Texture synthesis and the controlled generation of natural stimuli using convolutional neural networks

Leon A. Gatys
Werner Reichardt Centre for Integrative Neuroscience, University of Tübingen, Germany
Bernstein Center for Computational Neuroscience, Tübingen, Germany
Graduate School of Neural Information Processing, University of Tübingen, Germany
leon.gatys@bethgelab.org

Alexander S. Ecker
Werner Reichardt Centre for Integrative Neuroscience, University of Tübingen, Germany
Bernstein Center for Computational Neuroscience, Tübingen, Germany
Max Planck Institute for Biological Cybernetics, Tübingen, Germany
Baylor College of Medicine, Houston, TX, USA

Matthias Bethge
Werner Reichardt Centre for Integrative Neuroscience, University of Tübingen, Germany
Bernstein Center for Computational Neuroscience, Tübingen, Germany
Max Planck Institute for Biological Cybernetics, Tübingen, Germany

Abstract
It is a long standing question how biological systems transform visual inputs to robustly infer high-level visual information. Research in the last decades has established that much of the underlying computations take place in a hierarchical fashion along the ventral visual pathway. However, the exact processing stages along this hierarchy are difficult to characterise. Here we present a method to generate stimuli that will allow a principled description of the processing stages along the ventral stream. We introduce a new parametric texture model based on the powerful feature spaces of convolutional neural networks optimised for object recognition. We show that constraining a spatial summary statistic over feature maps suffices to synthesise high-quality natural textures. Moreover we establish that our texture representations continuously disentangle high-level visual information and demonstrate that the hierarchical parameterisation of the texture model naturally enables us to generate novel types of stimuli for systematically probing mid-level vision.

1 Introduction
Deep convolutional neural networks are the first artificial systems that rival biology in terms of difficult perceptual inference tasks such as object recognition [10] [19] [20] [7]. At the same time, their hierarchical architecture and basic computational properties admit a fundamental similarity to real neural systems. Together with the increasing amount of evidence for the similarity of the representations in convolutional networks and those in the ventral visual pathway [21] [9], these properties make them compelling candidate models for studying visual information processing in the brain. In fact, it was recently suggested that textures generated from the representations of performance-optimised convolutional networks “may therefore prove useful as stimuli in perceptual or physiological investigations” [13].
In recent years, texture models inspired by biological vision have provided a fruitful new analysis tool for studying visual perception. In particular, the parametric texture model proposed by Portilla and Simoncelli [15] has sparked a great number of studies in neuroscience and psychophysics [5, 4, 16, 14]. The model took its inspiration from the early visual system and is based on a set of carefully handcrafted summary statistics computed on the responses of a linear filter bank called Steerable Pyramid [18].

One of the most exciting results with respect to neuroscience that originated from this texture model is its ability to differentiate neural responses between primary (V1) and secondary visual cortex (V2) [5]. The authors measure the average responses of neurons in both areas to textures generated with their texture model [15] and to spectrally matched noise. Neurons in V1 respond equally to both sets of stimuli, while neurons in V2 respond stronger to the textures generated by the texture model. In a later fMRI study, the authors compare the BOLD signal in response to textures generated with their algorithm and the original natural texture used for the texture generation. They find comparable activity in areas V1–V3 but some differences in areas V4 and IT [13]. Thus, they identified different classes of stimuli that can distinguish three different processing stages along the ventral stream, which differ in their mean response to spectrally matched noise, textures generated with their texture model and true natural textures.

This finding is consistent with the idea that high-level visual information encoded in the complex statistical structure of natural images is made more and more explicit along the ventral stream [3]. However, as this disentanglement of information is a very difficult computation, it likely requires more than only the three processing stages that were previously identified. We rather expect a more fine-grained increase in the explicit representation of complex natural patterns along the ventral stream and thus, the question arises whether we can find a more comprehensive way of probing the system. That is, we would like to generate stimuli that interpolate in their degree of naturalness between phase-randomised images (i.e., spectrally matched noise) and true natural images to not only give a difference in responses between V1 and V2 but also between e.g., V2 and V4 and V4 and IT or even between different regions or layers within a visual area.

In this work, we propose a new parametric texture model to tackle this problem (Fig. 1). Instead of describing textures on the basis of a model for the early visual system [15], we use a convolutional neural network—a functional model for the entire ventral stream—as the foundation for our texture model. We combine the conceptual framework of spatial summary statistics on feature responses with the powerful feature space of a convolutional neural network that has been trained on object recognition. In that way, we obtain a texture model that is parameterised by spatially invariant representations built on the hierarchical processing architecture of the convolutional neural network.

We show that high-level visual information is made increasingly explicit along the hierarchy of our texture model and demonstrate how the layered structure of the convolutional network naturally enables our texture model to generate a novel set of stimuli to systematically probe mid-level visual areas.

2 Convolutional neural network

We use the VGG-19 network, a convolutional neural network trained on object recognition that was introduced and extensively described previously [19]. Here we give only a brief summary of its architecture.

We used the feature space provided by the 16 convolutional and 5 pooling layers of the VGG-19 network. We did not use any of the fully connected layers. The network’s architecture is based on two fundamental computations:

1. Linear rectified convolution with filters of size $3 \times 3 \times k$ where $k$ is the number of input feature maps. Stride and padding of the convolution is equal to one such that the output feature map has the same spatial dimensions as the input feature maps.

2. Maximum pooling in non-overlapping $2 \times 2$ regions, which down-samples the feature maps by a factor of two.

These two computations are applied in an alternating manner (see Fig. 1). A number of convolutional layers is followed by a max-pooling layer. After each of the first three pooling layers the number of
Figure 1: Conceptual framework. Based on the responses of a convolutional neural network to a natural texture, we generate stimuli to probe the ventral visual pathway. The stimuli are designed to match texture representations at different layers of the convolutional network. We control the naturalness of the stimuli by matching the representations only up to a certain processing stage in the network. In that way we create stimuli that can systematically identify different processing stages along the ventral visual pathway.

Feature maps is doubled. Together with the spatial down-sampling, this transformation results in a reduction of the total number of feature responses by a factor of two. Fig. 1 provides a schematic overview over the network architecture and the number of feature maps in each layer. Since we use only the convolutional layers, the input images can be arbitrarily large. The first convolutional layer has the same size as the image and for the following layers the ratio between the feature map sizes remains fixed. Generally each layer in the network defines a non-linear filter bank, whose complexity increases with the position of the layer in the network.

The trained convolutional network is publicly available and its usability for new applications is supported by the caffe-framework [8]. For texture generation we found that replacing the max-pooling operation by average pooling improved the gradient flow and one obtains slightly cleaner results, which is why the images shown below were generated with average pooling.

3 Texture model

The texture model we describe in the following is much in the spirit of that proposed by Portilla and Simoncelli [15]. To generate a texture from a given source image, we first extract features of different sizes homogeneously from this image. Next we compute a spatial summary statistic on the feature responses to obtain a stationary description of the source image. Finally we find a new image with the same stationary description by performing gradient descent on a random image that has been initialised with white noise.

The main difference to Portilla and Simoncelli’s work is that instead of using a linear filter bank and a set of carefully chosen summary statistics, we use the feature space provided by a high-performing deep neural network and only one spatial summary statistic: the correlations between feature responses in each layer of the network.
To characterise a given vectorised texture $\vec{x}$ in our model, we first pass $\vec{x}$ through the convolutional neural network and compute the activations for each layer $l$ in the network. Since each layer in the network can be understood as a non-linear filter bank, its activations in response to an image form a set of filtered images (so-called feature maps). A layer with $N_l$ distinct filters has $N_l$ feature maps each of size $M_l$ when vectorised. These feature maps can be stored in a matrix $F^l \in \mathbb{R}^{N_l \times M_l}$, where $F^l_{ik}$ is the activation of the $i$th filter at position $k$ in layer $l$. Textures are per definition stationary, so a texture model needs to be agnostic to spatial information. A summary statistic that discards the spatial information in the feature maps is given by the correlations between the responses of different features. These feature correlations are, up to a constant of proportionality, given by the Gram matrix $G^l \in \mathbb{R}^{N_l \times N_l}$, where $G^l_{ij}$ is the inner product between feature map $i$ and $j$ in layer $l$:

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}.$$  \hfill (1)

The set of correlation matrices $\{G^1, G^2, \ldots, G^L\}$ from all layers 1, 1, $L$ in the network in response to a given texture provides a stationary description of the texture, which fully specifies a texture in our model.

### 4 Texture generation

To generate a new texture on the basis of a given image, we use gradient descent from a white noise image to find another image that matches the correlation-matrix representation of the original image. This optimisation is done by minimising the mean-squared distance between the entries of the correlation matrix of the original image and the correlation matrix of the image being generated. Let $\vec{x}_t$ and $\vec{x}_g$ be the original image and the image that is generated, and $T^l$ and $G^l$ their respective correlation-matrix representations in layer $l$ (Eq. [1]). The contribution of layer $l$ to the total loss is then

$$E_l = \frac{1}{4N^2 M^2} \sum_{i,j} (G^l_{ij} - T^l_{ij})^2$$  \hfill (2)

and the total loss is

$$\mathcal{L}(\vec{x}_t, \vec{x}_g) = \sum_{l=0}^L w_l E_l$$  \hfill (3)

where $w_l$ are weighting factors of the contribution of each layer to the total loss. The derivative of $E_l$ with respect to the activations in layer $l$ can be computed analytically:

$$\frac{\partial E_l}{\partial F^l_{ij}} = \begin{cases} \frac{1}{N^2 M^2} ((F^l)^T (G^l - T^l))_{ji} & \text{if } F^l_{ij} > 0 \\ 0 & \text{if } F^l_{ij} < 0 \end{cases}. \hfill (4)$$

The gradient of $E_l$ with respect to the activations in lower layers of the network can be readily computed using standard error back-propagation [12]. Thus, the following procedure computes the gradient of the total loss with respect to the image:

1. Pass $\vec{x}_g$ through the network and compute correlation matrices $G^l$ in all layers.
2. In the highest layer $L$ calculate the gradient $w_L \frac{\partial E_L}{\partial F^L}$ and propagate it back to layer $L - 1$ to give $w_L \frac{\partial E_L}{\partial F^L}$.
3. Calculate $w_{L-1} \frac{\partial E_{L-1}}{\partial F^{L-1}}$ and propagate the sum $w_L \frac{\partial E_L}{\partial F^L} + w_{L-1} \frac{\partial E_{L-1}}{\partial F^{L-1}}$ back to layer $L - 2$.
4. Repeat this procedure until layer 1 from which the gradient can be propagated to give \frac{\partial \mathcal{L}}{\partial \vec{x}_g}.

The gradient can be used as input for some numerical optimisation strategy. In our work we used L-BFGS [22], which seemed a reasonable choice for the high-dimensional optimisation problem at hand. The entire procedure relies mainly on the standard forward-backward pass that is used to train the convolutional network. Therefore, in spite of the large complexity of the model, texture generation can be done in reasonable time using GPUs and performance-optimised toolboxes for training deep neural networks [8].
Figure 2: Generated stimuli. Each row corresponds to a different processing stage in the network. When only constraining the texture representation on the lowest layer, the synthesised textures have little structure, similarly to spectrally matched noise (first row). With increasing number of layers on which we match the texture representation we find that we generate images with increasing degree of naturalness (rows 2–5; labels on the left indicate the top-most layer included). The source textures in the first three columns were previously used by Portilla and Simoncelli [15]. For better comparison we also show their results (last row). The last column shows textures generated from a non-texture image to give a better intuition about how the texture model represents image information.
5 Results

We show textures generated by our model from four different source images (Fig. 2). Each row of images was generated using an increasing number of layers in the texture model to constrain the gradient descent (the labels in the figure indicate the top-most layer included). In other words, for the loss terms above a certain layer we set the weights \( w_l = 0 \), while for the loss terms below and including that layer, we set \( w_l = 1 \). For example the images in the first row ('conv1_1') were generated only from the texture representation of the first layer ('conv1_1') of the VGG network. The images in the second row ('pool1') where generated by jointly matching the texture representations on top of layer 'conv1_1', 'conv1_2' and 'pool1'. In this way we obtain textures that are equal to the original texture up to a certain computational processing stage of the texture model.

The first three columns show images generated from natural textures. We find that constraining all layers up to layer ‘pool4’ generates complex natural textures that are almost indistinguishable from the original texture (Fig. 2, fifth row). In contrast, when constraining only the feature correlations on the lowest layer, the textures contain little structure and are not far from spectrally matched noise (Fig. 2 first row). We can interpolate between these two extremes by using only the constraints from all layers up to some intermediate layer. We find that the statistical structure of natural images is matched on an increasing scale as the number of layers we use for texture generation increases. For comparability we used source textures that were previously used by Portilla and Simoncelli [15] and also show the results of their texture model (Fig. 2 last row).

To give a better intuition for how the texture synthesis works, we also show textures generated from a non-texture image taken from the ImageNet validation set [17] (Fig. 2 last column). Our algorithm produces a texturised version of the image that preserves local spatial information but loses the global spatial arrangement of the image. The size of the regions in which spatial information is preserved increases with the number of layers used for texture generation. This property can be explained by the increasing receptive field sizes of the units over the layers of the deep convolutional neural network.

We also find that the very deep architecture of the VGG network with small convolutional filters seems to be particularly well suited for texture generation purposes. When performing the same experiment with the caffe reference network [8], which is very similar to the AlexNet [10], the quality of the generated textures decreases in two ways. First, the statistical structure of the source texture is not fully matched even when using all constraints (Fig. 3A, ‘conv5’). Second, we observe an artifactual grid that overlays the generated textures (Fig. 3A). We believe that the artifactual grid originates from the larger receptive field sizes and strides in the caffe reference network.

While the results from the caffe reference network show that the architecture of the network is important, the learned feature spaces are equally crucial for texture generation. When synthesising a texture with a network with the VGG architecture but random weights, texture generation fails (Fig. 3B), underscoring the importance of using a trained network.

6 Interpretation of features in our texture model

It is thought that a main computation in the ventral visual pathway is to make high-level visual information increasingly explicit [3]. For areas V4 and IT this was previously demonstrated by linearly decoding the identity of presented objects from neural activity, which worked significantly better from the neural representation in IT than V4 [21]. To argue that the stimuli we generate with our texture model provide a meaningful tool to probe the computational hierarchy in the ventral stream we need to show that the feature spaces in our model correspond to a similar computational hierarchy.

We therefore evaluated how explicitly high-level visual information is represented in a certain layer of our texture model by linearly decoding object identity using the publically available ImageNet training and validation images [17]. For each layer we computed the correlation-matrix representation of each image in the ImageNet training set and trained a linear soft-max classifier to predict object identity. As we were not interested in optimising prediction performance, we did not use any data augmentation and trained and tested only on the 224 × 224 centre crop of the images. We computed the accuracy of these linear classifiers on the ImageNet validation set and compared them
Figure 3: Textures generated with different networks. A, Textures generated from the different layers of the caffe reference network [8, 10]. The textures are of lesser quality than those generated with the VGG network. B, Textures generated with the VGG architecture but random weights. Texture synthesis fails in this case, indicating that learned filters are crucial for texture generation.

Figure 4: Performance of a linear classifier on top of the texture representations in different layers in classifying objects from the ImageNet dataset. High-level information is made increasingly explicit along the hierarchy of our texture model.
to the performance of the original VGG-19 network also evaluated on the 224 × 224 centre crops of the validation images.

Our analysis suggests that our texture representation continuously disentangles object identity (Fig. 4). Object identity can be decoded increasingly well over the layers. In fact, linear decoding from the final convolutional layer performs almost as well as the original network, suggesting that our texture representation preserves almost all high-level information. Therefore we can interpret the feature space of a particular layer in our texture model as a processing stage in a computational hierarchy that makes high-level visual information increasingly explicit.

If the ventral visual stream consists of a similar computational hierarchy, then the textures generated with our texture model should be able to tell apart the different processing stages along this hierarchy: Textures generated from the different layers of our texture model should lead to equal responses up to a certain processing stage an to diverging responses in the processing stages thereafter.

7 Discussion

We introduced a new parametric texture model based on a high-performing convolutional neural network. In difference to Portilla and Simoncelli’s texture model [15], the individual features in the convolutional network are highly non-linear and thus difficult to interpret. Nevertheless, the representation layers in our texture model offer a parameterisation with clear interpretability: They make high-level visual information increasingly explicit in analogy to the ventral visual pathway in the primate brain.

By computing the feature correlation matrices, our texture model transforms the representations from the convolutional neural network into a stationary feature space. This general strategy has recently been employed to improve performance in object recognition and detection [6] or texture recognition and segmentation [2]. In particular Cimpoi et al. report impressive performance in material recognition and scene segmentation by using a stationary Fisher-Vector representation built on the highest convolutional layer of readily trained neural networks [2]. In agreement with our results, they show that performance in natural texture recognition continuously improves when using higher convolutional layers as the input to their Fisher-Vector representation. As our main aim is to provide a new tool for understanding biological vision, we have not evaluated the correlation matrix representation on texture recognition benchmarks, but would expect that it also provides a good feature space for those tasks.

Our model, although capable of producing high quality natural textures, is not designed to compete with state of the art non-parametric texture synthesis algorithms. Patch-based resampling algorithms are usually considerably faster in generating textures of very high quality (see e.g. [11]).

Nevertheless, parametric texture synthesis has proven a very useful tool for vision research. Arguably, the current state of the art is the texture model introduced by Portilla and Simoncelli [15]. Here we present a new texture model which exceeds previous work in parametric texture modelling in two major ways. First, the quality of the textures synthesised with our model shows a substantial improvement compared to the current state of the art in parametric texture synthesis (Fig. 2, fourth row compared to last row). Second, the fundamentally different parameterisation of our texture model allows a more fine-grained link to biological vision. Texture information is captured in terms of layers of representations that, similar to the ventral stream, make high-level visual information increasingly explicit. It is this hierarchical architecture of our texture model, which makes it naturally suited for the design of stimuli to probe the computational hierarchy along the ventral visual pathway in a controlled manner.

Acknowledgments

This work was funded by the German National Academic Foundation (L.A.G.), the Bernstein Center for Computational Neuroscience (FKZ 01GQ1002) and the German Excellency Initiative through the Centre for Integrative Neuroscience Tübingen (EXC307)(M.B., A.S.E, L.A.G.)
References

[1] Benjamin Balas, Lisa Nakano, and Ruth Rosenholtz. A summary-statistic representation in peripheral vision explains visual crowding. *Journal of vision*, 9(12):13, 2009.

[2] Mircea Cimpoi, Subhransu Maji, and Andrea Vedaldi. Deep convolutional filter banks for texture recognition and segmentation. *arXiv:1411.6836 [cs]*, November 2014. arXiv: 1411.6836.

[3] James J. DiCarlo, Davide Zoccolan, and Nicole C. Rust. How Does the Brain Solve Visual Object Recognition? *Neuron*, 73(3):415–434, February 2012.

[4] Jeremy Freeman and Eero P. Simoncelli. Metamers of the ventral stream. *Nature Neuroscience*, 14(9):1195–1201, September 2011.

[5] Jeremy Freeman, Corey M. Ziemba, David J. Heeger, Eero P. Simoncelli, and J. Anthony Movshon. A functional and perceptual signature of the second visual area in primates. *Nature Neuroscience*, 16(7):974–981, July 2013.

[6] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Spatial pyramid pooling in deep convolutional networks for visual recognition. *arXiv preprint arXiv:1406.4729*, 2014.

[7] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification. *arXiv:1502.01852 [cs]*, February 2015. arXiv: 1502.01852.

[8] Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the ACM International Conference on Multimedia*, pages 675–678. ACM, 2014.

[9] Seyed-Mahdi Khaligh-Razavi and Nikolaus Kriegeskorte. Deep Supervised, but Not Unsupervised, Models May Explain IT Cortical Representation. *PLoS Comput Biol*, 10(11):e1003915, November 2014.

[10] Vivek Kwatra, Arno Schödl, Irfan Essa, Greg Turk, and Aaron Bobick. Graphcut textures: image and video synthesis using graph cuts. In *ACM Transactions on Graphics (ToG)*, volume 22, pages 277–286. ACM, 2003.

[11] Yann A. LeCun, Léon Bottou, Genevieve B. Orr, and Klaus-Robert Müller. Efficient backprop. In *Neural networks: Tricks of the trade*, pages 9–48. Springer, 2012.

[12] J. Anthony Movshon and Eero P. Simoncelli. Representation of naturalistic image structure in the primate visual cortex. *Cold Spring Harbor Symposia on Quantitative Biology: Cognition*, 2015.

[13] Gouki Okazawa, Satohiro Tajima, and Hidehiko Komatsu. Image statistics underlying natural texture selectivity of neurons in macaque V4. *Proceedings of the National Academy of Sciences*, 112(4):E351–E360, January 2015.

[14] Javier Portilla and Eero P. Simoncelli. A Parametric Texture Model Based on Joint Statistics of Complex Wavelet Coefficients. *International Journal of Computer Vision*, 40(1):49–70, October 2000.

[15] Ciyou Zhu, Richard H. Byrd, Peihuang Lu, and Jorge Nocedal. Algorithm 778: L-BFGS-B: Fortran subroutines for large-scale bound-constrained optimization. *ACM Transactions on Mathematical Software (TOMS)*, 23(4):550–560, 1997.