Neural Image Style Transfer Using Modified Histogram Matching

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Abstract: Neural Image Style Transfer is an algorithm which was first introduced in 2016 for transferring the style of an image using a CNN. Over the years, a large portion of the research has been devoted in balancing the trade-off between time taken by the algorithm to process the images and the quality of the results generated. In addition, the application of traditional image processing algorithms has been limited. In this paper, we aim to introduce a modification to the traditional method by utilizing a localized histogram matching algorithm combined with Contrast Limited Adaptive Histogram Equalization (CLAHE). The results show that the quality of style transferred and the colour of images obtained by this method is much better than the traditional method for the same number of iterations.

Keywords: Neural Style Transfer, Histogram Matching, CLAHE, Laplacian operator, Gaussian Operator, Marr-Hildreth Function, CNN, VGG-19 model.

1. Introduction

Neural style transfer refers to the process of transferring style from an image, typically a painting or a work of art, to a *content* image (Gatys et al., 2016a). This process is carried out by the usage of pre-trained CNN by exploiting the feature activations to recombine the *content* of a given photo and the *style* of a given artwork. It is further defined as the output image being iteratively optimised *"with the objective of matching desired CNN feature distributions, which involves both the photo's content information and artwork's style information"* (Jing et al., 2019).

Histogram equalization is an image processing algorithm which transforms the intensity histogram into a uniformly distributed histogram while enhancing the global contrast of the image as well as introducing unwanted artifacts (Walt et al., 2014). For colour images in RGB or BGR format, the image can be first transformed into HSV or CIELAB space, followed by equalizing the V or L channel, respectively, and finally converting the image back to its original format. To address the artifacts and to better capture the local aspects of the image, improvements such as Adaptive Histogram Equalization and Contrast Limited Adaptive Histogram Equalization have been used. Histogram matching is an algorithm used to transform an image such that its histogram matches a specified histogram. This transformation is obtained by first equalizing the histograms of both the source and target image (Tu and Dong, 2013).

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A large amount of the work performed in the domain of Neural Style Transfer has been focused on ways to speed up the time taken to obtain good quality output images. There are approaches which have succeeded in increasing the speed but the number of styles available are limited (Johnson et al., 2016; Ulyanov et al., 2016). Another area of research has been the development of various loss functions for representing the style loss. Even though the results of such efforts generate better quality images, the speed of the overall process remains slow, which hinders its ability to be used for practical applications. In addition, it was observed that the application of histogram matching techniques has been limited. Histogram matching has been used for texture modelling and to retain the colour distribution of the content image, therefore transferring the style only (Gatys et al., 2016b). In addition, a different approach used histogram matching at each layer of the CNN network (Risser et al., 2017) to obtain statistical information but the drawback is the increased computational complexity. However, these algorithms are applied to the image(s) on the *global* scale. The disadvantage of this method is that it can result in introduction of artifacts and distortions if the target image is either too sparse or too concentrated. This is most commonly observed in images which have large amounts of a single colour. Finally, the input image at the start of the process is not paid much attention to, primarily because of the reliance on the loss functions to ensure that the output images produced are of almost the same quality, irrespective of the initialization of the input image. This paper addresses the issues caused by using histogram matching on a global scale by using a localized histogram matching algorithm on the content image. This processed image is used as the input image, and it is shown that output images generated using fewer iterations are comparable and for some instances, are better than the output images generated by the traditional algorithm run for higher iterations.

2. Literature Survey

The loss function computes the content and style losses. Given a content image C and style image S, the goal of the program is to minimise the loss, *J*,generated by the sum of difference between

$$J = alpha * L_C + beta * L_S \tag{1}$$

The difference generated by content loss L_C and style loss L_S is adjusted by varying the values of alpha and beta. L_C ensures that the features of the output image remain similar to the content image and L_S calculates the Gram-matrix statistical information for transferring the style. The constants alpha and beta are used to vary which loss will be weighted more and hence will be minimized more than the other. Similar to other papers, in this work the style loss, called beta, is given greater weightage than the content loss, alpha, to ensure that the output image imbibes the desired style while retaining some distinct features of the content image. Further, it has been researched that the Gram matrices calculated for each feature level can be seen as minimizing a specific Maximum Mean Discrepancy (Li et al., 2017a).

To overcome the limitations of speed in the original procedure, the usage of pre-trained feed forwards networks was proposed for image transformation tasks using perceptual loss functions and by using downsampling and upsampling instead of pooling layers (Johnson et al., 2016). A feed forward network where a generator network is trained on a particular texture using the feedback given by the descriptor network has also been suggested (Ulyanov et al., 2016). In addition, generative adversarial network (Goodfellow et al., 2014) has been used to capture feature statistics of Markovian patches and this model overcomes the run-time costs of the iterative approach (Li and Wand, 2016). These methods, though fast in practice, suffer from limitations on the number of styles which can be used as for each style a new network has to be trained.

The drawback of a single style network was addressed by using a noise vector and a selection unit, the former intended to enable diverse samples being generated and the latter being one hot vector intended to allow the user to control the styles used (Li et al., 2017b). In addition, a collection of multiple mid-level convolutional feature representations called filter banks (also known as StyleBanks) was developed, where each filter bank represents one style only (Chen et al., 2017). Further, a 2D layer for embedding style called CoMatch Layer which learns to match the feature statistics of the Gram Matrix was introduced (Zhang and Dana, 2018), with the drawback being that the different styles mixed amongst themselves. Also, the combination of different styles was also achieved by the usage of conditional instance normalization (Dumoulin et al., 2017). However, the number of styles in these papers are limited to a fixed number, thereby not resolving the lack of generality in feed forward networks.

The modification or the usage of new loss functions included the proposal of usage of Laplacian loss for preserving the detail structures of the content image and preventing unwanted artifacts (Li et al., 2017c). In addition, histogram loss at each feature level was calculated by utilizing histogram matching and then subsequently calculating the loss function as the Frobenius norm between the original and the remapped histograms at each feature level (Risser et al., 2017) though provided more stable style transfer it increased the computation time for the calculation of histogram losses at each feature level.

Taking cognizance of the limitations of feed forward networks, conditional instance normalization was modified in an approach known as Adaptive Instance Normalization (AdaIN) which aligns the channel wise mean and variance of content image *x* to style image *y* (Huang and Belongie, 2017) and it provided one of the first real-time arbitrary style transfer algorithms.

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The limitation of AdaIN layer has been addressed by the usage of histogram-matched instance normalization (HdaIN) which allows more statistics to be considered in addition to mean and variance obtained from AdaIN layer (Peng and Zhu, 2019).

Differing from the typical pixel-level loss functions such as Gram matrix, the usage of a ‘Style Swap’ has been proposed in which the feature activations of the content and style images at different layers and then computed the closest matching style patch for each content patch (Chen and Schmidt, 2016). After the spatial replacement or swap of the content patch with the style patch, the image is reconstructed by “averaging overlapping areas that may have different values” due to the swap. However, since the image is reconstructed to represent the content image, the style of the output image is not captured effectively even though content features are preserved.

Histogram equalization was experimented with by applying it prior to extraction and matching of image feature points and it was observed that the quality of results improved (Tu and Dong, 2013). To deal with the problem of artifacts, Adaptive Histogram Equalization (AHE) was used to compute local histograms but it had a tendency to amplify the noise. Therefore, a variant known as Contrast Limited Adaptive Histogram Equalization (CLAHE) (Zuiderveld, 1994) was used which does not suffer from the aforementioned problem of AHE. In addition, the usage of a Gaussian filter has been suggested for histogram equalization (Yang and Wu, 2010) with the first step being that the input image is convolved by a Gaussian filter with optimum parameters. Further, they divided the original histogram into different areas by the valley values of the image histogram. The drawback of the latter method is the large storage required as well as the increased computing complexity due to the multiple intermediate steps (Mallikeswari and Sripriya, 2018).

Histogram matching also witnesses issues with regards to unwanted artifacts. An algorithm which works independently of the source image and keeps the image distortion to a minimum has been proposed (Bevilacqua and Azzari, 2007) which uses a sparse matrix for storing the one-to-many mapping as opposed to the conventional point mapping. The problem of histogram matching with dark images has been attempted to be resolved by first transforming the original image by dividing the image in several segments and modifying the histogram of each segment to have desired characteristics followed by matching this transformed image with the target image (Hussain et al., 2018).

3. Methodology

The algorithm typically optimises two functions, namely, the content loss and the style loss. The content loss function is calculated by choosing a layer of the CNN, with the CNN usually being a VGG-16 or VGG-19 model. Then, both the content and the output images of the same dimensions are fed to the network and feature activations generated by both the images at that particular layer are obtained. The images can be understood as matrices, which are then *unrolled* into a single vector and the summation of the squared differences between the two vectors are calculated. This quantity is then divided by a factor that differs across many implementations.

In this paper, the content, style and output image are referred to as C_i, S_i, and O_i, respectively, where the subscript *i* is used for denoting the layer of the VGG-19 model. Also, the content and style loss are known as L_C and L_S. The gram matrix at layer *i* for style and output image is defined as $G(S_i)$ and $G(O_i)$. Finally, to smoothen the output image, the total variation loss *TVL* is also considered. This loss is defined by calculation of the difference in neighbour pixel values of the output image. The equations are defined as follows:

$G(M) = M * M^T$ where M refers to an invertible matrix (2)

$L_C = (C_i - O_i)^2 / 2$ where *i* is set to ‘block4_conv1’ in this paper (3)

$L_S = G(S_i) - G(O_i)$ where *i* goes from ‘block1_conv1’ to ‘block5_conv1’ (4)

$J = alpha * L_C + beta * L_S + TVL$ where alpha and beta are 10^{-5} and 10^{-2}, respectively (5)

After the computation of the losses, they are added together and then iteratively optimised to minimise the said total in Eq. (5). Since the application of neural networks can be understood as a black box function, i.e., a complex mathematical function which adjusts itself, the application of traditional image processing methods in neural style transfer has been limited. In this paper, a technique known as histogram matching has been used to improve the results obtained.

The proposed method focuses on the improvement of results by image processing of the initial input image in Neural Style Transfer where the size of images is considered to be 512x512x3. This is carried out by performing local histogram matching, followed by blending each local block/part using Laplacian transforms (Adelson et al., 1984) to prevent distinct lines at the border where blocks of images were joined together. Finally, the CLAHE algorithm is applied to improve the contrast damaged due to image blending.

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The content and style images are split into four patches (or blocks), each of size 256x256x3. The image M after split can be referred to as $M_{i\,j}$, where *i* refers to the row and *j* refers to the column. Thus, the patches of content image C after split will be matched with the corresponding patches of style image S. The advantage of this approach is that the local aspects of the style image will be captured better when smaller histograms are to be equalized and matched instead of a global histogram as shown in Table 1. The matching process is applied by using the *skimage* library in Python (Walt et al., 2014). After the matching is done, the patches are concatenated together and we observe that there are distinctly visible lines at the borders where the patches were concatenated together.

Table 1. An illustration of local histogram matching using *A Starry Night* by Van Gogh and a version of *Scent of Rain* by Leonid Afremov. It can be observed that the dominant colour of each patch is captured in the transformed image

Type	Original	Patch [0,0]	Patch [0,1]	Patch [1,0]	Patch [1,1]
Content Image					
Style Image					
Local Histogram Matched Image					

It is observed in Figure 1 that the local colour of each patch is captured better than the typical global histogram matching process. However, as mentioned earlier, there are distinct differences at the border present. To address this problem, this paper utilizes Laplacian transforms to perform pyramid blending (Adelson et al., 1984. Instead of using the typical Laplacian operator to directly build the pyramid, the operator is used after the application of Gaussian smoothing which is an approach known as Marr-Hildreth algorithm (Marr and Hildreth, 1980). Also, the Gaussian operator has to be used since the Laplacian operator *"contains no smoothing and will again respond to noise, more so than a first-order operator since it is differentiation of a higher order"* (Nixon and Aguado, 2002, p. 122). However, this process not only causes some information to be lost, but also affects the contrast. CLAHE is used to address the latter whereas the iterative process of backpropagation is relied upon to deal with the former. Before applying CLAHE, the RGB image is first converted to CIELAB space and CLAHE is applied on the Perceptual Lightness (L) channel followed by converting the image back to RGB colour space. In this paper, OpenCVs implementation of CLAHE has been used. It requires two parameters to be specified, known as the *clipLimit (8.0)* and *gridsize (8,8).* The former is used to set the threshold of the pixels in histogram of the local region, clipping those values which exceed the defined limit, whereas *gridsize* is used for defining the size of each local grid. The output is shown in Figure 2.

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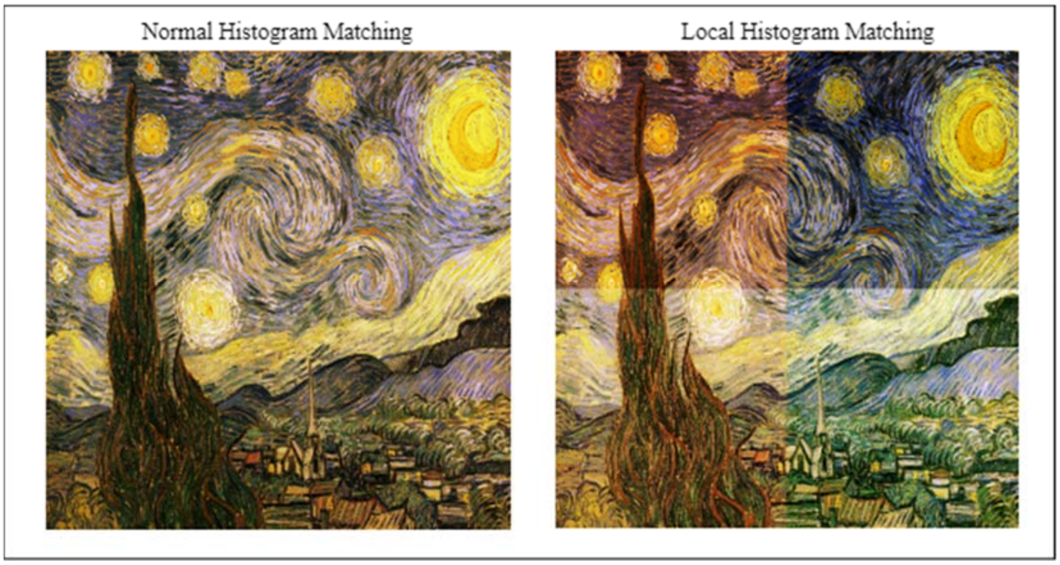

Figure 1. The figure compares histogram matching applied globally with the localized application

Figure 2. The transformation of the image obtained after local histogram matching is shown

For quantitative proof, Figure 3 illustrates the cumulative pdf of each channel of the image using normal histogram matching and the proposed method. It is observed that local histogram matching combined with CLAHE resulted in source images matching the shape of the cumulative pdf of reference image more closely than normal global usage of histogram matching. The image obtained after the application of CLAHE is used as the initial output image. The benefits are that the colour distribution of style image is captured as well as the features of content image are retained. We suggest that this allows for the backpropagation to focus more on the transfer of style rather than the transfer of colour involved. In contrast to most implementations, this paper does not normalize the value of pixels from [0,255] to [0,1]. Adam optimizer (optimizer rate of 7) is used for backpropagation and the number of iterations is set to 200. The alpha and beta values in Eq. (5) are 10^{-5} and 10^{-2}, respectively.

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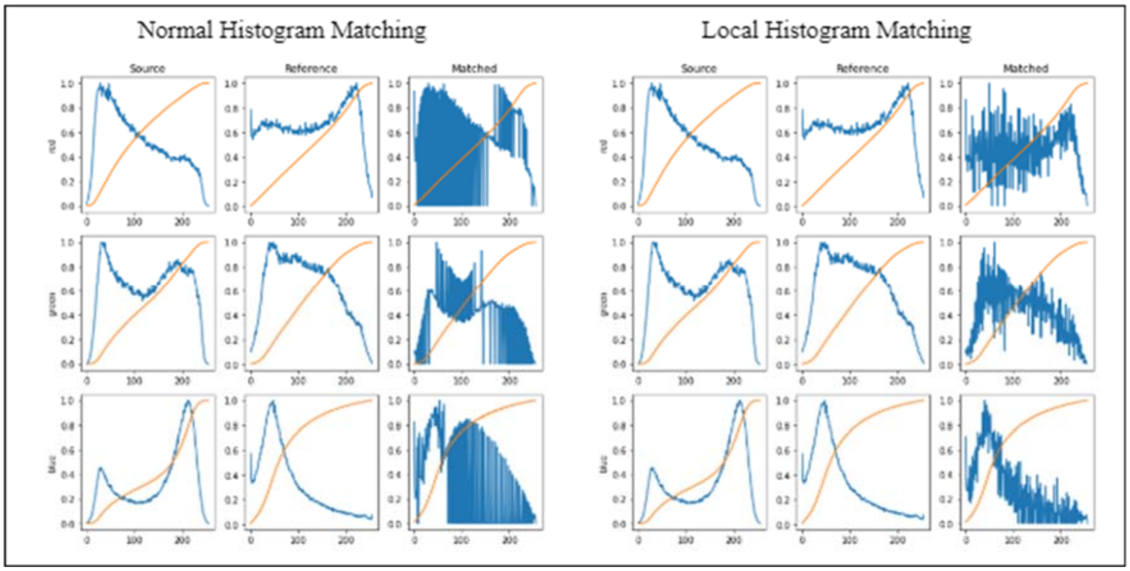

Figure 3. The cumulative pdf RGB channels of the source, reference and matched imaged are shown.

4. Results

In this paper, the best results obtained using the algorithm are presented in Figure 4. This is followed by the results being compared with one model each based on Laplacian loss function, feed-forward and Adaptive Instance Normalization in Figures 5, 6 and 7, respectively.

Figure 4. The content images used are *The Starry Night* by Vincent Van Gogh, Paris Rooftops and Neckarfront in Tubingen, Germany (Photo: Andreas Praefcke) respectively. The style images used are *The Scream* by Edvard Munch and *Scent of Rain* by Leonid Afremov.

Figure 5 compares the output generated by Laplacian loss function (Li et al., 2017c) and the proposed method. In the style image *A Muse* the majority of the artwork has shades of green interspersed with yellow. In addition, the bottom right region is dominated by a shade of peach. In the output generated by the proposed method, we can see that the colour and distribution of the style image has been captured better as compared to the use of Laplacian loss function. It is observed that the low-level content features are retained better by Laplacian loss function.

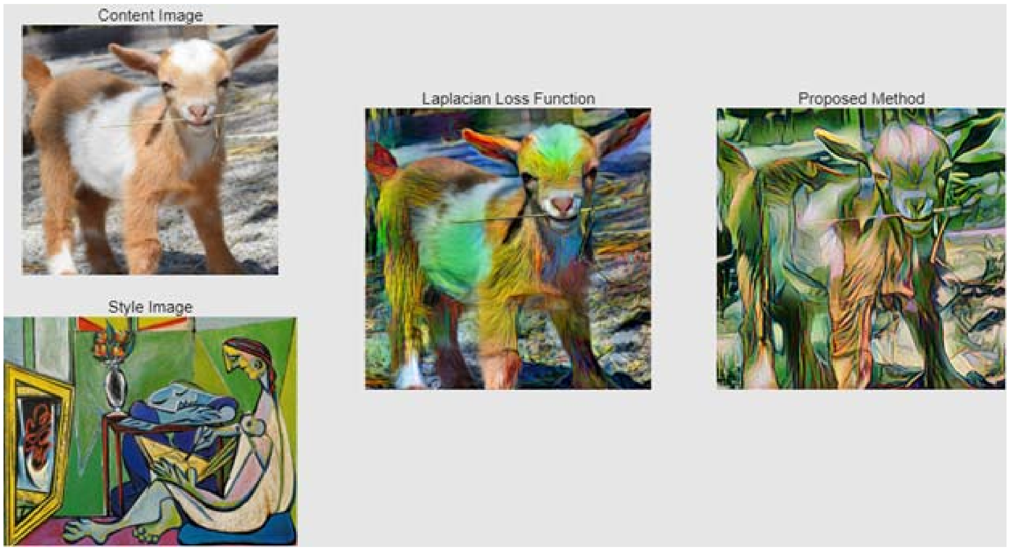

Figure 5. The style image is *A Muse* by Pablo Picasso, 1935 and content image is a goat. These images are used for comparing the output with Laplacian loss function (Li et al., 2017c).

Figure 6 shows the difference between the output generated by the feed-forward network (Johnson et al., 2016) and by the proposed method. In the style image Scent of Rain, it can be seen that there is a concentration of blue colour on the left-hand side as well as the top right whereas the central and bottom right part of the image has a concentration of red. This colour distribution is captured better in our proposed method as compared to the output by Johnson et al., however, the content features are retained better by the latter method. It should be noted that the training time for the feed-forward networks is much higher than our proposed method. In addition, feed-forward networks can be trained on a limited number of styles only (in this case, only one) whereas in this paper's method, the number of styles is not limited. Similar to Laplacian loss function, the feed forward network retains the low-level content features to a better extent.

Figure 7 presents a comparison between the usage of Adaptive Instance Normalization (AdaIn) layer (Huang and Belongie, 2018) and the proposed method in this paper. It can be seen that the features of the content image retained are similar in both images. In the style image Woman with a Hat, the right side of the image is occupied by shades of pink whereas the left side has green in the top left and yellow in the middle. Finally, the bottom of the style image has a concentration of light blue and pink. In the output it can be observed that the colour and style distribution has been captured better by our method as compared to the usage of AdaIn layer.

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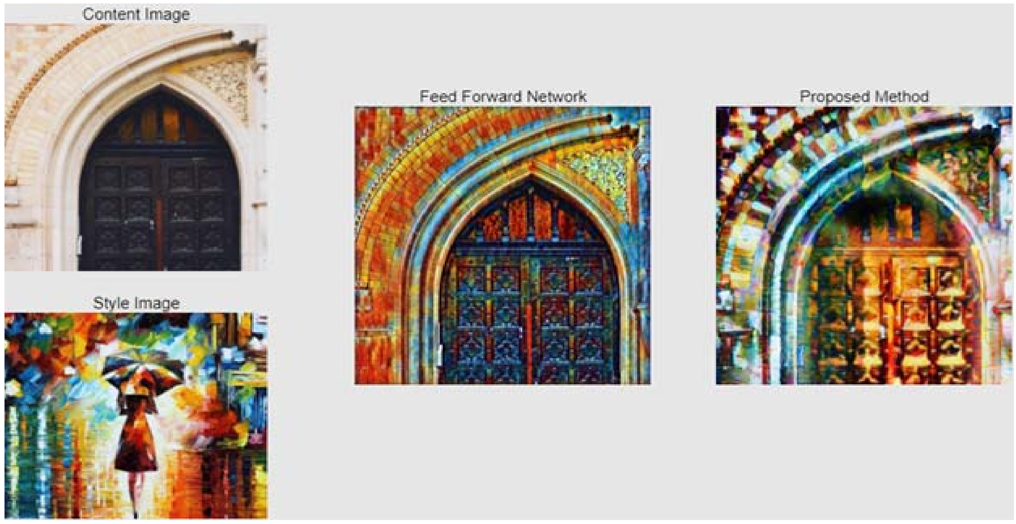

Figure 6. The style image is another version of *Scent of Rain* by Leonid Afremov and content image is the image used by authors of paper which used a trained single style network (Johnson et al., 2016)

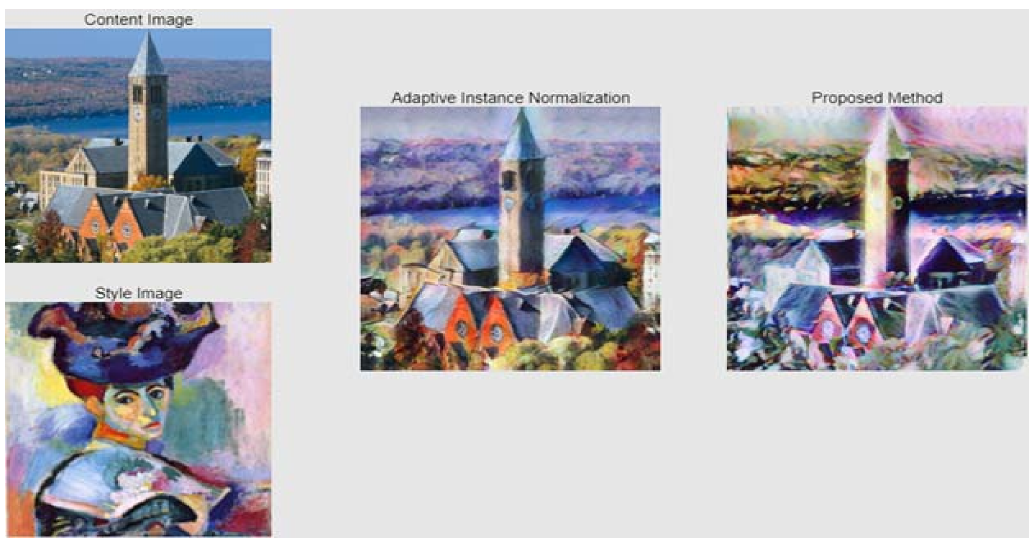

Figure 7. The style image is *Woman with a Hat* by Henri Matisse and content image is the image of Cornell University.

To demonstrate the quantitative improvement, Figure 8 shows the plot of the *style loss* over 200 iterations. The initial image used in the normal method is the content image itself, keeping the rest of the architecture unchanged. Due to the large magnitude of the values which hinder the ability to discern differences in the graph, the logarithm of the loss is taken with the base equal to ten.

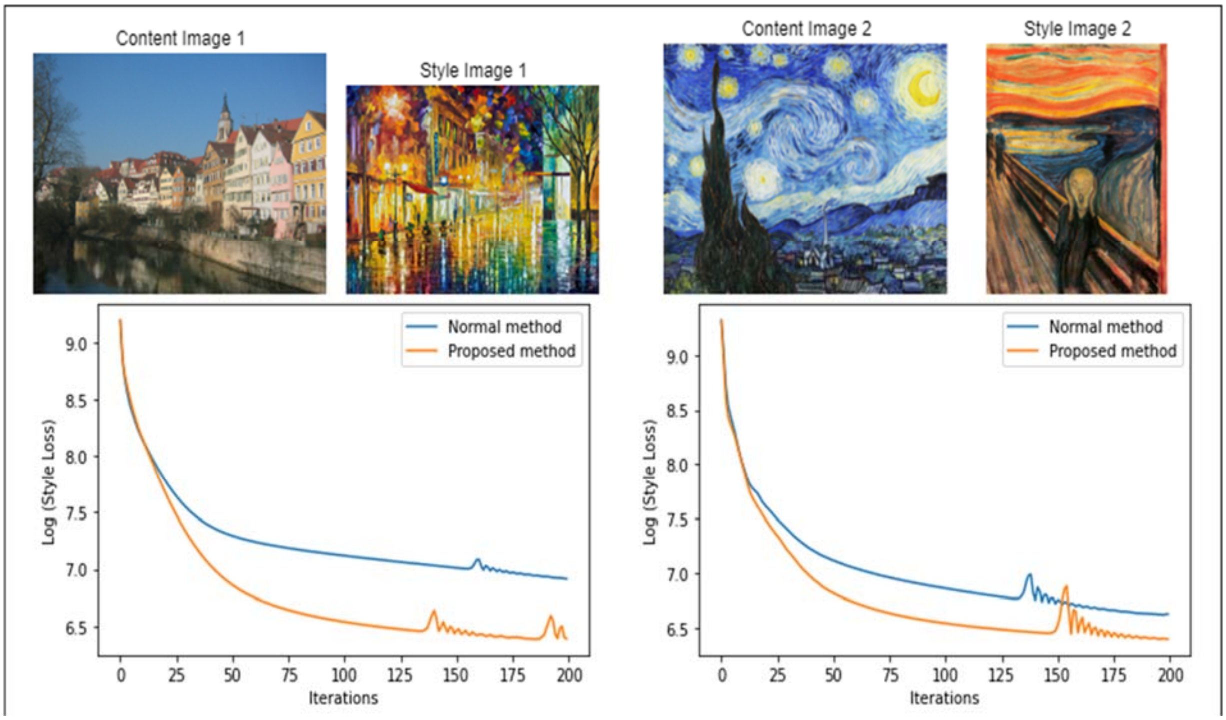

Figure 8. The content and style images in the first example are Neckarfront in Tubingen, Germany (Photo: Andreas Praefcke) and *Scent of Rain* by Leonid Afremov. The second example has *The Starry Night* by Vincent Van Gogh as the content image and *The Scream* by Edvard Munch as the style image. In both the graphs, it is observed that the style loss converges much more quickly in the proposed method as compared to the normal method.

5. Conclusion

In this paper, we have proposed a new approach towards Neural Style Transfer which relies on the application of image processing techniques for the initial input image. This approach is unique as it is focused on an aspect which has not been considered in many other works due to the reliance on backpropagation for adjusting the input image to give the final output. In addition, we have addressed the issue of improper colour transfer caused by application of histogram matching when applied on the global scale by splitting the images in 4 blocks of equal dimensions and therefore localizing the histogram matching process. This localized approach helps in capturing the colour of specific regions of the target/reference image while retaining the main features of the source image. The image blocks are then blended together to prevent the appearance of distinct lines due to variation in colour and the contrast is restored by the usage of Laplacian transforms and CLAHE, respectively. Therefore, the final input image has its colour transformed to match the style image to the maximum possible extent and we suggest that this allows the backpropagation to be almost solely focused on the transfer of style as compared to other methods where the style and colour are both gradually transferred. This paper has compared the results obtained with other approaches and it has been shown that the style is transferred in a faster manner when compared to other iterative methods as well as the colour distribution of the style image is captured more accurately.

6. References

Adelson, E. H., Anderson, C. H., Bergen, J. R., Burt, P. J. and Ogden, J. M. (1984). 1984, Pyramid methods in image processing. *RCA Engineer*, 29, 33-41.

Bevilacqua, A. and Azzari, P. (2007). "A High Performance Exact Histogram Specification Algorithm," 14th International Conference on Image Analysis and Processing (ICIAP 2007), 2007, pp. 623-628, doi: 10.1109/ICIAP.2007.4362846.

Chen, D., Yuan, L., Liao, J., Yu, N., and Hua, G. (2017). "StyleBank: An Explicit Representation for Neural Image Style Transfer," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 2770-2779, doi: 10.1109/CVPR.2017.296.

Chen, T.Q. and Schmidt, M. (2016). "Fast patch-based style transfer of arbitrary style," in Proceedings of the NIPS Workshop on Constructive Machine Learning, 2016.

Dumoulin, V., Shlens, J., and Kudlur, M. (2017). A Learned Representation For Artistic Style. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net

Gatys, L., Bethge, M., Hertzmann, A, and Shechtman, E. (2016b). Preserving Color in Neural Artistic Style Transfer. *ArXiv, abs/1606.05897*

Gatys, L., Ecker, A., and Bethge, M. (2016a). "Image Style Transfer Using Convolutional Neural Networks," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 2414-2423, doi: 10.1109/CVPR.2016.265.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B, Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014). Generative Adversarial Networks. Advances in Neural Information Processing Systems. 3. 10.1145/3422622.

Huang, X. and Belongie, S. (2017). "Arbitrary style transfer in real-time with adaptive instance normalization," in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 1501–1510.

Hussain, K., Rahman, S., Rahman, M., Shah, K., Abdullah-Al-Wadud, M., Khan, M., and Shoyaib, M. (2018). A histogram specification technique for dark image enhancement using a local transformation method. *IPSJ Transactions on Computer Vision and Applications*. 10. 10.1186/s41074-018-0040-0.

Jing, Y., Yang, Y., Feng, Z., Ye, J., Yu, Y., and Song, M. (2019). "Neural Style Transfer: A Review" in *IEEE Transactions on Visualization & Computer Graphics*, vol. 26, no. 11, pp. 3365-3385, 2020. doi: 10.1109/TVCG.2019.2921336.

Johnson, J., Alahi, A., and Fei-Fei, L. (2016). Perceptual Losses for Real-Time Style Transfer and Super-Resolution. In: Leibe B., Matas J., Sebe N., Welling M. (eds) Computer Vision – ECCV 2016. ECCV 2016. Lecture Notes in Computer Science, vol 9906. Springer, Cham. https://doi.org/10.1007/978-3-319-46475-6_43

Li, C. and Wand, M. (2016). Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks. In: Leibe B., Matas J., Sebe N., Welling M. (eds) Computer Vision – ECCV 2016. ECCV 2016. Lecture Notes in Computer Science, vol 9907. Springer, Cham. https://doi.org/10.1007/978-3-319-46487-9_43

Li, Y., Wang, N., Liu, J., and Hou, X. (2017a). "Demystifying neural style transfer." In Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI'17). AAAI Press, 2230–2236.

Li, Y., Fang, C., Yang, J., Wang, Z., Lu, X., and Yang, M. (2017b). "Diversified Texture Synthesis with Feed-Forward Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 266-274, doi: 10.1109/CVPR.2017.36.

Li, S., Xu, X., Nie, L., and Chua, T.-S. (2017c). "Laplacian-steered neural style transfer." In Proceedings of the 2017 ACM on Multimedia Conference. ACM, 2017, pp. 1716–1724.

Marr, D. and Hildreth, E. (1980). Theory of Edge Detection. Proceedings of the Royal Society of London. Series B, Containing papers of a Biological character. Royal Society (Great Britain). 207. 187-217. 10.1098/rspb.1980.0020.

Mallikeswari, B. and Sripriya, P. (2018). "A Review of Image Enhancement Algorithms for Low-Contrast, Infra-red and Night Image." *International Journal of Creative Research Thoughts* (IJCRT), ISSN:2320-2882, Volume.6, Issue 1, Page No pp.200 - 207, January 2018, Available at : http://www.ijpub.org/IJPUB1801033

Nixon, M and Aguado A.S. (2002). Feature Extraction & Image Processing for Computer Vision, First Edition (1st. ed.). Academic Press, Inc., USA.

Peng, M. and Zhu, Z. (2019). "Enhanced Style Transfer in Real-Time with Histogram-Matched Instance Normalization." 2019 IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), 2019, pp. 2001-2006, doi: 10.1109/HPCC/SmartCity/DSS.2019.00276.

Risser, E., Wilmot, P., and Barnes, C. (2017). Stable and Controllable Neural Texture Synthesis and Style Transfer Using Histogram Losses. *ArXiv, abs/1701.08893.*

Tu, L. and Dong, C. (2013). "Histogram equalization and image feature matching." 2013 6th International Congress on Image and Signal Processing (CISP), 2013, pp. 443-447, doi: 10.1109/CISP.2013.6744035.

Ulyanov, D., Lebedev, V., Vedaldi, A., and Lempitsky, V. (2016). "Texture networks: feed-forward synthesis of textures and stylized images." In Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48 (ICML'16). JMLR.org, 1349–1357.

Walt, S., Schönberger, J., Nunez-Iglesias, J., Boulogne, F., Warner, J., Yager, N., Gouillart, E., Yu, T., and the scikit-image contributors (2014). scikit-image: Image processing in Python. PeerJ 2:e453 (2014) https://doi.org/10.7717/peerj.453.

Yang, F. and Wu, J. (2010). "An improved image contrast enhancement in multiple-peak images based on histogram equalization." 2010 International Conference On Computer Design and Applications, 2010, pp. V1-346-V1-349, doi: 10.1109/ICCDA.2010.5540857.

Zhang, H. and Dana, K. (2018). Multi-style Generative Network for Real-Time Transfer. In: Leal-Taixé L., Roth S. (eds) Computer Vision – ECCV 2018 Workshops. ECCV 2018. Lecture Notes in Computer Science, vol 11132. Springer, Cham. https://doi.org/10.1007/978-3-030-11018-5_32.

Zuiderveld, K. (1994). Contrast limited adaptive histogram equalization. Graphics gems IV. Academic Press Professional, Inc., USA, 474–485.

DOI: https://doi.org/10.37266/ISER.2022v10i1.pp44-54