Photorealistic Video Style Transfer
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1 Introduction
It entails huge amount of time for a professional artist to re-draw an image manually in a particular artistic style. Far more difficult than this is to accomplish this task for a certain video sequence. Nowadays, the advancement in computing technology has revolutionized many aspects of problem solving. In this project we show how to transfer the style from one photorealistic image to a whole video sequence using deep learning. We make use of two of the most prominent works in style transfer which are as follows:

- Ruder et al. [1] - They portrayed a technique which enables to transfer the style from an artistic image (for instance, a painting) to a complete video sequence. Basically, they extended the previous research by Gatys et al. [2] and Johnson et al. [3] to complete video sequences. Their technique transferred the style captured from an artistic image to the entire video. They deduced that independently processing each frame of the video leads to glimmering and untrue irregularities. This was because the solution of the style transfer task was not steady. With the goal of stabilizing the transfer process and preserving an even changeover between independent video frames, they established a temporal constraint that penalized divergence between two consecutive frames. The temporal constraint introduced by them considered the optical flow present in the original video and in place of inflicting a penalty to the deviations from the previous frame, they applied penalty to the divergence along the trajectories of points. The regions which were not concealed and the boundaries of the motion were eliminated from the penalizer. This imparted the liberty to rerender the unconcealed regions and deformed motion boundaries while conserving the look of the rest of the image.

- Luan et al. [4] - They portrayed a deep-learning technique particularly for style transfer in photorealistic images that was able to control a huge diversity of image content while reliably transplanting the style from reference image. Their cardinal contribution was to impel the process of conversion from the input to the output to be locally affine in colorspace, and to depict this restriction as a custom and completely differentiable loss function (which they call as energy term). They proved that their technique successfully subdues the deformations and produces convincing photorealistic style transfers in a wide variety of outlines, including transfer of the parameters like time of day, season, weather and artistic edits. They utilised the Matting Laplacian to restrict the conversion from the input to the output to be locally affine in colorspace. Furthermore, they used semantic segmentation which instigated more meaningful style transfer.

In the implementation of this project we merge the loss functions used by Luan et al. [4] and Ruder et al. [1] to get a cumulative loss function used for optimizing the style transimmission from photorealistic image to video.

2 Loss Functions
- Ruder et al. [1] - The main aim is to render a stylized image \( x \) describing the style of an image \( a \) and the content of an image \( p \). Gatys et al. [2] devised an energy minimization problem consisting of a content loss and a style loss. The central concept is that attributes extracted by a convolutional neural network contain details about the content of the image, whereas the correlations of these attributes store the details related to style. Johnson et al. [3] depicted that in lieu of solving an optimization problem, a faster technique would be to straightaway learn a function for style transfer for one specific style mapping through an input image to its corresponding stylized image. Convolutional Neural Network could be used to express such a function using the parameters \( w \). The expected loss can be minimized by training the network over a random image. Ruder et al. proposed two losses by considering the approaches proposed by Gatys and Johnson:
• In both of the above short and long term losses, \( L_{\text{content}} \) and \( L_{\text{style}} \) are defined by Gatys et al. [2].
• Luan et al. [4] - Apart from the \( L_{\text{content}} \) and \( L_{\text{style}} \) described above, they explained how to regularize these losses to preserve the structure of the input image and generate outputs that are photorealistic. Rather than directly imposing this constraint on the output image they applied it on the transformation which has been applied to the input image. Describing the space of photorealistic images is a problem that remains unsolved.
• One limitation of the style loss presented by Gatys et al. [2] was that the Gram matrix is computed over the entire image. A precise distribution of neural responses is completely encoded by Gram matrix as it computes its vector components up till an isometry. However, this can cause spillovers as that limits its power to adapt to variations in semantic context. The solution to this problem was that keeping the set of labels constant (i.e. sky, buildings, water, etc.) we can render image segmentation masks for both the input as well as reference images. This solution was similar to Neural Doodle [6] and semantic segmentation method [7]. Hence, they included the masks to the input image as supplementary channels and by appending the segmentation channels they built up the neural style algorithm. Finally that style loss was updated as follows

\[
Loss_{\text{content}}(f^{(i)}, a, x^{(i)}) = \alpha Loss_{\text{content}}(f^{(i)}, x^{(i)}) + \beta Loss_{\text{style}}(a, x^{(i)}) + \gamma Loss_{\text{temporal}}(x^{(i)}, w^{i}_{t-1}(x^{(i)}-1), c^{i-1,t})
\]

where \( i \) denotes the index of a frame, \( f^{(i)} \) is the \( i^{th} \) frame of the video, \( a \) is the style image, \( x^{(i)} \) is the \( i^{th} \) stylized frame to be generated, \( c \) denotes weight, \( w \) is the function that warps a given frame using the optical flow field that was estimated between two images.

- Short term loss:

\[
Loss_{\text{shortterm}}(f^{(i)}, a, x^{(i)}) = \alpha Loss_{\text{content}}(f^{(i)}, x^{(i)})
\]

- Long term loss:

\[
Loss_{\text{longterm}}(f^{(i)}, a, x^{(i)}) = \alpha Loss_{\text{content}}(f^{(i)}, x^{(i)}) + \beta Loss_{\text{style}}(a, x^{(i)}) + \gamma \sum_{j \in J, (i-j) \geq 1} Loss_{\text{temporal}}(x^{(i)}, w^{i}_{t-j}(x^{(i)}-j), c^{i-j,t}_{(i-j)})
\]

all other notations are same as defined previously, \( J \) denote the set of indices each frame should take into account relative to the frame number, e.g., with \( J = 1, 2, 4 \), frame \( i \) takes frames \( i-1, i-2, \) and \( i-4 \) into account.

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3 Merging and Challenges

To implement the style transfer from one photorealistic image to a whole video sequence using deep learning we merged the concepts from both the works i.e from Ruder et al. [1] and Luan et al. [4]. Precisely, we accomplished this in two parts:

- We integrate the the loss functions used in style transfer in photorealistic images [4] to the loss functions used in artistic style transfer in videos [1].
- The semantic segmentation used by Luan et al. [4] was done manually. We use the semantic segmentation technique proposed by Zhou et al. [7]. This helped us to automate the task of segmentation which can then be used in computing the overall loss for the videos.

4 Results

5 References

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