Deformable Style Transfer

Abstract

Geometry and shape are fundamental aspects of visual style. Existing style transfer methods focus on texture-like components of style, ignoring geometry. We propose deformable style transfer (DST), an optimization-based approach that integrates texture and geometry style transfer. Our method is the first to allow geometry-aware stylization not restricted to any domain and not requiring training sets of matching style/content pairs. We demonstrate our method on a diverse set of content and style images including portraits, animals, objects, scenes, and paintings.

1. Introduction

The goal of style transfer algorithms is to re-render the content of one image using the style of one or several other images. Most modern approaches [7][18][2][8][14][9][20][21] capture a definition of “style” that focuses on color and texture. Art historians and other experts on image creation, however, define style more broadly and almost always consider the shapes and geometric forms present in an artwork as an integral part of its style [13][6]. Shape and form play a vital role in recognizing the distinctive style of many artists in painting (e.g. Picasso, Modigliani, El Greco), sculpture (e.g., Botero or Giacometti), and other forms of media. While the results of style transfer algorithms thus far have been impressive and captured the public’s attention, we propose a method of extending style transfer to better match the geometry of an artist’s style.

Most current methods, due to their reliance on local feature extraction, do not explicitly consider the global properties of shape and geometry and thus, do not capture these important facets of style. Because of this gap in their definition of style, the outputs of these algorithms tend to be easily identified as altered or “filtered” versions of the con-
tent images, rather than novel images created using the content image as references. Our focus in this work is to consider shape and geometry as important markers of style and loosen the constraints on content as a receptive canvas. We achieve this by introducing domain-agnostic geometric deformation of the content image, considered in conjunction with the other style components.

Our proposed method, deformable style transfer (DST), takes two images as input: a content image and a style image which we assume to share a same domain (e.g. both are images of faces or both are images of cars) and have some approximate alignment. This is a general scenario likely to arise in recreational or artistic uses of style transfer, as well as in tools for tasks such as data augmentation. The nature of this task makes learning to transfer style challenging since the variation in unconstrained domains and styles can not be reasonably presumed to be captured in any feasible training set. Therefore, like other style transfer work applied in this setting, we develop an optimization-based method, relying on a pre-trained and fixed feature extractor that is a part of a convolutional network (CNN) trained on ImageNet classification.

Recent works include methods that learn to mimic spatial style, using an explicit model of landmark constellations [25] or a learned deformation model representing the style [23]. These methods require a dataset of images in the chosen style, and work only in a specific domain (often faces, due to their importance in culture and applications). Therefore they are not applicable to our more general scenario. Nonetheless, we compare our results to the results of these methods in their specific domains in Section 5.

In this work we propose the first, to our knowledge, method for incorporating geometry into a one-shot, domain-agnostic style transfer method. The key idea in our approach is to consider a spatial deformation of the content image that would bring it into a spatial alignment with the style image. This deformation is guided by a set of matching keypoints, chosen to maximize the feature similarity between paired keypoints across the two images. After normalizing these keypoints to share the same reference frame, a simple $\ell_2$ loss encourages the style transfer output to be warped in such a way that the keypoints are spatially aligned. The alignment loss associated with the deformation is combined with the more traditional style and content loss terms, and is regularized with a total variation penalty to reduce artefacts due to drastic deformations. This joint, regularized objective simultaneously encourages preserving content, minimizing the style loss, and obtaining the desired deformation, weighing these goals against each other; this objective can be solved using standard iterative techniques.

We evaluate DST on a range of style transfer instances, with images of faces, animals, vehicles, and landscapes. Our results demonstrate spatial deformations in stylized images that are not achieved by existing methods. To summarize the contributions of this paper:

- We expand the spatial variability of style transfer via automatic deformation of images integrated into an optimization-based method, allowing explicit user guidance and control of stylization tradeoffs.
- We demonstrate, for the first time, geometry-aware style transfer in a one-shot scenario. DST works in a domain-agnostic setting, in contrast to previous works that are limited to human portraits.

2. Related Work

Early style transfer methods relied on hand-crafted features and algorithms [10][11][12][5]. Gatys et al. [7] introduced Neural Style Transfer, an optimization-based method that uses CNNs to capture the style of an image, and dramatically improved the state-of-the-art. It represents “style” in terms of the Gram matrix of features extracted from multiple layers of a CNN and “content” as the feature tensors extracted from another set of layers. A stylized output image is iteratively optimized by matching the high-level neural encodings with the content image and the Gram matrices with the style image. Subsequent works improve upon [7] with different complementary schemes, including spatial constraints [22], semantic guidance [3], Markov Random Field prior [18], and other modifications to the objectives and representation [20][9]. Kolkin et al. [17] further improves the results by motivating the optimization to match a non-parametric approximation of the features of the style image while preserving self-similarity to the content image.

Optimization-based methods produce high quality stylizations, but they can be computationally expensive as they require backpropagation at every iteration and gradually change the image, usually at a pixel level, until the desired statistics are matched. To overcome this limitation, model-based neural methods were introduced. These methods optimize a generative model offline, and at test time produce the stylized image with a single forward pass. These methods fall into two families with different tradeoffs relative to optimization based style transfer. Some methods [21] trade flexibility for speed and quality, quickly producing excellent stylizations but only for a predetermined set of styles. Other methods [15][14] trade off quality for speed, allowing for fast transfer of arbitrary styles, but typically produces lower quality outputs than optimization-based style transfer. Each family of method excels in a different regime, and in this work we sacrifice speed for flexibility and quality.

Until recently, style transfer methods could not transfer geometric style and were limited to transferring color and texture. Outside the domain of style transfer, however, there have been many works that apply geometric transformation to an image via automatic warping. Early works required
predicting a set of global transformation parameters or a dense deformation field. Cole et al. [4] enabled fine-grained local warping by proposing a method that takes a sparse set of control points and warps an image with spline interpolation. The introduced warping module is differentiable and thus can be trained as part of an end-to-end system, although [4] requires pre-detected landmarks as input for its face synthesis task.

Several recent works have attempted to combine image warping with neural networks to learn both texture and geometric style of human portraits. CariGAN [19] translates a photo to a caricature by training a Generative Adversarial Network (GAN) that models geometric transformation with manually annotated facial landmarks and another GAN that translates the usual non-geometric style appearances. Face of Art (FoA). [25] trains a neural network model to automatically detect the 68 canonical facial landmarks in artistic portraits and uses them to warp a photo so that the geometry of its face is closer to that of an artistic portrait. WarpGAN [23], on the other hand, adds a warping module to the generator of a GAN and trains it as part of an end-to-end system by optimizing both the location of keypoints and their displacements, using a dataset that contains a caricature and photo pair for each identity.

The main distinction of our work from these efforts is that ours is not limited to human faces (or any other particular domain) and does not require an offline training stage on a specially prepared data set. In terms of methodology, FoA separates transferring geometry and transferring "texture" while we transfer them jointly. WarpGAN also treats shape and texture jointly, but it has to learn the warping module on paired examples from the face caricature domain while we do not. We show in Section 5 that the results of our more general method, even when applied to faces, can be competitive with the results of these two face-specific methods.

On finding correspondences between images, two recent works use CNN-based descriptors to identify matching keypoints between paired images outside the domain of human faces. Fully Convolutional Self-Similarity [16] is a descriptor for dense semantic correspondence that uses local self-similarity to match keypoints among different instances within the same object class. Neural Best Buddies (NBB) [11] is a more general method for finding a set of sparse cross-domain correspondences that leverages the hierarchical encoding of features by pre-trained CNNs. We use a modified NBB in our method, as described in detail in the next section.

3. Geometry Transfer via Correspondences

One path for introducing geometric style transfer is establishing spatial associations between the style and content images. In particular, defining a deformation between the images can bring the content image into (approximate) alignment with the style image. Assuming content and style share an (arbitrary) domain (e.g. both are faces or both are images of vehicles) we can aim to find meaningful spatial correspondences to help define the deformation. The correspondences would specify displacement “targets” derived from the style for points in the content. A thin-plate spline interpolation can extend this set of displacements to a full displacement field specifying how to deform every pixel in the output image.

![Figure 2: Illustration of our method using keypoints taken from FoA (rows 1-3) or generated manually (row 4). Keypoints are overlayed on the content and style images with matching points in the same color. *Output of standard style transfer warped by moving source points to target points. Finding keypoints. If we fix a domain and further assume availability of a training set drawn from the domain, we may be able to learn a domain-specific mechanism for finding salient, meaningful correspondences. This can be done through facial landmark detection [25] or through learning another data-driven detector for relevant points [16,23]. Alternatively, we can expect a user interacting with the style transfer tool to manually select points they consider matching in the two images. If matching points are provided by such approaches, they can be used in our proposed algorithm as we show in Figure 2. However, we are interested in a more general one-shot, domain-agnostic scenario where we may not have access to such points. Hence we use NBB, a generic method for point matching between images.

NBB finds a sparse set of correspondences between two images that could be from different domains or semantic categories. It utilizes the hierarchies of deep features of a
pre-trained CNN, that is, the characteristic that deeper layers extract high-level semantically meaningful and spatially invariant features and shallow layers encode low-level features such as edge and color features. Starting from the deepest layer, NBB searches for pairs of correspondences that are mutual nearest neighbors, filters them based on activation values, and percolates them through the hierarchy to narrow down the search region at each level. At the end of the algorithm, it clusters the set of pixel-level correspondences into $k$ spatial clusters and returns $k$ keypoint pairs.

The keypoint pairs returned by NBB, however, are often not well spatially distributed in spite of the clustering. Specifically, we use a greedy algorithm that selects a keypoint with the highest activation value (calculated by NBB) that is at least 10 pixels away from any already selected keypoint. We select up to 80 keypoint pairs and filter out keypoints with activation values smaller than 1. After the initial selection, we map the keypoints in the style image onto the content image by finding a linear similarity transformation that will minimize the squared distance between the two point clusters \[24\]. We then additionally clean up the selected keypoints by removing keypoint pairs that cross each other, to prevent a discontinuous warp. Finally, we add to narrow down the search region at each level. At the end of the algorithm, it clusters the set of pixel-level correspondences into $k$ spatial clusters and returns $k$ keypoint pairs.

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Figure 3: An image can be spatially deformed by moving a set of source points to a set of target points. Matching keypoints are indicated by color. (a) Content image with all correspondences. (b) Style image with all correspondences. (c) Content image with original NBB keypoints. (d) Style image with original NBB keypoints. (e) Content image with our selected keypoints. (f) Style image with our selected keypoints. (g) Content image with keypoints aligned by just matching the centers. (h) Content image warped with keypoints aligned by a similarity transformation. The lines indicate where the content keypoints (circle source points) should move to (square target points).

3.1. Differentiable Image Warping

We specify an image deformation by a set of source keypoints $P = \{p_1, \ldots, p_k\}$ and the associated 2D displacement vectors $\theta = \{\theta_1, \ldots, \theta_k\}$. The $\theta$s specify for each source keypoint $p_i$ the destination coordinates $p_i + \theta_i$. Following \[23\], we use thin-plate spline interpolation \[4\] to produce a dense flow field from the coordinates of the unwarped image $I$ to a warped image $W(I, \theta)$. This is a closed form procedure which finds parameters $w, v, b$ that minimize $\sum_{i=1}^{k} ||f_\theta(p_i + \theta_i) - p_j||^2$ subject to a curvature constraint. With these parameters, we have the inverse mapping function

$$ f_\theta(q) = \sum_{i=1}^{k} w_i \phi(||q - p_i - \theta_i||) + v^T q + b $$

(1)

where $q$ denotes the location of a pixel in the warped image and $\phi$ is a kernel function which we choose to be $\phi(r) = r^2 \log(r)$. $f_\theta(q)$ gives the inverse mapping of the pixel $q$ in the original image; that is, the pixel coordinates in the unwarped image from which we should derive the color of pixel $q$ in the warped image. The color of each pixel can then be generated through bilinear sampling. This entire warping module is differentiable w.r.t. $\theta$.

4. Spatially Guided Style Transfer

The input to DST consists of a style image $I_s$, a content image $I_c$, and aligned keypoint pairs $P$ (source) and $P'$ (target). Recall that these points may not be influenced with any domain- or category-specific semantics. DST optimizes the stylization parameters (usually the pixels of the output image) $X$ and the deformation parameters $\theta$. The final output is the warped stylized image $W(X, \theta)$.

4.1. Content and Style Loss Terms

Our DST framework can be used with any one-shot, optimization-based style transfer method with a content loss and a style loss. In this work, we demonstrate our framework with two such methods: Gatys et al. \[7\] and Kolkin et al. \[17\], which we will refer to as Gatys and STROTSS, respectively. Each method defines a content loss $L_{\text{content}}(I_c, X)$ and a style loss $L_{\text{style}}(I_s, X)$. These aim to preserve visual content of $I_c$ and visual style of $I_s$, respectively, in the output $X$. Below we briefly summarize the content/style loss for these methods. For more details, we direct the reader to \[7, 17\].

Gatys represents “style” in terms of the Gram matrix of features extracted from multiple layers of a CNN and “content” as the feature tensors extracted from another set of layers. It defines the content loss $l_c$ as the squared-error between the feature representation of the content image and that of the output image. Similarly, it defines the style loss
\[ l_s \text{ as a weighted sum of the squared-error between the Gram matrices of the feature representations of the style image and that of the output image.} \]

STROTSS, inspired by the concept of self-similarity, defines the content loss \( l_c \) as the absolute error between the normalized pairwise cosine distance between feature vectors extracted from the content image and that of the output image. Its style loss \( l_s \) is composed of three terms: the Relaxed Earth Movers Distance (EMD), the moment matching term, and the color matching term. Relaxed EMD helps transfer the structural forms of the content image to the output image. The moment matching term, which aims to match the mean and covariance of the feature vectors in the two images, combats over- or under-saturation. The color matching term, defined as the Relaxed Earth Movers Distance (EMD), the moment matching term, and the color matching term. Relaxed EMD helps transfer the structural forms of the content image to the output image. The moment matching term, which aims to match the mean and covariance of the feature vectors in the two images, combats over- or under-saturation. The color matching term, defined as the Relaxed Earth Movers Distance (EMD), the moment matching term, and the color matching term.

Aggresively minimizing the deformation loss may lead to significant artefacts, due to keypoint match errors, or incompatibility of the content with the style geometry. To avoid these artefacts, we add a regularization term encouraging smooth deformations. Specifically, we use the (anisotropic) total variation norm of the 2D warp field \( f \)

\[ R_{\text{TV}}(f) = \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} \| f_{i+1,j} - f_{i,j} \|_1 + \| f_{i,j+1} - f_{i,j} \|_1. \]  

(4)

This regularization term smooths the warp field by encouraging nearby pixels to move in a similar direction.

### 4.3. Joint Optimization

Putting it all together, the objective function of DST is

\[ L(X, \theta, I_c, I_s, P) = \alpha L_{\text{content}}(I_c, X) + L_{\text{style}}(I_s, W(X, \theta)) + \beta L_{\text{warp}}(P, P', \theta) + \gamma R_{\text{TV}}(f_0), \]

(5)

where \( X \) is the stylized image and \( \theta \) parameterizes the spatial deformation of the content. Hyperparameters \( \alpha \) and \( \beta \) control the relative importance of content preservation and spatial deformation to stylization. Hyperparameter \( \gamma \) controls the amount of regularization on the spatial deformation.

The objective Eq. (5) defines a joint optimization of the stylized image \( X \) and deformation \( \theta \). We can use standard iterative optimization algorithms such as stochastic gradient descent or L-BFGS to minimize Eq. (5) with respect to \( X \) and \( \theta \). The final output of DST is the warped \( W(X, \theta) \).

### 5. Results

We observe that DST often captures the geometric style of the target. One visually striking effect is that the resulting images no longer look like “filtered” versions of the original content, as they often do with traditional style transfer. We show results of deformable style transfer with Gatys and STROTSS in Figures 4 and 5. For a pair of content and style images, we show the output of DST and the output of original Gatys/STROTSS that doesn’t have the spatial deformation capability. To highlight the effect of DST, we also provide the warped content and the Gatys/STROTSS output naively warped with the selected keypoints without any optimization of the deformation.

While, so far as we are aware, we are the first work to allow open domain deformable style transfer, other works have tackled this problem in the domain of human faces. To compare performance, we show results of DST and results of FoA [25] and WarpGAN [23] on the same content-style pairs in Figures 6 and 7. Note that both of these methods require training a model on a dataset of stylized portraits or caricatures, while DST operates with access to only a single content and single style image.

While DST jointly optimizes the geometric and non-geometric style parameters, FoA transfers the geometric
Figure 4: Results of DST with Gatys. *Gatys output warped by moving source points to target points. †Warp learned by DST applied to the content image.

Figure 5: Results of DST with STROTSS. *STROTSS output warped by moving source points to target points. †Warp learned by DST applied to the content image.
style by warping the facial landmarks in the content image to a specific artist’s (e.g. Modigliani) facial landmark pattern (with small variations added) learned by training a model on a dataset of stylized portraits. FoA then separately transfers the texture style with an existing neural style transfer method (e.g. Gatys). For comparisons with DST, since the style images used to produce the outputs in the FoA paper are unavailable, we demonstrate “one-shot FoA” in Figure 6. That is, we assume that we have access to one content image, one style image, and the trained FoA landmark detector. Then we follow FoA’s two-step style transfer and transfer the texture style by an existing neural style transfer method (STROTSS) and transfer the geometric style by warping the output image by moving source points to target points. More details on the FoA stylization can be found in their paper [25].

The biggest difference between WarpGAN and DST is that DST is a one-shot style transfer method that works with a single style image and a single content image. WarpGAN, on the other hand, is trained on a dataset of paired pictures and caricatures, and generates a caricature for an input content image from its learned deformation model. To compare the performance of WarpGAN and DST, we used a content/style image pair from their paper and ran DST. In Figure 7, we compare the outputs of DST and the outputs of WarpGAN taken from their paper. Despite the lack of a learning component, our method produces comparable results to both approaches.

![Figure 6: Comparison of DST and FoA.](image)

### 5.1. Human Evaluation

Evaluating and comparing style transfer quantitatively is challenging, in part because of the subjective nature of aesthetic properties defining style and visual quality, and in part due to the inherent tradeoff between content preservation and stylization [25,17]. Following the intuition developed in those papers, we conducted a human evaluation study using Amazon Mechanical Turk, on a set of 75 diverse style/content pairs. The goal is to study the effect of DST on the stylization/content preservation tradeoff, in comparison to the original style transfer methods. The evaluation was conducted separately for STROTSS and Gatys-based methods. We considered three deformation regimes: low ($\beta = 0.3, \gamma = 75$), medium ($\beta = 0.5, \gamma = 50$), and high ($\beta = 0.7, \gamma = 10$) for STROTSS; low ($\beta = 3, \gamma = 750$), medium ($\beta = 7, \gamma = 100$), and high ($\beta = 15, \gamma = 100$) for Gatys. The effect of changing $\beta$ and $\gamma$ (in the STROTSS setting) is illustrated in Figure 8.

![Figure 7: Comparison of DST and WarpGAN.](image)

![Figure 8: DST outputs with varying $\beta$ and $\gamma$. Image in the upper right corner (low $\beta$, high $\gamma$) has the least deformation, and the image in the bottom left corner (high $\beta$, low $\gamma$) has the most deformation.](image)
scene as image B”, where A referred to the output of style transfer and B to the content image. The users were forced to choose one of four answers: “Yes”, “Yes, with minor errors”, “Yes, with major errors” and “No”. Converting these answers to numerical scores (1 for “No”, 4 for “Yes”) and averaging across content/style pairs and users for a given method, we get a content score between 0 and 4.

To evaluate the effect of the proposed deformable framework, we presented the users with a pair of outputs, one from the original, non-deformable style transfer method (Gatys or STROTSS) and the other from the deformable reformulation of the same method, along with the style image. The order of the first two is randomized. We asked the users to choose which of the two output images better matches the style. The fraction of time a method is preferred in all the comparisons (across methods compared to, users, content/style pairs) gives the style score between 0 and 1; 0.7 means that the method “wins” 70% of all comparisons it was a part of.

Figure 9: Human evaluation results, comparing DST in different deformation regimes with STROTSS (green) and Gatys (blue). DST provides much higher perceived degree of style capture without a significant sacrifice in content preservation.

In total, there were 600 unique content comparisons: 4 questions×75 images for Gatys and likewise for STROTSS. 123 users participated in the content evaluation, and each comparison was evaluated by 9.55 users on average. The standard deviation of the content choice agreement was 0.79. There were in total 450 unique style comparisons: 3 comparisons between each of the 3 deformation regimes×75 images for Gatys and likewise for STROTSS. 103 users participated in the style evaluation, and each comparison was evaluated by 8.76 users on average. For each comparison, 6.47 users agreed in their choice on average.

Results of this human evaluation are shown in Figure 9. Across the deformation regimes (low, medium, high), for both STROTSS and Gatys, DST significantly increases the perceived stylization quality, while only minimally reducing perceived content preservation. Note that some hit to content score can be expected since we in a sense willfully alter the content by deforming it.

Figure 10: Examples of DST failures.

In Figure 10 we show unsuccessful examples of DST where the output image did not deform towards having a similar shape as the style image or deformed only partially. We observe that bad deformations often stem from poorly matching or too sparse set of keypoints. Hence we expect finding better matching and well-distributed keypoints between images and making the method more robust to poor matches will improve the results.

5.2. Implementation Details

To produce the results of deformable style transfer with Gatys, we initialized the output image as the content image resized to have a long side of 256 pixels. During the optimization, we updated the image pixels and the warp parameters 100 times with a learning rate of 1 with L-BFGS. Since the content and style loss terms and the deformation loss terms have vastly different magnitudes, we scaled down the content loss and the style loss by $\frac{1}{50000}$ and $\frac{1}{100000}$, respectively. We also scaled down the warp parameter gradients by $\frac{1}{1000000}$ to update them at a much smaller rate.

To produce Gatys outputs, we used the authors’ code and default settings.

To produce the results of deformable style transfer with STROTSS, we followed the authors’ implementation setting and optimized the output image at multiple scales, starting from a low-resolution image scaled to have a long side of 64 pixels. The output image was initialized as the bottom level of a Laplacian pyramid of the content image added to the mean color of the style image. During the optimization, instead of optimizing the pixels directly, we optimized the Laplacian pyramid of the image for faster convergence, in addition to the spatial deformation parameters $\theta$. At every scale, we used the output at the previous scale as the initial image, use bilinear upsampling to increase the resolution, and halve the content weight $\alpha$ that controls the relative importance of content preservation to stylization. We produced the stylized images in this paper at three scales, starting from content weight $\alpha = 32$. At each scale, we made 350 updates of the parameters using stochastic gradient descent with a learning rate of 0.2.
6. Conclusion

Prior work on style transfer has largely ignored geometry and shape, despite the role these play in the essence of visual style. We present deformable style transfer, a novel approach that combines the traditional texture and color transfer with spatial deformations. Our method incorporates deformation targets, derived from domain-agnostic point matching between content and style images, into the objective of an optimization-based style transfer framework. This is to our knowledge the first effort to develop a domain-agnostic, one-shot method for capturing and transferring geometric aspects of style.

Even in the constrained face domain where existing methods have attempted to capture geometry using tailored mechanisms, we show DST results that are competitive and interesting on par with results from those methods. Still, much remains unexplored, including finding better matching keypoints between images, making the method more robust to poor matches, and improving the parameterization of deformations and the associated loss terms that would avoid undesirable artefacts still visible in many results.

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