal. Let F be a feature layer generated on one application of the expansion rule:

$$F(x) := \sigma\left(\frac{(\sigma \circ f_C \circ \sigma \circ f_B)(x) + (\sigma \circ f_A)(x)}{2} \right)$$

where, similarly, $\{A, B, C\}$ are learnable convolutional kernels and σ is the ReLU activation function. Note that both ResNet and FractalNet have three convolution operations arranged (layered) differently.

The target style image to be learned was chosen to be an image of *Cannabis sativa* [12]. The source content image was chosen to be the CGR of the Dagestani *Cannabis sativa*. Results are shown in Figure 2.

Summary and Conclusions

Presented are numerical experiments in both chaos game representations and neural style transfer. The CGRs of previously unanalyzed *Cannabis sativa* DNA sequences are reported, demonstrating a fractal structure, as expected. A comparison between two state-of-the-art neural network architectures trained to stylize an image of *Cannabis sativa* is then reported, using the aforementioned CGR as a content image. The artistic motivation of this experiment is as a synthesis of two distinct, obverse representations of *Cannabis sativa*. CGR uniquely represents the genotypic information of the whole chloroplast genome while the target image contains phenotypic information (i.e. the leaves and blooming of a plant). The style transfer process superimposes these two representations into a synthesized image of *Cannabis sativa* where, in a reversal of biology, the genotypic has been expressed in the texture of the phenotypic.

Acknowledgements

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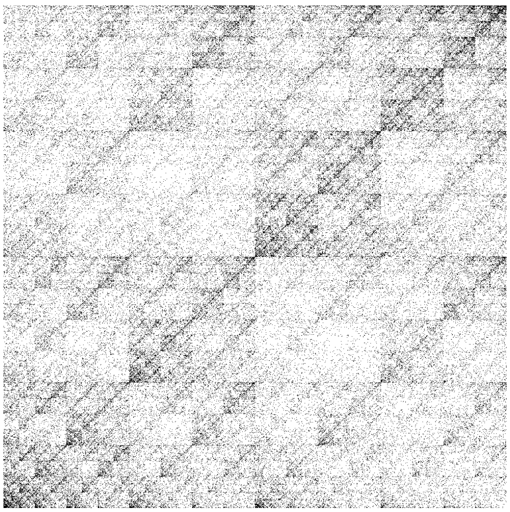
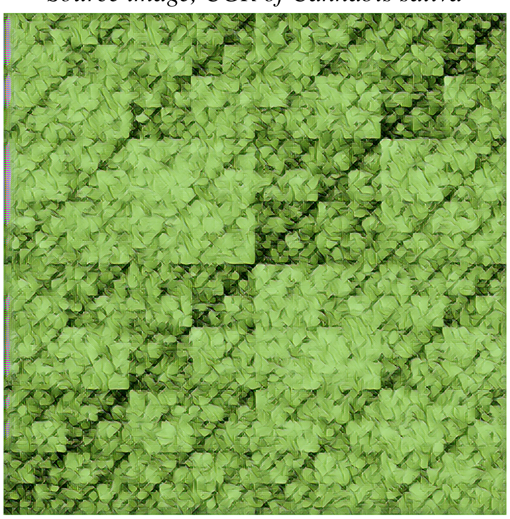
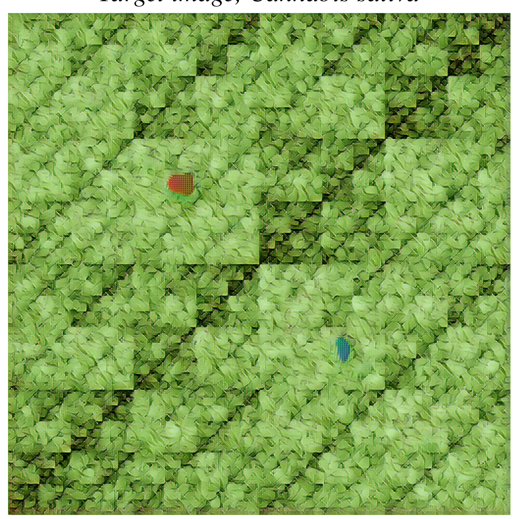


Source image, CGR of Cannabis sativa

Target image, Cannabis sativa



FractalNet style transfer



ResNet style transfer

Figure 2: *Neural style transfer applied to genotypic and phenotypic representations of Cannabis sativa. The chaos game representation of whole chloroplast genome is used as content for the neural style transfer of an image of hemp.*

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[12] Photograph by ‘Hendrike’, distributed under a CC BY-SA 2.5 license. https://commons.wikimedia.org/wiki/Cannabis_sativa#/media/File:Hanf.jpg