

One-shot Detail Retouching with Patch Space Neural Field based Transformation Blending

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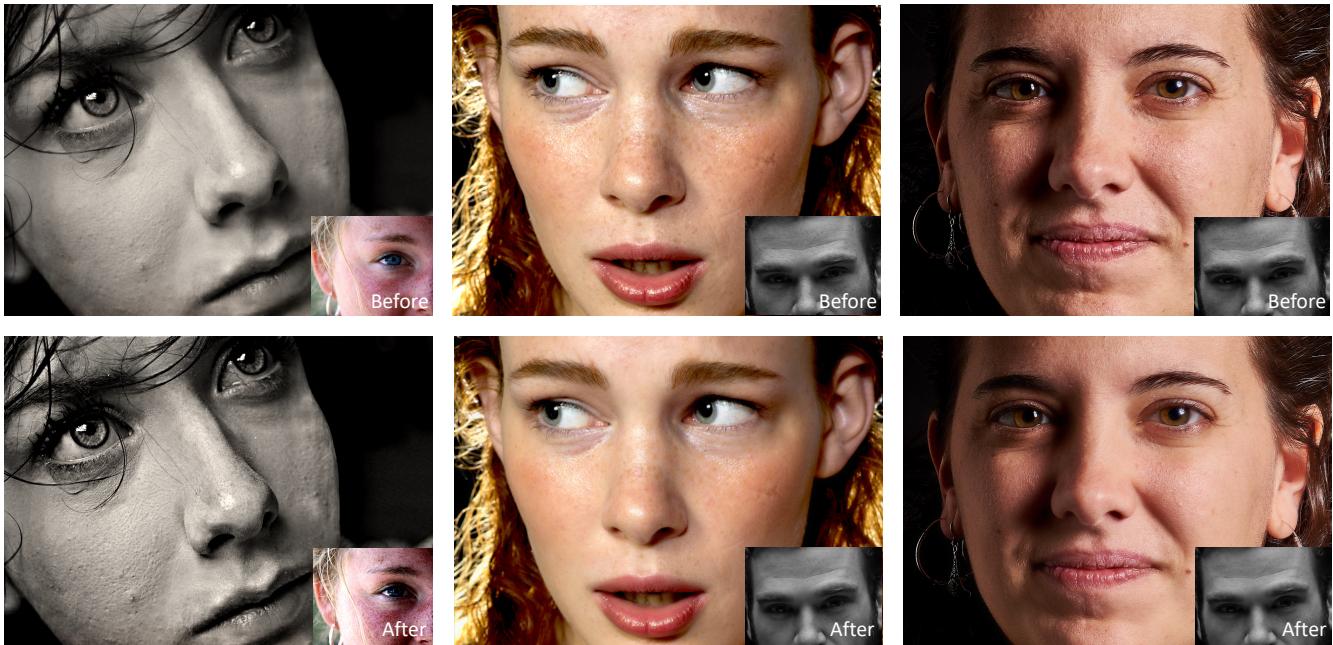


Figure 1: Our technique automatically transfers retouching edits to new images by learning the desired edits from one example before-after pair (insets). The transferred edits accurately capture intricate details such as wrinkles, dark spots, strands of hair, or eyelashes, as shown in the input (top) and retouched (bottom) pairs.

Abstract

Photo retouching is a difficult task for novice users as it requires expert knowledge and advanced tools. Photographers often spend a great deal of time generating high-quality retouched photos with intricate details. In this paper, we introduce a one-shot learning based technique to automatically retouch details of an input image based on just a single pair of before and after example images. Our approach provides accurate and generalizable detail edit transfer to new images. We achieve these by proposing a new representation for image to image maps. Specifically, we propose neural field based transformation blending in the patch space for defining patch to patch transformations for each frequency band. This parametrization of the map with anchor transformations and associated weights, and spatio-spectral localized patches, allows us to capture details well while staying generalizable. We evaluate our technique both on known ground truth filters and artist retouching edits. Our method accurately transfers complex detail retouching edits.

CCS Concepts

- Computing methodologies → Computational photography; Image processing;

1. Introduction

Photo retouching is often desirable as it improves the aesthetic quality of photographs by eliminating imperfections and highlighting subjects of interest. Even with significant progress in digital photography owing to advancements in camera sensors and image processing algorithms, professional retouches via manual adjustments are still needed to achieve a desired look. These artistic edits require considerable manual effort as they consist of global adjustments, such as brightening and contrast enhancement, as well as fine edits applied to local regions. Professionals spend a great deal of time to acquire such retouches, which motivates us to automatically mimic a specific style or type of retouch.

The development of automatic photo retouching tools can be helpful for both novice users and experts as it offers a basis for a professional retouching style. However, automating detailed edits of professionals is challenging as their editing pipelines are spatially varying, context-aware, and highly nonlinear, containing per-pixel adjustments. Recent learning-based methods address this complexity in image-to-image translation by proposing local context-aware methods, such as pixel-adaptive neural network architectures [SGZ*21; LZQ*20], learning parameters of local filters [MMM*20], or multi-stream models to extract global and local features separately [GCB*17]. However, these data-driven methods require a large dataset of matching example image pairs to capture context-aware mappings. Even then, the mappings are sensitive to segmentation errors, unseen semantic regions, and image content [YZW*16].

Motivated by the gap between manual and automatic enhancement, we propose a novel photo retouching technique that can learn global and local adjustments from just a *single example image pair*. Our method thus sidesteps the need for large datasets, which are very difficult to obtain for the detail retouching task. We allow users to choose one example *before-after* pair from which our technique learns the underlying retouching style. Subsequently, we can apply the retouching edit to a different input image.

We assume that example and input images share similar local content. The user can thus decide on the semantics of the example and input photos and the structural changes to be transferred. This is easy for humans and practical for many scenarios, e.g. face edits transferred to faces. Our method then handles the difficult part for humans: capturing how fine details change in an edit and applying those automatically to a new image. The method can further be combined with brushes if fully automatic transfers are not desired.

We achieve these by defining the retouching problem as a map that is given by a *spatio-spectral patch-space neural field based transformation blending*. This representation is primarily inspired by professional detail retouching pipelines as we elaborate on in Section 3. Our map representation is composed of learned patch maps at multiple scales, i.e. frequency bands. Each of these maps is represented by a number of *transformation matrices* blended with *patch-adaptive weights* that are represented as neural fields. We jointly optimize the transformation matrices and corresponding weights for each band. This representation captures edits to details better than any previous techniques while staying generalizable to new images. It is also simple enough to be extended in many different ways in future works.

In summary, there are two main contributions of this work:

- **A novel patch-space image map representation** as a blending of transformation matrices with neural fields.
- **A one-shot detail retouching** algorithm that allows transfer of edits to details to new images based on a single before-after image pair.

2. Related Work

Photo retouching has been explored in image processing and computer vision communities under different domains, such as photo enhancement and image-to-image translation. Below we first discuss recent methods on photo enhancement and then image to image map definitions with the main focus on learning-based methods.

2.1. Digital Photo Enhancement

Global image enhancement. Color and tone transfer has been considered a very effective technique to improve the perceptual quality of photos with pre-defined rules or examples [FPC*14]. Earlier methods typically apply global changes and adjust image statistics [BPCD11; BPD06; PKD05; PKD07; RAGS01; SJMPI0; HLQD20; PLYK18], e.g., mean and standard deviation, without considering image content and local variations [CSG*06]. These methods generally transfer color changes, ignoring edits in fine details. On the other hand, our method learns a mapping per frequency band, capturing transfers even in high frequencies. BYCHKOVSKY, PARIS, CHAN, and DURAND [BPCD11] collected the MIT-Adobe FiveK dataset of 5,000 photographs and their retouched versions by five artists. The authors propose a regression model to learn artists' retouching styles from before-retouched pairs. CHEN, XU, and KOLTUN [CKX17] introduce a fully-convolutional neural network model to learn global image processing operators, such as photographic style, nonlocal dehazing, and pencil drawing. In [HHX*18], a photo retouching pipeline for various post-processing operations is presented, where global adjustment curves are approximated. The authors suggest a deep reinforcement learning approach to model users' edit preferences from a given photo collection.

Nevertheless, global transfers cannot capture local and regional variations in a photo [CSG*06]. They may result in artifacts when the local target regions of the example and input images do not match. We adapt our mappings to each image patch separately, thus accurately capturing local edits in intricate details.

Local context-aware image enhancement. To capture local variations, different methods have been proposed, such as learning local representative color transform [KCKK21], estimating an image-to-illumination mapping with a local feature extractor [WZF*19], local histogram matching [SAH13], segmentation [LRT*14; TJT07], combining and learning pre-defined filters [BLDA11; CWKC18a; HZL*14; OSII18; SHD*18] or with further user guidance [AP10; PR11; TJT05], detection or learning of image semantics and context [GCB*17; HKK12; KLW12; NK17; YZW*14; ZY18], matching [HSGL11], or precise alignment [KMH09; SPDF13].

Furthermore, recent work has focused on learning global and local adjustments via spatially-varying filters [MMM*20; GCB*17; CWKC18b; SGZ*21; LZQ*20]. CHEN, WANG, KAO, and CHUANG [CWKC18b] introduce a global feature extraction layer along with per-pixel adjustments to enhance photos. Bilateral guided joint upsampling [CAWH16] also allows for local and global image processing with an encoder-decoder approach. HDR-Net [GCB*17] learn content-aware, global, and local adjustments via a two-stream convolutional architecture, which extracts local and global features separately to fit local affine transformations and encode the high-level description of images, respectively. Also, MORAN, MARZA, McDONAGH, et al. [MMM*20] propose to learn the parameters of three different spatially local filters to automatically enhance photos.

Local color and tone adjustments might still be insufficient to capture intricate details [BPD06]. Transfer of such details, in general, requires a dense matching [HSGL11] or alignment between example and input images [SPB*14]. To achieve either dense matching or alignment, methods constrain their datasets to contain very similar example and input images, for example, faces with similar characteristics and views [SPB*14]. On the other hand, our method does not require dense correspondences between input and example images but still transfers intricate details. It accurately represents such complex mappings with an operator summing the effects of various transformations multiplied with corresponding patch-adaptive weights, applied at multiple frequency bands.

2.2. Defining Maps between Images

Unsupervised methods. Some learning-based techniques only require one or more examples of retouched photos without their before examples to learn the transfer. Such unsupervised methods capture a certain style by decomposing images into a reflection map and an illumination map [MGY*21], extracting and recomposing band representations of training images [YWF*20], regularizing the unpaired training using the information extracted from the input [JGL*21], segmenting the image into semantic regions [LOQ*16], adaptive image regions [FSDH16], learning semantic and global features [CWKC18a], or utilizing artistic principles and pre-defined filters [ZCC*13; HHX*18]. These methods transfer pre-defined elements of the desired style, or global color and tone. Defining the desired style and the content of the input image that is to remain is challenging. Hence, these methods typically assume prior knowledge of the type of desired adjustments.

Supervised methods. Establishing semantic correspondences between example and input images is needed to achieve meaningful results [YZW*16a; GCB*17]. For a conceivable representation, many supervised transfer methods require a large dataset of well-aligned example image pairs whose contents are very similar [KCKK21; WZF*19]. However, finding or generating such a dataset is difficult as the content of images can change dramatically. Even with such a dataset, segmentation errors, unseen semantic regions, or image content can still change the results significantly [YZW*16a]. In contrast, our method allows users to choose the example pairs from which the desired style is learned, hence sidestepping the challenging semantics problem. Similar content

and structures between example and input images lead to more natural transfers.

Neural image processing. Convolutional neural networks (CNNs) are the de-facto model for image processing with supervised learning methods. While CNNs present state-of-the-art results in computer vision tasks, they are not required [THK*21]. MLP-based architectures have recently gained popularity in image classification and image-to-image translation. CAZENAVETTE and DE GUEVARA [CD21] propose the MLP-Mixer architecture that only uses simple MLP blocks to learn image classification. CAZENAVETTE and DE GUEVARA [CD21] also show an application of an MLP-based architecture for image synthesis. They adapt the MLP-Mixer architecture [THK*21] to perform unpaired image-to-image translation. Similarly, YAN, ZHANG, WANG, et al. [YZW*16a], a closely related work on photo retouching [YZW*16a], introduce a fully-connected network architecture to learn pixel-level color mappings.

Our observation that MLP-based architectures attain competitive results in challenging vision tasks motivated us to explore the use of an MLP block as an alternative to CNNs in the context of photo retouching.

3. Overview and Motivations

Given a pair of example images X and Y , we aim to learn a map M such that $Y = M(X)$. The learned map can then be applied to a new input image I to obtain the retouched output $O = M(I)$.

To define this map, we first decompose the example images into multiple feature maps X_l, Y_l capturing details at different scales, such as coefficients at different bands of a Laplacian pyramid. We then define a separate mapping for each X_l, Y_l pair in the patch space as a blending of transformation matrices with neural field based weights, all learned jointly. We illustrate the overall map representation in Figure 2.

For transfer of edits, the M_l are computed and applied to each patch of the decomposition I_l of an input image I to obtain the corresponding output patch of O_l . The patches are finally placed at their spatial locations and averaged to reconstruct each image O_l , which are summed to get the output image O .

Our motivation behind designing such a map representation with frequency decomposition and transformation blending comes from studying the nature of retouching edits. First, artists often decompose images into different frequency bands to have better control over structural and textural edits to details. Second, image patches of similar content, e.g. skin or hair, are retouched similarly. This means clusters in the patch space translate into clusters in the edits. Our representation leads to a different transformation for each learned patch cluster. Third, these edits are typically applied via brushes for smooth transitions. Our neural field based blending allows for such smooth interpolation, mimicking such brush strokes.

Although we are inspired by professional artist pipelines, we illustrate in the next sections that this new image to image mapping representation can replicate the effect of and transfer edits for many filters.

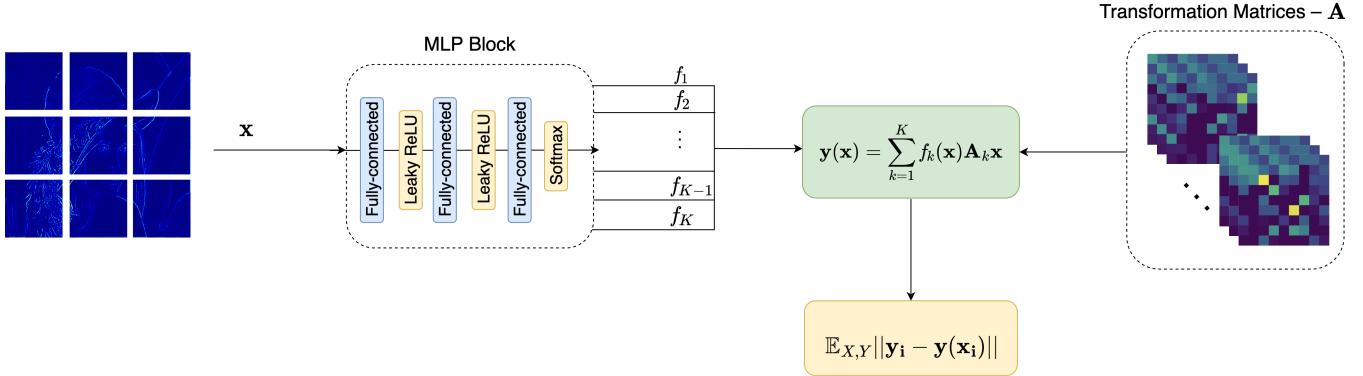


Figure 2: Our technique learns a different mapping per frequency band by decomposing images into their Laplacian bands (The first band of an example before image is shown on the left). At each band, we define a mapping between patches \mathbf{x}_i , \mathbf{y}_i extracted from X_l , Y_l . Our field based method (MLP block) adapts transformations to input patches, providing local context-aware adjustments.

4. One-shot Retouching

4.1. Frequency Decomposition

We first decompose example and input images into different frequency bands by constructing a Laplacian pyramid to capture details at multiple scales. In principle, it is possible to utilize any multiscale image decomposition method. However, we observed that a basic Laplacian pyramid helped us capture more accurate and generalizable results compared to a guided or bilateral pyramid. Therefore, we decompose images by

$$X_l = L_l(X) = \begin{cases} X - G(2) * X & l = 0 \\ G(2^l) * X - G(2^{l+1}) * X & l > 0, \end{cases} \quad (1)$$

where $G(\sigma)$ is the normalized Gaussian kernel, and $*$ denotes convolution. We also store the low-pass filtered image $S(X)$ such that $X = S(X) + \sum_{l=0}^{n_L} L_l(X)$. We then downsample each $L_l(X)$ and $S(X)$ according to the maximum frequency present at that band. This allows us to use small 3×3 patches at each band. In our experiments, we used $n_L = 5$ bands for the Laplacian pyramid.

At test time, we obtain the output image O by applying the learned mappings M_l to the corresponding bands $L_l(I)$ and summing the outputs and the residual of the input image:

$$O = S(I) + \sum_{l=0}^{n_L} M_l(L_l(I)). \quad (2)$$

Since each band is processed independently, we explain the steps of our technique below for two generic images X and Y .

4.2. Transformation Blending

The mapping is defined from patches $\mathbf{x} \in \mathbb{R}^{d_X}$ to $\mathbf{y} \in \mathbb{R}^{d_Y}$ extracted from X and Y , respectively, where we denote the patches with vectors stacking the pixel values and define the patch spaces as \mathbb{R}^{d_X} and \mathbb{R}^{d_Y} . For all results in this work, we work with 3×3 patches and thus $d_X = d_Y = 9$.

Our mapping takes the form of a weighted average of learned transformation matrices.

$$\mathbf{y}(\mathbf{x}) = \sum_{k=1}^K f_k(\mathbf{x}) \mathbf{A}_k \mathbf{x}, \quad (3)$$

where K is the total number of transformation matrices, and f_k are the blending weights defined as neural fields in the patch space. The \mathbf{A}_k 's and f_k 's are jointly learned by minimizing the following loss on patches extracted from the before and after images.

$$\mathbb{E}_{X,Y} ||\mathbf{y}_i - \mathbf{y}(\mathbf{x}_i)|| \quad (4)$$

Each \mathbf{A}_k corresponds to a different group of patches and the $f_k(\mathbf{x})$, represented with MLPs, allow for smooth transition between different groups. The form of f_k 's is relatively simple with three fully-connected layers and nonlinear activation functions applied after each layer. This blending forms a simple but expressive transform as we illustrate in the next section.

5. Discussion and Analysis

Patch size and stride. In order to capture each frequency band at the right level of detail, we do not resize the images $L_l(X)$ and use a small 3×3 patch size (with stride 1). We experimented with larger patch sizes. However, this turned out to be counterproductive for the detail level we target, as details are blurred in larger patches. They also lead to overfitting and are harder to optimize for in general. We used a stride of 1, and hence patches overlap on the image plane. The overlapping patches are averaged while reconstructing the image.

Detail and color modifications. We aim to capture intricate details present in highly detailed retouches and a wide range of image processing operators. Based on the observation that various operators can edit materials in the image space using the luminance

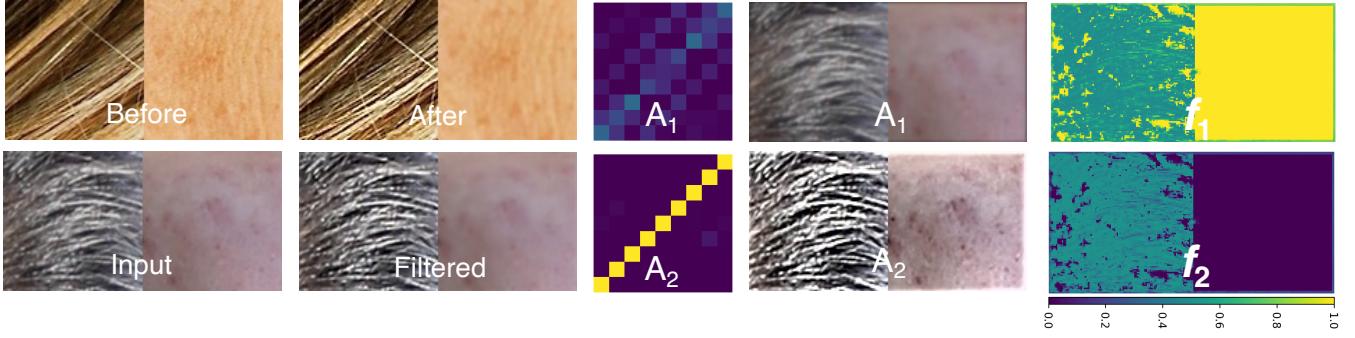


Figure 3: We illustrate that our neural field based method captures the effects of different filters and adapts the patch weights accordingly. Here, we apply a Gaussian filter to a hair texture and unsharp masking to a skin texture and apply learned matrices separately without weight multiplication to observe the effect of each matrix. Matrix A_1 smooths both textures, while A_2 highlights high-frequency components. The weights f_1 and f_2 blend these learned filters and result in a filtered image that shows very similar features with the after image (Matrix and weight results are shown for the first Laplacian band $l = 0$).

component [BBPA15], we focus on learning changes in luminance while preserving the input chrominance channels. In case desired retouching edits also involve color changes, we learn the mapping independently for luminance and chrominance channels to keep the dimensionality of the patch space low. We achieved satisfactory results with mild color changes.

Accuracy and generalizability. Suppose an algorithm produces the desired retouching edits. In that case, we can measure the accuracy of the learned retouching edits by comparing the filtered image to the ground truth obtained by the direct application of the algorithm to the input image. Such comparisons for simple algorithmic filters are shown in Figure 4. The learned filters are generalizable enough to accurately represent the algorithm, resulting in filtered images that are frequency-wise close to the ground truth, as shown by the difference in the Fourier domain. We computed the frequency-level differences by first taking the Fast Fourier Transform (FFT) of the filtered and ground truth images and then their absolute difference in the Fourier domain. The FFT difference figures are scaled to $[1, 10^5]$ for images of dynamic range $[0, 255]$. We also compared our results with state-of-the-art techniques for more complex ground truth filters in Section 6.1.

Evaluation Metrics. To quantitatively compare our method with state-of-the-art methods, we used PSNR and SSIM metrics. This is only possible if the before-after image pair was processed with a known, reproducible operator such as simple image processing filters (see Section 6.1 for details).

Training Details. In all our experiments, we employed an MLP block consisting of three fully-connected layers and nonlinearities applied after each layer. The output size of the last layer is the same as the number of transformation matrices, with each output, i.e., a scalar weight, corresponding to one matrix. To normalize the weights, we chose the last activation function to be Softmax, while for the first two layers, we applied Leaky ReLU nonlinearity. All experiments used the Adam optimizer with a learning rate of 10^{-2} , which exponentially decayed with a decay rate 0.96. We used l_1 loss function in all our experiments.

5.1. Ablation Study

The success of our learned mappings relies on two key components: patch-adaptive retouching and transformation blending. We thus conduct experiments to illustrate the contribution of these design choices.

Transformation Matrices. As the complexity of a retouching style depends on multiple factors, such as artists’ design choices, user preferences, or the artist toolbox, it is challenging to analyze such effects on retouching examples quantitatively. For simple algorithmic filters, such as a Gaussian filter or unsharp masking, $K = 1$ can sufficiently reproduce the filter. In contrast, more complex algorithms, such as a bilateral filter, require more matrices to capture the algorithmic edits accurately (Figure 5). Since retouching edits combine the effect of multiple operators and are highly non-linear, we empirically chose $K = 256$ for our retouching examples.

Patch-adaptive Transformation Blending. We also compare our patch-adaptive mapping to an MLP regressor which directly learns the mapping from the decomposition of example before-after images. The MLP regressor follows a similar architecture as our MLP block (Figure 2), with the only difference being the last activation function. We use Leaky ReLU here, since the Softmax function outputs pseudo-probabilities and is unsuitable for regression. Ignoring the spatially-varying structure of the mapping and directly regressing the model for each frequency band, limits the expressiveness of the model. This results in blurry results as shown in Figure 6 because such a model cannot capture edits in intricate details, such as highlights around eyes and hair or brightening of the skin. We also tried increasing the capacity of the MLP regressor but did not observe much improvement in performance.

6. Results

We tested our technique on a diverse range of before-after pairs, including face images from the FFHQ dataset [KLA18] but not limited. We focus on human portraits and face retouching in our exper-

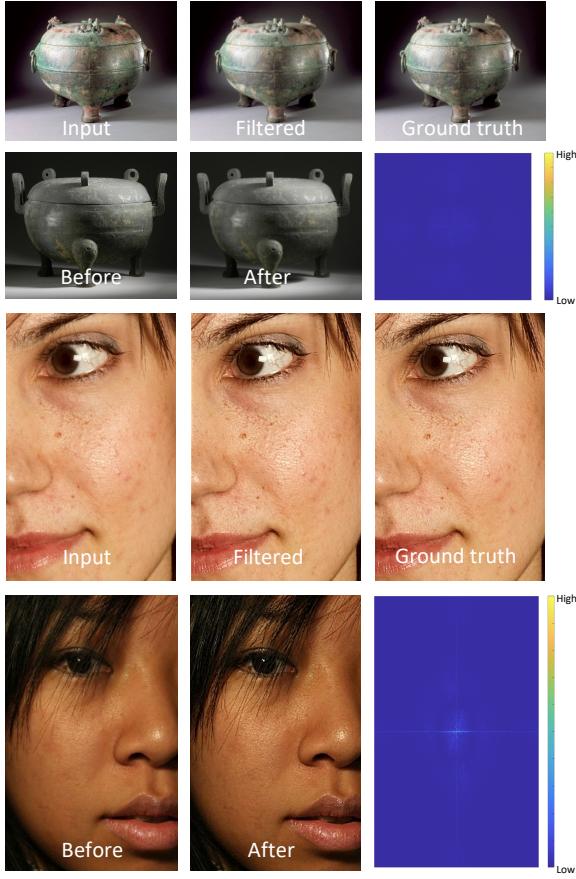


Figure 4: Our algorithm accurately represents simple algorithmic filters, such as Gaussian (top) and unsharp masking (bottom), learned from a before-after pair. The filtered images obtained by applying the learned mapping to the input images have very small frequency-wise difference to the ground truth images obtained by the direct application of the algorithm. Here, we show the frequency-wise difference in Fourier domain (PSNRs: 45.59 and 39.79 dB, respectively.)

iments as they are arguably the most common and prioritized types of photos for retouching. We illustrate that our technique provides visually pleasing results for various retouching edits and accurately captures image processing filters.

Human faces pose a particular challenge for our technique. However, our model can still capture highly nonlinear retouching edits and generalizes well to different types of faces, view directions, and lighting conditions, as illustrated in Figures 1, 7, and 10, as well as Figures 4 and 8.

The example pairs in Figures 1, 8, 10 and 7 were generated by brushing onto the skin with artist created brushes, eye sharpening (last pair in Figure 10), and further brightness/contrast adjustments. These brushes first decompose the skin into a detail and base layer, typically with frequency decomposition, alter the detail layer and blend it with the base layer. They differ in how (1) they decompose

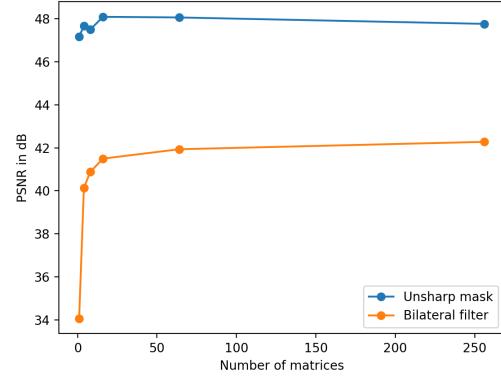


Figure 5: The higher the complexity of the learned algorithm, the more transformation matrices our technique requires to capture the effects on local regions accurately. While $K = 1$ can be sufficient for our model to capture unsharp masking, it requires more matrices to represent bilateral filtering precisely.



Figure 6: An MLP regressor cannot capture local edits, resulting in inaccurate retouching edits, such as blurring on the skin or around the eyes. Images in each row have the following order: input, filtered with our map design, filtered with an MLP regressor.

the skin into the layers, i.e., what frequencies are in each layer, and (2) they edit and blend each layer with different opacity values. This variation creates retouching nuances, as shown in Figure 8. Our method can still accurately capture such slight differences in styles.

In all our experiments, intricate details of the desired retouching, such as small-scale skin texture, eye, and facial hair details, and global features, such as overall lighting and tone, are accurately reproduced. It is interesting to observe that the *glamour* implied by, e.g., the example retouchings in Figures 7, and 10 (last example pair) is transferred from the example pair very accurately without



Figure 7: The reproduced retouching style from the example pair (shown as small images) improves skin texture without affecting fine details, such as eyes and hair, for a visually improved portrait. Moreover, our technique generalizes well to faces with different lighting conditions and accurately reproduces the example retouching style.



Figure 8: Our patch-adaptive technique can precisely reproduce nuances of retouching styles. The top and bottom rows show the example pairs and their corresponding retouched photos, respectively.

causing an artificial look. Also, such a learned retouching generalizes well to faces with different view directions and lighting conditions, as illustrated in Figure 7 and 10. Zooming into the skin reveals that pores and wrinkles are minimized, and the blemishes and discoloring of the skin are eliminated. At the same time, depending on the retouching edit, eyes are more highlighted or preserved, and delicate features such as hair are preserved well (Figures 7, 10).

In summary, our technique efficiently edits such intricate details, due to the significantly distinct local statistics of the skin at multiple scales, without affecting overlaying structures thanks to its spatially-varying nature and frequency decomposition.

6.1. Comparison with the state-of-the-art

Although there are various works related to automatic photo enhancement, to the best of our knowledge, none of them works with a single example pair for detail retouching. We thus compare our results with state-of-the-art automatic image-to-image translation methods, namely HDRNet [GCB*17], ASAPNet generator [SGZ*21], and Deep edge-aware filters [XYR*15]. Such methods usually require a large dataset to accurately capture the desired edits and hence cannot generalize well to new input images when trained with a single example pair.

To compare the results qualitatively, we trained each network with *before-after* pairs resized to 256×256 pixels. Both HDRNet and Deep edge-aware filters were trained with images of RGB

channels. Similar to our method, ASAPNet is also a spatially-adaptive network. However, it is instead designed to hallucinate new details. Therefore, we similarly trained their generator model to ours with $L1$ loss, removing the discriminator and positional encoding. We observed that bilinear downsampling in their model causes checkerboard artifacts. Hence, we also removed this operator and learned an MLP per pixel, which caused the model to be highly complex with too many parameters.

Qualitative comparison. Figure 9 shows retouching results on images of different skin colors, poses, and lighting conditions. HDRNet overfits to the colors of the before image, causing unnatural color transfers. Also, as shown in the first row, it cannot capture changes in details, such as the removal of wrinkles on the forehead. Despite its complex architecture, the ASAPNet generator cannot fully capture local edits, leading to blurry effects (first row in Figure 9). It also overfits to the example pair, not generalizing well to input images (third row). Deep edge-aware filters can provide more visually pleasing results comparable with ours. However, they run another optimizer for image reconstruction from their gradient results, which introduces a bias in low-frequency components.

Quantitative comparison. For a fair comparison with contemporary methods, we trained each network with the same example pair of face images processed by four algorithmic filters: Gaussian, unsharp masking, Bilateral, and local Laplacian filters. As local



Figure 9: Qualitative comparisons with existing methods. The first two rows were obtained by training the example pair in the third row of Figure 10, and the last two rows were obtained with the example pair in the first row of Figure 10.

Comparison results (PSNR in dB / SSIM)				
Filter Type	HDRNet	ASAPNet Generator	Deep Edge-aware	Ours
Gaussian	31.77 / 0.875	40.33 / 0.986	35.95 / 0.970	41.30 / 0.986
Unsharp Mask	32.70 / 0.915	33.14 / 0.910	31.32 / 0.896	34.07 / 0.920
Bilateral Filter	34.35 / 0.907	37.40 / 0.972	33.90 / 0.949	38.93 / 0.971
Local Laplacian ($\alpha = 2, \sigma = 0.2$)	29.71 / 0.848	33.42 / 0.948	32.09 / 0.941	33.54 / 0.951
Local Laplacian ($\alpha = 0.5, \sigma = 0.1$)	34.37 / 0.922	34.72 / 0.926	31.54 / 0.89	34.75 / 0.921
#Weights	0.48 M	1.1 M	-	0.16 M

Table 1: Quantitative performance comparison for the reproduction of various image processing filters

Laplacian filters can perform a wide range of edge-aware operations, we apply two different versions of the filter, one for smoothing ($\alpha = 2, \sigma = 0.2$) and one for enhancing details ($\alpha = 0.7, \sigma = 0.4$).

We tested the models with 100 face images, randomly sampled from MIT-Adobe FiveK [BPCD11], and evaluated the models using average PSNR and SSIM values. To generate the ground truths

of the input images, we applied the same filter as applied to the before example image to obtain the after image. We trained each model in Y-channel after converting RGB images to their YCbCr versions and evaluated the results for Y-channel images. We duplicated the Y-channel in case the model requires three-channel images.

Our method can outperform HDRNet and Deep edge-aware fil-

ters for all considered filters in terms of both PSNR and SSIM values. Similarly, it outperforms ASAPNet generator [SGZ*21] according to the PSNR metric and shows competitive results in terms of SSIM. Our model achieves these results with a significantly lower parameter count, as shown in Table 1. Our technique proves more generalizable in learning different image processing operators from a single example pair with a lower model capacity.

6.2. Limitations and Future Work

A primary limitation of our work is its dependence on local patches at different scales, disregarding their spatial location with respect to each other. Hence, our method is most useful when details are retouched based on local and repeated characteristics of an image. Non-repeating spatially-dependent strong effects, e.g., portrait stylizations with spatially varying lighting [SPB*14], cannot be handled by the current technique. However, extending it to spatially adaptive transfer is easy, as we process each patch independently, which we leave as future work.

Since we rely on a single example image pair, transferring filters applied to arbitrary images [YZW*14] is out of the scope of our current work. We require example and input images to have similar semantics for predictable transfer. Extending the technique to more than one pair of example images will require us to have consistently retouched details on all those example images. Finally, we require the example before and after images to be perfectly aligned. This requirement can be alleviated by incorporating an ICP [BM92]-like approach into the optimization in Section 4.

Although our main focus in this paper is on artist-driven subjective retouching edits, the proposed technique is general. It can be applied to summarize and transfer arbitrary image transformations, significantly where details are modified. We are thus planning to investigate our technique further as a general transfer method for image-to-image translation. The patch-adaptive nature of our mappings makes them amenable to analysis.

7. Conclusions

We presented a neural field based technique for example-based automatic retouching of images. By formulating the transfer problem in the patch space, we showed that blending multiple transformation matrices with patch-adaptive weights can be utilized to learn an accurate and generalizable map. This allowed us to use images of different scenes, people, views, and environmental conditions as the example pair and input. We illustrated the technique’s utility on various retouching examples. We believe that our technique-based image map representation can be helpful in many other image processing tasks.

Acknowledgements

We thank Param Hanji for valuable feedback on the manuscript. We also thank Dr. Mauricio Delbracio for useful discussions.

This work was supported by a UKRI Future Leaders Fellowship [grant number G104084].

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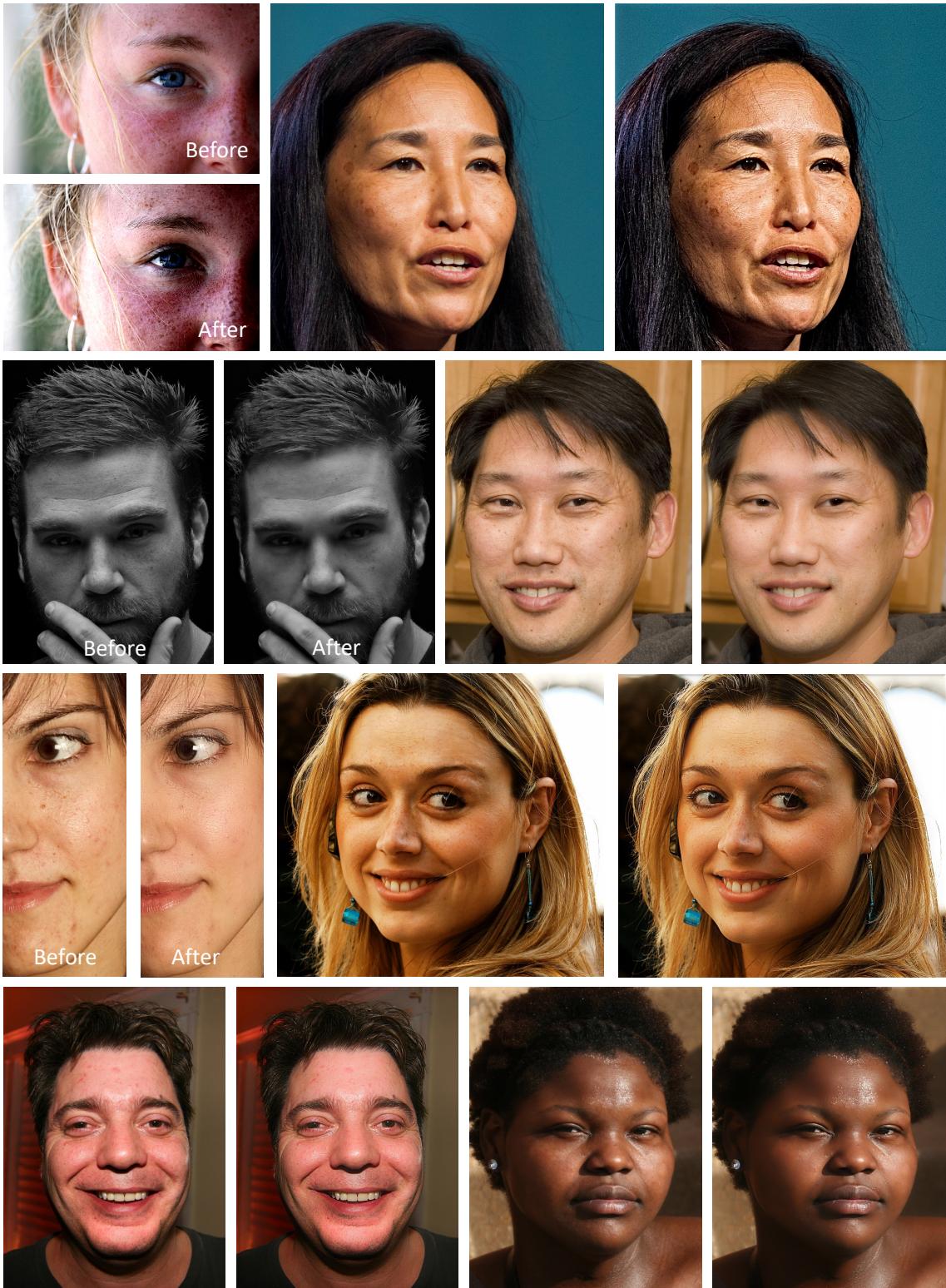


Figure 10: Retouches reproduced by our algorithm based on single before-after pairs.

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