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Feature-Oriented Artistic Styles Transfer Based on Effective Texture Synthesis

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Abstract. *The research of image visual characteristics transfer is motivated from texture synthesis techniques. Generally, the success of these applications is inherently useroriented and highly depends on the subjective personal thoughts also. Therefore, a method with the reasonable estimation values to synthesize a styled texture which would meet the user preference is highly desirable. In this paper, the algorithm starts with an activityguided analysis for adaptive patch-based visual characteristics transfer, which is not only more efficient than conventional methods but also with pleasing visual quality. Then, the Particle Swarm Optimization (PSO) accelerated scheme with a modified match criterion which can effectively search and the approximate best location that matches the synthesized target patch according to user-specified feature(s). In addition, a hybrid blending approach ensures the Coherence Match to improve the transition effect between the overlapping boundaries of adjacent patches is proposed. The experimental results demonstrate that our method provides greater flexibility and better performance of perceptual visualization for the applications of artistic styles transfer.*
Keywords: Artistic styles transfer, Texture synthesis, Particle Swarm Optimization.

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1. **Introduction.** In the research of non-photorealistic rendering, most developed techniques focus on establishing a painting model, and then render according to the given framework and direction [1-5]. Although these approaches achieve very well in rendering effect, they need huge interactive work that is strongly related with artistic painting. Therefore, it makes them difficult for those users who are not familiar with artistic paintings, to accomplish an image with desired visual style that belongs to a particular painting. In 2001, Hertzmann et al. [10] applied the technique of texture synthesis onto the texture transfer, further onto the application of non-photorealistic rendering, and produced very surprising results from it. After then, Lee et al.[11] proposed a fast texture transfer algorithm to express the directional effect based on the flow of the target image, and render images depends on the image size and simple parameters, thus improve the efficiency comparing to [10].

The aim of artistic styles transfer is to synthesize a target image with the media and style of source image. More precisely, transferring style means transferring macro visual features (color, texture) to an image while retaining structuralize features (objects) of realistic photo image [1]. For texture synthesis algorithm, a clear criterion of the synthesized results should be in a visual plausible way as compared with the given source texture, thus it is the same as artistic styles. Although texture transfer shares many of the same challenges as texture synthesis, the degree of similarity with the source image for artistic styles transfer is a matter of personal preference [20], on the contrary, the texture synthesis in which to avoid the human involvement is generally required for most cases [2]. In literature, there are two different approaches for texture synthesis. Instead of constructing a complex and expensive mathematical model in [3], Efros et al. [4] demonstrated the power of nonparametric sampling from the local conditional Markov Random Field (MRF) density function. Wei et al. [5] applied tree structured vector quantization (TSVQ) to accelerate the exhaustive search in [4] to match the L-shaped neighborhood around the target pixels. Ashikhmin et al. [6] further proposed a faster coherence search and produced results that often look much better than the output from previous synthesis methods in [4, 5]. However, pixel-based synthesis approaches tend to wander into the wrong part of search space and blur out small objects while doesnt resemble the input texture [7]. In 2001, Efros et al. [8] and L. Liang et al. [9] concurrently developed two similar patch-based sampling algorithms to texture synthesis. Patch-based texture synthesis algorithms with the characteristic of preserving global structure and produce high-quality results for a wide variety of texture classes. They perform more than an order of magnitude faster than the pixel-based algorithms. In [9], they used various search data-structures (kd-tree, quadtree pyramid and principal components analysis) which lead to real-time texture synthesis application. However, patch-based approaches often introduce unwanted visual artifacts along overlapped boundaries. Therefore, the minimum error boundary cut (MEBC) [8] and feathering techniques [9] are applied to smooth the transition between the overlapping boundaries of adjacent patches. As pointed out in [9], image quilting [8] has a tendency to produce abrupt color changes along the overlapping zones. However, we find that the faster alpha-blends approach in [9] tends to blur high frequency features along patch boundaries.

On the other hand, the research of artistic styles transfer is inspired by texture synthesis techniques. Efros et al. [8] first presented the ability of synthesizing a new transferred image by stitching small patches of source image through a weighted sum of two independent constrains. That is, the Coherence Match attempts to have coherence between the neighbor patches and Fidelity Match attempts to efficiently select a source patch, which matches the synthesized target patch according to user-specified feature(s). Basically, one synthesis pass through the image is not enough to produce a visually pleasing result in [8]. As a consequence, the algorithm iterated over the synthesized image several times ( ) and reduced the patch size with each iteration to compensate the drawback.

Hertzmann et al. [10] proposed a framework by choosing different types of source image pairs as input, and the target image was trained to create an analogous filtered result. Although this multi-resolution and pixel-based approach produced impressive results but required few hours for the artistic rendering. Another restriction of the technique is that the user must provide additional unfiltered maps which restricted to make exact point-wise correspondence with the original image. This is not only inconvenience but even impracticality for user. The objective of artistic styles transfer is to render a new stylized image which the novel styles is synthesized by style example from source image but preserve the content of the target image. Therefore, the synthesis approaches need to define/extract the image styles (features) and contents from the source and the target images, respectively [12]. In [11], in order to enhance the transferred image quality, Lee et al. added an additional energy term that respects the image gradient to the previous fast texture transfer algorithm in [2]. The developed approach can express a coherent direction of the objects shape in target image. However, the success of artistic styles transfer is the global sense for users perception, but not deal with details of low-level statistical features. In our work, motivated by the advantages of patch-based texture sampling algorithms, we tend to present an effective synthesis-based transferred algorithm with the reasonable consideration to achieve not only optimal visual artistic effect but meet the user needs. For this purpose, there are several major issues that will be discussed in this paper, we describe as follows.

1. Synthesized by variable patch size: The performance of patch-based synthesis approaches strongly depends on patch size, thus patch size is a hidden variable in these algorithms. Generally, the large patch can preserve more texture characteristics but smooth the details of objects structure especially in their shapes, and the small patch works just the opposite. Therefore, in order to render in source image style and preserve the target image content, synthesis by variable patch size is a good choice. In our work, the patch size will be varied depending on the features of source image you want to capture. A randomness parameter to estimate the scale of texture elements of sample texture may impact the synthetic quality. Therefore, an activity-guided algorithm for adaptive patch-based artistic styles transfer is proposed.

2. Artistic styles selection and transfer: Artistic style is a very subjective perception for human; it is thus difficult to clearly define. However, from the viewpoint of painting, the style is composed by the contents of colors, line types, texture or their combination. Therefore, the algorithm must provide a sufficiently rich feature space of example to explore [2]. Furthermore, the clue of proposed activity estimation has the advantages which can reduce trial-and-error costs in finding the better weight value to infuse novel styles form example and preserve the salient structures of the target image simultaneously.

3. Boundary processing (blending): The blending scheme can smooth the transition between overlapping regions. L. Liang et al. [9] claimed that the feathering produces more smooth color changes than MEBC [8], but it also produces a smeary effect in some cases. Therefore, we propose a dynamic weighting function to the minimum cut path to preserve coherence between the adjacent patches in the paper.

4. Accelerated scheme: Although, patch-based texture synthesis algorithms can produce high-quality results for a wide variety of texture classes and perform more than an order of magnitude faster than the pixel-based algorithms. However, they used various search data-structures (kd-tree, quadtree pyramid and principal components analysis) which are very complex to implement and relatively slow in a mid-level PC [14]. Therefore, a simpler accelerating method should be developed. The paper is organized as follows: we first analyze the essence of source texture as priori information, and then the adaptive patch-based and reasonable estimated weight approaches are proposed to guide texture transfer procedure. Then, a modified match criterion which provides better measure of subjective perceptive similarity based on the user-oriented feature fields, and a swarm intelligence approach which is easy to implement and significantly improves the searching process is introduced in Section 3. In Section 4, the hybrid blending approach preserves both advantages of MEBC and feathering is introduced. The comparisons of artistic styles transfer results with existing algorithms are evaluated in Section 5. Finally, our conclusions are made in Section 6.

2. **Activity Analysis for Adaptive Patch-based Synthesis Approach.** performance of patch-based synthesis approaches strongly depends on patch size [9], generally,

the large patch can preserve more texture characteristics but smooth the details of objects structure especially in their shapes and the small patch works just the opposite. In order to demonstrate the patch size effect, an example is illustrated in FIGURE 1. For oil painting, to synthesis with large patch size, the presented painting styles in FIGURE 1(c) are clearly better than that of FIGURE 1(d), however, the details preservation is worse. Therefore, in order to render in source image style and preserve the target image content, synthesis by variable patch size is an appropriate choice. In summary, the patch-based texture rendering suffers from the following fundamental problems: do not incur apparent block patterns, smooth transition for the overlapping boundary zones and low time cost during the synthesized procedure. In this Section, we will derive an adaptive patch size scheme to gain the both advantages in large and small patch sizes. The new scheme is also different from the iterative or pixel-based texture transfer method used in [8, 10, 11]. In the meantime, the performance of artistic transfer quality and speed can be improved simultaneously. The detailed adaptive algorithm is explained as follows.

(a) Styled texture (b) Target texture (c) Patch size:24x24 (d) Patch size:12x12

FIGURE 1. The comparisons of transferred effect based on different patch sizes

Although the transfer of desired artistic styles is really all subjective and dependents on the user's perception which it is thus difficult to clearly define. However, from the viewpoint of features, the artistic style can be considered as various combinations of low level features such as colors, lines, edges, corners, texture, etc. In other words, the general idea of artistic style transfer is to preserve large features (i.e., main structure) of the target image but replace high-frequency details to match those of the artistic images [2]. Therefore, the idea behind the proposed scheme is that the large patch is used to render the artistic style in less variation region and the small patch used to quick variation region in target image, respectively. Finally, the overall performance is satisfactory for both artistic styles in source image and contents in target image. Based on aforementioned observations, the proposed activity analysis is the criteria for adaptive synthesis process to achieve better transformation of style and preservation content in the target image at the same time. In [12], a distance-based interpolation method (Radial Basis Functions) [19] was proposed to calculate the significant feature in target image to guide texture synthesis for artistic transfer. In our work, similar idea is proposed to detect the activity in target image and then the patch size is determined accordingly. Since human perceptual system is very sensitive to the features of abrupt change such as edges, corners and some specific salient structures in image, thus to select such features to describe image is a simple way. Meanwhile, we assume the pixels that close to these features have more important information of the image, and the information drop off gradually when move away from these features. Therefore, we denote the edge-based feature field distribution to represent the activity of the target image.

In our algorithm, the first step of the preprocess is to extract the line information from sample texture. However, in order to extract the significant structure, we need to reduce the inference due to color variation. For simplicity, we firstly re-quantize the RGB components in texture image into 8 levels as shown in FIGURE 2. The details that are not related to the structure have been removed effectively. Then, a well-known Sobel operator is applied to extract the possible line candidates. Furthermore, in order to enhance the reliability of the shape so that they can be counts or recognized; the morphology operations with a structuring element (predefined rectangular symmetric 5x5 mask) is performed to remove the isolated or noise like edge pixels accordingly. Generally, the dilation and erosion in Eq. (1)-(2) smooth the boundaries of objects without significantly changing their area.

$$A \oplus B = \left\{ x | (\hat{B})_x \bigcap A \neq \right\} \tag{1}$$

$$A \theta B = \{ x | (B)_x \subseteq A \} \tag{2}$$

The last step of pre-processing, the skeleton technique was introduced to describe the global properties of objects and reduce the original image into a more compact representation. For visual clarification, we illustrate a perspective distorted example to explain the above steps as shown in FIGURE 3.

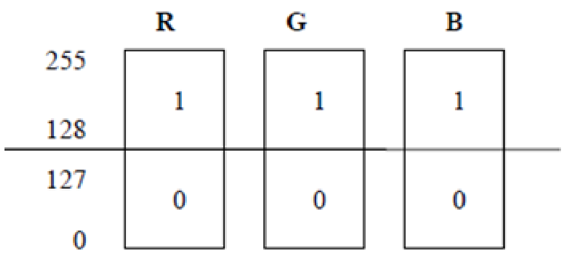


FIGURE 2. Quantization for RGB components

We can define the results of skelton in FIGURE 3(f) as the salient structure of image. As above-mentioned, we assume the pixels that close to the salient structure have more important information of the image, and the information drop off gradually when move away from these features. Therefore, we can simply dilate the salient structure and then a low-pass filter (RBF) to obtain the high activity region of the image, and we define as salient map hereafter. For visual clarification, we illustrate the distribution of significant feature points shown in Figure 4. In this example, the white regions in FIGURE 4(d) represent the salient structures with high activity of an image; the black regions might carry less amount of information and we can assume that the pixels which are background of an image.

Since the user desired result should look similar to the content of the target image and infuse novel style (high-frequency details) from the styled example. Thus, the approximate activity analysis is suitable to derive an adaptive patch-based sampling approach and a reasonable estimation value to control the output texture making it preserve more content of target texture or styled image for the texture transfer process. For the adaptive patch size based on activity analysis, the following condition should be considered:

$$activity\_index = \frac{\sum_q q \in \psi_p \cap \text{Salient map}}{|\psi_p|} \tag{3}$$

where $|\psi_p|$ is the area of a given patch which centered at point p. Since the large value of activity-index indicate that the pixels are nearer to the significant features and carry more

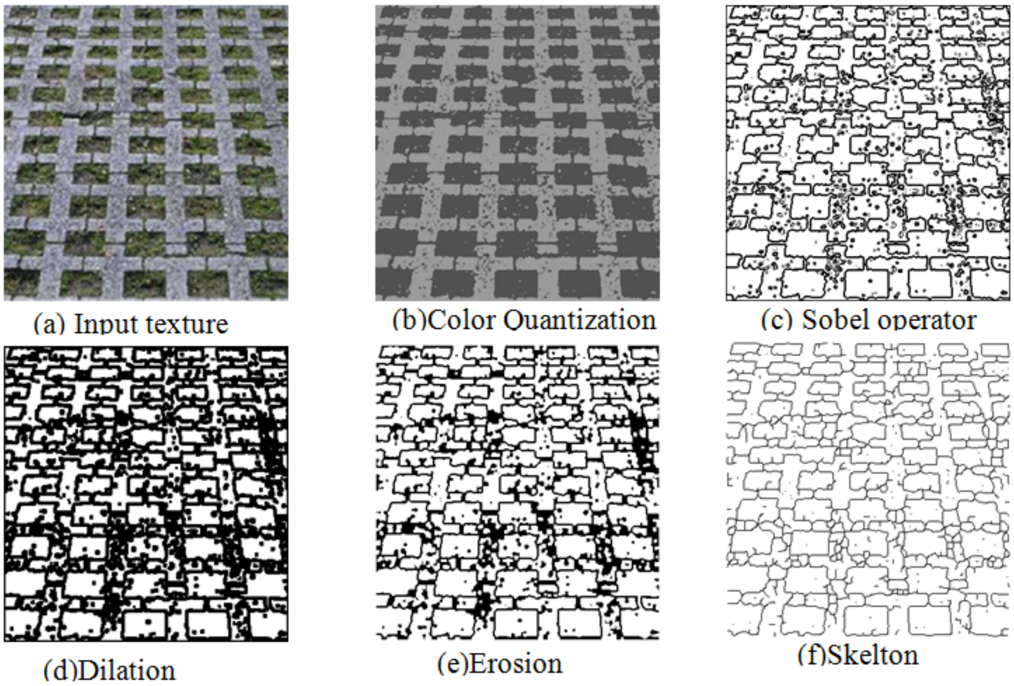


FIGURE 3. The preprocess for adaptive patch-based synthesis approach

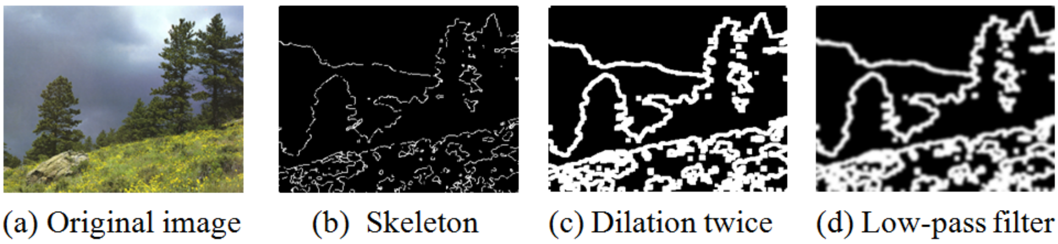


FIGURE 4. The features points of distance-based interpolation by radial basis functions

information of an image [9]. Therefore, a relative smaller patch is adopted to preserve the details of objects in target image; otherwise, a larger patch means better transferring the style to the background of target by capturing more characteristics of source image. Since human visual perception is more sensitive to low frequency components of an image, thus the adaptive patch-based synthesis approach will effectively enhance the visual effect.

3. **Artistic Styles Transfer.** Although artistic styles is a kind of human perception that is very subjective characteristic, it is still composed by some fundamental elements such as color, line, corner, etc. Therefore, we need to extract these features from both source and target images, and according to the selected features to compare their similarity and then to decide which part in source image to render into target image.

3.1. **Features extraction and normalization.** In our work, we select luminance, chrominance, saturation, gradient magnitude and blurring luminance as image features, respectively. Therefore, texture transfer is similar to the feature extraction for expressing the painting style of source image and also preserving the structure content of target image during the synthesis process. In our implementation, the proposed feature-oriented approach that allows user preference for the matching process, which can balance a trade-off exists between patch-size and return, reduce trial-and-error costs in finding the better weight value to emphasize target image content. In our work, the color features are extracted from the YIQ color space due to its simplicity:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

Therefore, the feature can be express as: 1. $I_Y(i,j)$ is feature of luminance in an image. 2. Saturation can be calculated by Eq. (5), we can also define the average saturation (Eq. (6)) of a patch for fast comparison.

$$I_{sat}(i,j) = \sqrt{I_I(i,j)^2 + I_Q(i,j)^2} \tag{5}$$

$$I_{sat} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{sat}(i,j) \tag{6}$$

3. $I_E(i,j)$ is calculated by sobel operation as following:

$$\mathrm{I}_H(i,j) = I(i,j) * S_H(i,j),\ I_H(i,j) = I(i,j) * S_H(i,j) \tag{7}$$

$$I_E(i,j) = \sqrt{I_H^2(i,j) + I_V^2(i,j)} \tag{8}$$

where $S_H(i,j)$ and $S_V(i,j)$ are sobel operator for horizontal and vertical directions, respectively.

4. $I_{Blur}(i,j)$ is low-pass filtering to luminance channel, the operator is a simple 55 average filter. During artistic styles transfer procedures, amounts of brightness increasing and decreasing should be perceptually equal for a fixed change occurred everywhere in the color space. Since the luminance distributions are different between source image and the target image [14]. Therefore, an approximately uniform color space should be used in prior, and the luminance normalization can be defined as:

$$Y_{Taregt}(i,j) = \frac{\sigma_{Src}}{\sigma_{Taregt}}(Y_{Target}(i,j) - \mu_{Target}) + \mu_{Src} \tag{9}$$

where σ and μ represent the standard deviation and mean value of luminance component. For visual clarification, an example of normalized process as shown in FIGURE 5. That is, equal distances in the space represent approximately equal color difference. Then, the normalized feature is adopted to achieve better matching degree and coherence transition between the boundary zones.

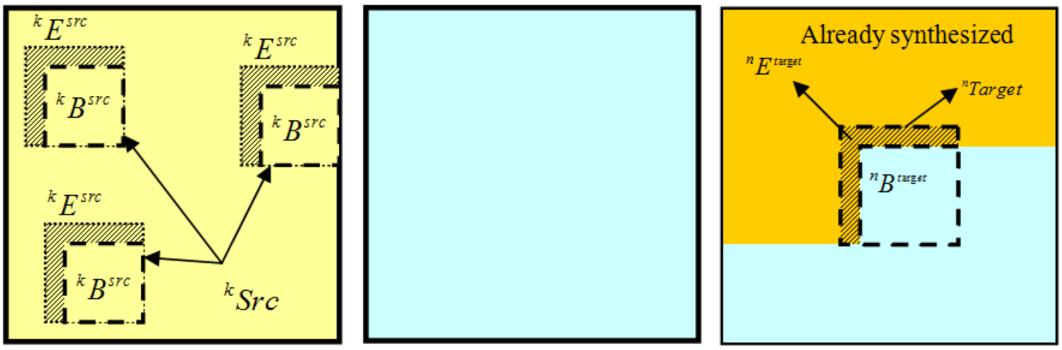
3.2. **Similarity matching.** In general, the procedure of artistic transfer is that the target image is assumed the initial output and then the transfer process is patch by patch from left top to right bottom in raster order. The implementation of texture transfer is to select one patch in source image to combine with target patch by weighting sum. Therefore, there are three issues should be discussed in this Section. First, we need to select the patch in source image not only with features similarity to target patch but also with continuation between neighboring patches. Second, the scheme of variable patch synthesis should develop to preserve target content with obvious source style. Third, the efficiency

(a) Source texture (b) Target texture (c) Luminance normalization

FIGURE 5. The example of luminance normalization

of the overall procedure should be considered. In the following, we will discuss these issues more detail.

In FIGURE 6, we define the symbols used in our algorithm. Let A, B and B represent the source, target and output image, respectively. The patch boundary in source and output image is denoted by ${}^{k}E^{src}$ and ${}^{n}E^{target}$, the rest part of these patch (i.e., main body of patch) is denoted by ${}^{k}B^{src}$, and ${}^{n}B^{target}$, and the symbols ${}^{k}Src$ and ^{n}Target represent the whole patch that includes A and B. In the texture transfer processing, we



Source *A* Target *B* Result *B'*

FIGURE 6. The texture transfer process

need to match the patch similarity between source image and target image, and then we can select the most suitable patch in source image to combine with the patch in target image. The matching criterion should consider the patch continuity and the feature similarity, thus the boundary and main body of a patch should calculate simultaneously. The similarity is expressed as the distance of two patches as:

$$\mathrm{d}({}^{k}Src, {}^{n}\mathrm{Target}) = \alpha \times \sqrt{\left(\sum_{k=1}^{Q} \sum_{(i,j)}^{(M',N')} ({}^{k}E^{src}(i,j) - {}^{n}E^{target}(i,j))^2\right)} + (1-\alpha) \times \sqrt{\left(\sum_{k=1}^{Q} \sum_{(i,j)}^{(M,N)} ({}^{k}B^{src}(i,j) - {}^{n}B^{target}(i,j))^2\right)} \quad (10)$$

where d(.) is the general form of distance of two patches. The first term in right side of the equation is the boundary distance which considers the patch continuity; the second term is the feature distance which considers the visual similarity. The superscript in target patch is the patch that is ready to synthesis, and in source patch means that to be searched in source image and Q is all possible patches in source image, (M', N') and (M, N) represent the boundary and main body of patch sizes, respectively. The is the weight value that used to emphasis the importance factor of patch similarity.

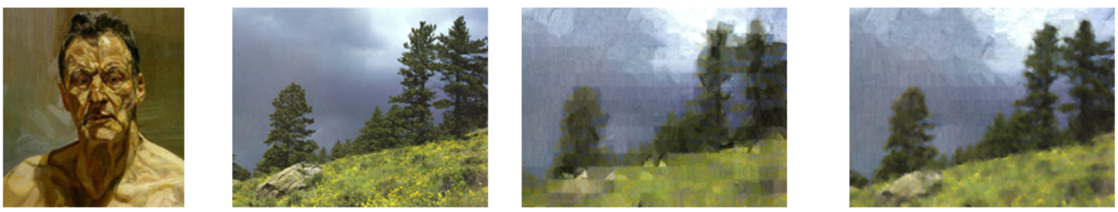
Moreover, in our work, the feature distance is calculated by the selected features as in above-mentioned. We can express as follows:

$$\begin{aligned}
&\mathrm{d}({}^{k}B^{src}, {}^{n}B^{t\arg et}) \\
&= \sqrt{W_y \times (\sum_{k=1}^{M} \sum_{(i,j)}^{(,)} ({}^{k}B_y^{src}(i,j) - {}^{N}B_y^{t\arg et}(i,j))^2} + \sqrt{W_{sat} \times (\sum_{i=1}^{M} ({}^{k}B_{sat}^{src}(i,j) - {}^{N}B_{sat}^{t\arg et}(i,j))^2)} \\
&+ \sqrt{W_E(\sum_{i=1}^{M} ({}^{k}B_E^{src}(i,j) - {}^{N}B_{\mathrm{E}}^{\mathrm{t\,arg\,et}}(i,j))^2)} + \sqrt{W_{Blur}(\sum_{i=1}^{M} ({}^{k}B_{Blur}^{src}(i,j) - {}^{N}B_{Blur}^{t\arg et}(i,j))^2)} \quad (11)
\end{aligned}$$

where W_* is the weighting value that can used to adjust user preference and their sum should equal 1. Obviously, we cannot expect single feature framework to do a perfect job in simulating all possible texture transfer styles. However, in our work, the determination of features selection corresponding to artistic style is flexible for user. In the following, the scheme of variable patches synthesis will be discussed. As mentioned in Section 2, the large patch is used to render the artistic style in less variation region and the small patch used to quick variation region in target image, and then the overall performance is satisfactory which can infuse novel artistic styles from source image and preserve the salient structures in target image. For this purpose, in Eq. (12), a simple criterion based on activity analysis in Eq. (3) will propose to decide the size of texture transfer patch.

$$activity\_index \geq TH_d \tag{12}$$

For visual clarification, we illustrate a styled output image in FIGURE 7, which was generated using 3232, 1616 patch size and the blurred image intensity, saturation features for texture transfer. The threshold TH_d is set 0.6 in this example. Through the normalization and adaptive procedures, we may observe that the synthesized output in FIGURE 7(d) not only keeping important (objects) information of target image but also can transfer novel high-frequency details from the source example. Obviously, the result achieves more pleasure and sensitive for human perception than that of FIGURE 7(c).



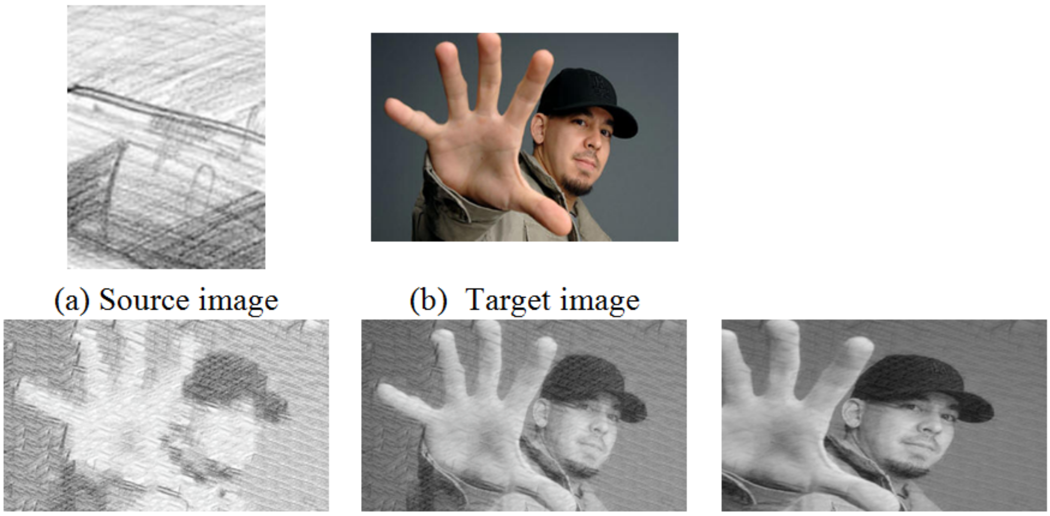
(a) Source texture (b) Target texture (320x250) (c) Output image Patch size: 32 x 32 (d) Adaptive patch approach

FIGURE 7. Artistic styles transfer comparisons for Van Gogh using proposed adaptive patch approach

On the other hand, the activity index in Eq. (12) also can help us to estimate a better weight value for preserving the salient structures of the target image. In the following, we use Eq. (13) to mix luminance of the source and target image, and remain the IQ value from source image during the transfer procedure. In Figure 8, we illustrate an example to demonstrate the styled result which uses fixed weighted combination based on luminance component. In order to trade off the content in target image and style in source image, we firmly believed that the clue of activity analysis is simple and efficient way to estimate the parameter values reasonably and meet the user inherent needs for artistic styles transfer.

$$P_{Traget}^{Y(i)} = w_{Traget} \times P_{Traget}^{Y(i)} + (1 - w_{Traget}) \times P_{Source}^{Y(i)} \tag{13}$$

where w_{Traget} is a floating value between 0 and 1, the parameter can be adjusted to control the output texture making it looks more like target or source texture. Later on, the approaches of adaptive patch size and estimated parameters which guide various transferred painting effects will be described in experimental results.



(a) Source image (b) Target image

(c) w_{src}:1 , w_{Target}:0 (d) w_{src}:0.5 , w_{Target}:0.5 (c) w_{src}:0.3 , w_{Target}:0.7

Figure 8. The effect of different weighted combination for texture transfer

In our work; the w_{Traget}can be estimated automatically from the target image based on activity analysis. This is, $w_{Traget} = activity_$index. If user selects higher value than calculated, more content effects of target image and less novel styles of source image can be expressed. In our algorithm, activity analysis offers a better design to reduce the cost of trial and error. Furthermore, it has the advantage to balance the trade-off exists between patch-size and return for the application of artistic styles transfer.

3.3. **Accelerated scheme.** For patch-based texture synthesis algorithms, the Markov Random Field (MRF) based methods are adopted to search the matching patch by many researches. However, most MRF based methods are very computational expensive [15]. Therefore, various search data-structures (kd-tree, quadtree pyramid and principal components analysis) are used to compensate the drawback.

As mentioned, we are not always aimed at finding the best match for searching procedure, due to special characteristic of artistic styles transfer. That is, a clear criterion of the synthesized result should look the source texture in a visual plausible way for texture synthesis; whereas, the success of artistic styles transfer is global in the sense of user preference. Therefore, an efficient accelerated method but not complex need to implement based on aforementioned observation.

Unlike GA, particle swarm optimization (PSO) has no evolution operators such as crossover and mutation, and most importantly PSO algorithm will either give us the best location or an approximate best location [15]. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods in some areas [18]. Thus, this approach is suitable for the application of artistic styles transfer as the accelerated search process.

In our work, the PSO algorithm [16, 17] with a modified matching criterion is proposed which can meet the synthesized patch according to user-specified feature(s) and more consistent transition between the neighbor patches efficiently. PSO is initialized with a group of random particles (solutions) and then used Markov Random field searches for optima by updating generations [17], the pseudo code of PSO is described as follows.

```
Random num K positions of particles P[i], i = 0 ~ k-1
Random num K velocity of particles V[i], i = 0 ~ k-1
Declaration num K of local best positions of LBest[i],
Declaration global best positions of GBest
while(D(GBest, Target_N ) < Threshold)
{
 For(i=0 ~ k-1)
 {
  If (D(P[i], Target_N ) <D(LBest[i], Target_N ))
    {
     LBest[i] = P[i];
     If (D(LBest[i], Target_N ) < D(GBest, Target_N ))
      GBest = LBest[i];
    }
  }
 For (i=0 ~ k-1)
   {
    V[i]=V[i]+rand()*c1*(LBest[i]-P[i])+rand()*c2*(GBest-P[i]);
    P[i] = P[i] + V[i];
    }
}
```

where c1,c2 are learning factors and these two rates control the relative influence of the memory of the neighborhood to the memory of the individual; usually c1 and c2 are set to 2 [17], rand () is a random number between (0, 1). The Fitness Function D() is the optima match which related to two independent constrains (Coherence Match and Fidelity Match) as shown in Eq.(10).

The PSO algorithm in [17] is an iteration process which initialized with a group of random particles, and it will be terminated when the group of random particles in source image reaches the minimum errors based on the Fitness Function D() or the maximum iteration number k. PSO is attractive since there are few parameters to adjust, and with slight variations, can works well in a wide variety of applications [18]. For our proposed adaptive patch size based on activity analysis, the computational costs of PSO roughly related to in terms of distance calculation, convergence criterion and the swarm size.

The algorithm is implemented on a Core2/3.0GHz's Computer with 4GB RAM using C++. The reported simulation as given below: using 156 seeds and averaged 6 iterations, the convergence criterion will be met when the mean-square-error (MSE) decrease is insignificant (¡0.0045) from the previous iteration; whereas, the cost of distance calculation is dependent on the length of feature vectors. With runtimes about several minutes for image quilting [8] and up to hours for image analogies [10], the proposed accelerated scheme can work well for large transferred textures (300300) in 20 seconds on average.

Finally, our improved work is primarily focused on examining the activity analysis of target image, and then with help of the adaptive patch-based sampling approach and accelerated scheme to perform the further matching procedure. Furthermore, it also provides reasonable weight estimations in Eq. (12) for artistic styles transfer. At the same time, the following proposed hybrid blending and user-controlled features interface are utilized to ensure the coherence and fidelity matches. From the resultant examples and performance comparison of proposed texture transfer algorithm will be demonstrated in experimental results.

4. **The Hybrid Blending Approach.** The blending procedure in the boundary zones is an important decorative step for texture synthesis. For a consistent transition between two overlapping boundaries, Efros et. al. [8] used a dynamic programming MEBC to find the minimal cost path through the error surface. The error for the pixel lactation (i,j) with red, green and blue color components of two overlapping blocks is defined as:

$$e_{i,j} = \left(B^1_{i,j}(R) - B^2_{i,j}(R)\right)^2 + \left(B^1_{i,j}(G) - B^2_{i,j}(G)\right)^2 + \left(B^1_{i,j}(B) - B^2_{i,j}(B)\right)^2 \tag{14}$$

and the path of the best cut can be obtained by using Eq. (15).

$$E_{i,j} = \begin{cases} e_{i,j} \text{ for i=1} \\ e_{i,j} + \min(E_{i-1,j-1}, E_{i-1,j}, E_{i-1,j+1}) \text{ for i=2..N} \end{cases} \tag{15}$$

where N is the vertical height of overlapping block. In [9], L. Liang et al. claimed that the feathering approach can produce more smooth transition than MEBC, which may generate abrupt color changes at various places along the boundary cut. But, the intrinsic problem with the alpha-blends feathering algorithm is that the blurring artifacts are noticeable in some cases. In [7], Nealen et al. used as large as possible patch which is satisfied the predefined error bound for synthesizing, and every pixel in the overlap region exceeding the pixel error threshold will be re-synthesized on a per-pixel basis. However, the existing acceleration schemes such as kd-tree, quadtree pyramid and PCA in [9] are not suitable in this case.

In this paper, we propose a hybrid blending approach that preserves both advantages of MEBC and feathering for texture synthesis. Firstly, the cut path with minimal cost of two overlapping zones is determined by MEBC. Then, a dynamic weighting feathering approach is utilized to avoid abrupt artifacts along the minimum cut path as follows.

$$P_{out}(i,j) = \alpha_{i,j}B^1(i,j) + (1-\alpha_{i,j})B^2(i,j) \tag{16}$$

where $P_{out}(i,j)$ is the blending pixel of two correspondent pixels in overlapping zone, and the weighting function $\alpha_{i,j}$ is used to control the blending effect. Institutively, it is linear proportioned to the minimum cut path and the boundary zone width w_e. For a vertical overlapping zone as an example, the dynamic weighting $\alpha_{i,j}$ is determined by:

$$\alpha_{i,j} = \begin{cases} {}^{1}/_{2} \text{ if j=k} \\ \dfrac{\mathrm{w_e} - (j-k)}{2w_e} \text{ if jk} \\ 1 - \dfrac{\mathrm{w_e} - (k-j)}{2w_e} \text{ if jk} \end{cases} \tag{17}$$

for i_{th} row in vertical overlapping zone, the weighting function $\alpha_{i,j}$ is adjusted according to the minimum cut point k adaptively, where $1 \leq j, k \leq w_e$. Naturally, the hybrid blending approach can be easily extended to the processes of horizontal and L-shaped overlapping zones.

The proposed algorithm looks complicated but the underlying mechanism is quite easy. A flowchart of the proposed algorithm is shown in Figure 9.

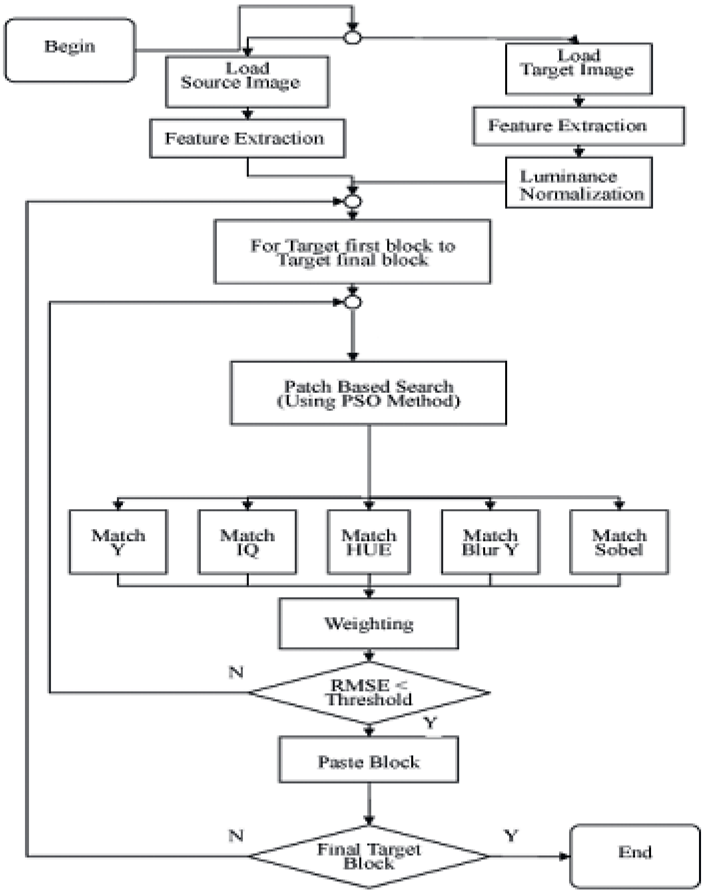


Figure 9. The features points of distance-based interpolation by radial basis functions

5. **Experimental Results and Comparisons.** Among existing texture transfer methods, image quilting [8] and image analogies [10] are two outstanding and representative methods in the literatures. As discussed in aforementioned section, both of these techniques come with the cost of significantly higher complexity, making it too complex to be implemented. Most importantly, the definition of artistic styles is subjective [11] and a potential trade-off that exists between patch-size and return. Therefore, a user-controlled interface and activity analysis approaches are developed in this paper. In our experiments, we try to verify the effectiveness of proposed method in three aspects. Firstly, the

activity-based scheme of variable patch size as mentioned in Section 2 will be compared to conventional fixed-size patch method. Secondly, we test different painting styles (oil, watercolor, and pen ink) and target images to examine the effectiveness of selected features in artistic styles transfer results. Thirdly, the hybrid blending and computational time is also considered in performance evaluation.

FIGURE 10 compares various fixed patch sizes (32x32, 8x8) and the proposed activity-based algorithms for artistic styles transfer. As shown in FIGURE 10(c), the artistic style of pencil strokes can be transferred successfully to target image, but with abrupt mismatch at the boundary zones (eyes and thumb parts). FIGURE 10(d) using the 8x8 patch can preserve more targets content; whereas, the stroke effect reveals very pixilated and superlative time-consuming. The result of adaptive patch-based and better weight estimation using activity analysis in FIGURE 10(e) shows much better quality in all of these parts. In this example, the luminance component is used for Coherence Match in overlapping boundary zones, the features of edge and blurred image intensity are adopted for Fidelity Match. The parameters in Fitness Function in Eq. (10) are set to α=0.5, W_E and W_{Blur}=0. 5 in this case, and the adaptive patch size approach with estimated parameter wTarget= *activity_degree* is set in mixed formula (Eq. 13). In FIGURE 10(e), the transferred output is generated using the 32x32 patch to ensure better transferring the style to the background of target, and a split procedure using 16x16 to enhance the details of target image. Experimentations shown that in most scenarios, the adaptive patch scheme (32x32/16x16) can obtain satisfactory results. Furthermore, a blending technique with dynamic weighting feathering approach is utilized to preserve coherence between the adjacent patches in this paper. For visualization, the dark pencil strokes style of source image can be transferred to the target and the characteristic of the target content also be preserved simultaneously.

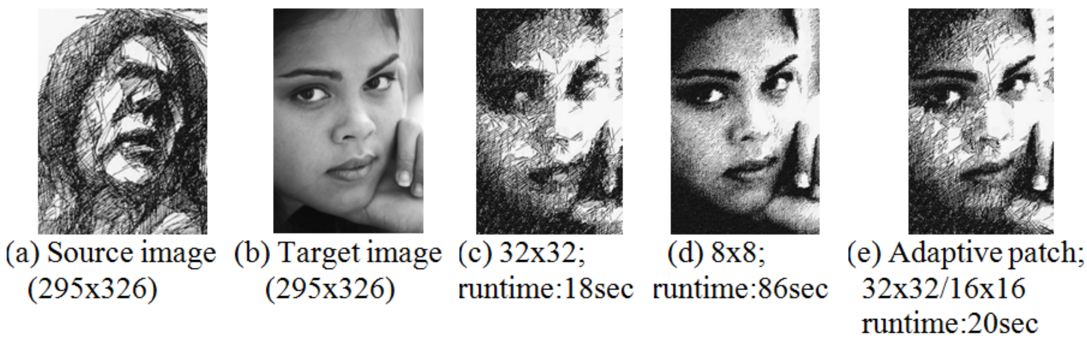


FIGURE 10. The first example for artistic styles transfer comparisons

In the following examples, we further intend to examine the interactive effects of different visual imagery perspectives. According to user-specified feature(s)/preference, we compared the visual effects of transferred textures using the famous artist works with watercolor, oil and pastel painting styles as shown in FIGURE 11, 12 and 13.

We are aware that the definition of "Percent transfer" means how much style to transfer [1]. That is, less transfer means the effect retains the large scale objects of the target; more transfer mea ns the effect leaves only a ghost of the large scale objects, and infuse novel styles from the style example. From above examples, we observe that the luminance component Y is an important feature to ensure the quality of Coherence Match, the blur effect is a common technique that smoothens edges to reduce aliasing artifacts; saturation is a feature to measure the color intensity in an image; and the effect of edge

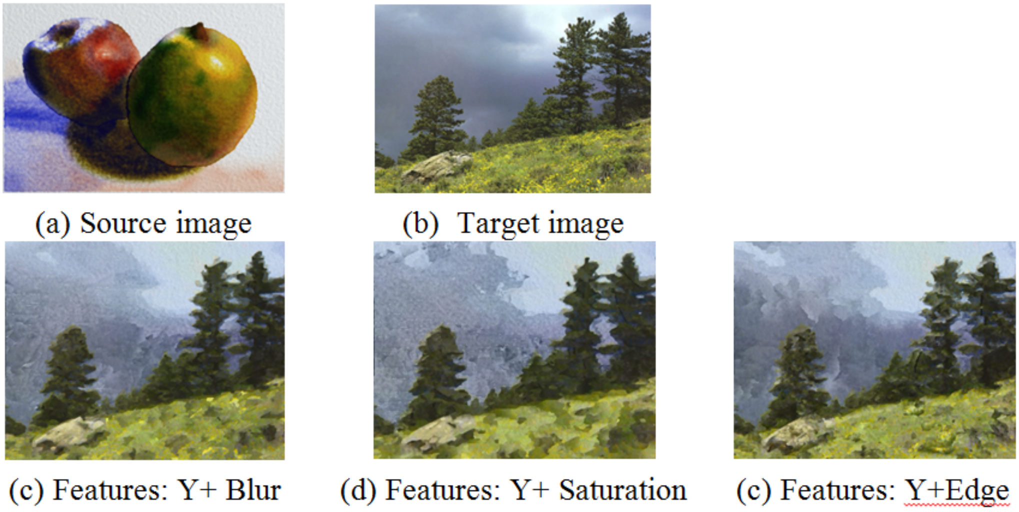


FIGURE 11. The first example for artistic styles transfer comparisons

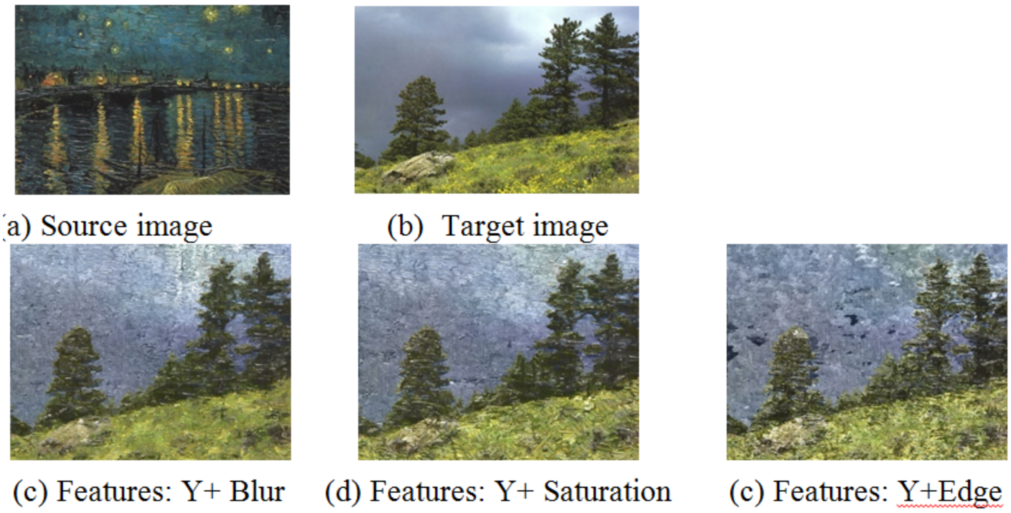


FIGURE 12. The second example for artistic styles transfer comparisons

feature can strength on object recognition. Since the success of artistic styles transfer is a subjective issue, our proposed feature-guided with activity analysis approach aiming at providing a user-oriented interface with the advantages of balancing a trade-off exists between patch-size and return, reducing trial-and-error costs in finding the better weight value to emphasize target image content as mentioned in Section 3.

On the other hands, we can further use the coherent pixel-based synthesis technique [2] as the basis, and slightly modified the Fitness Function D() which related to the terms of Coherence Match and Fidelity Match in Eq. (10). Figure 14(c) gives a some transferred examples which were generated using 5x5 neighborhoods, and the blurred image intensity and saturation features were adopted for creating candidate lists. Through the PSO algorithm, our approach with the runtimes about 45 seconds compared to several minutes for image analogies technique in [10].

The comparisons with Hertzmann [10] in above examples (cited from the web site http://www.mrl.nyu.edu/projects/image-analogies/artistic.html) showing that our approach can work well to generate better visual re-rendered appearances which preserve the large

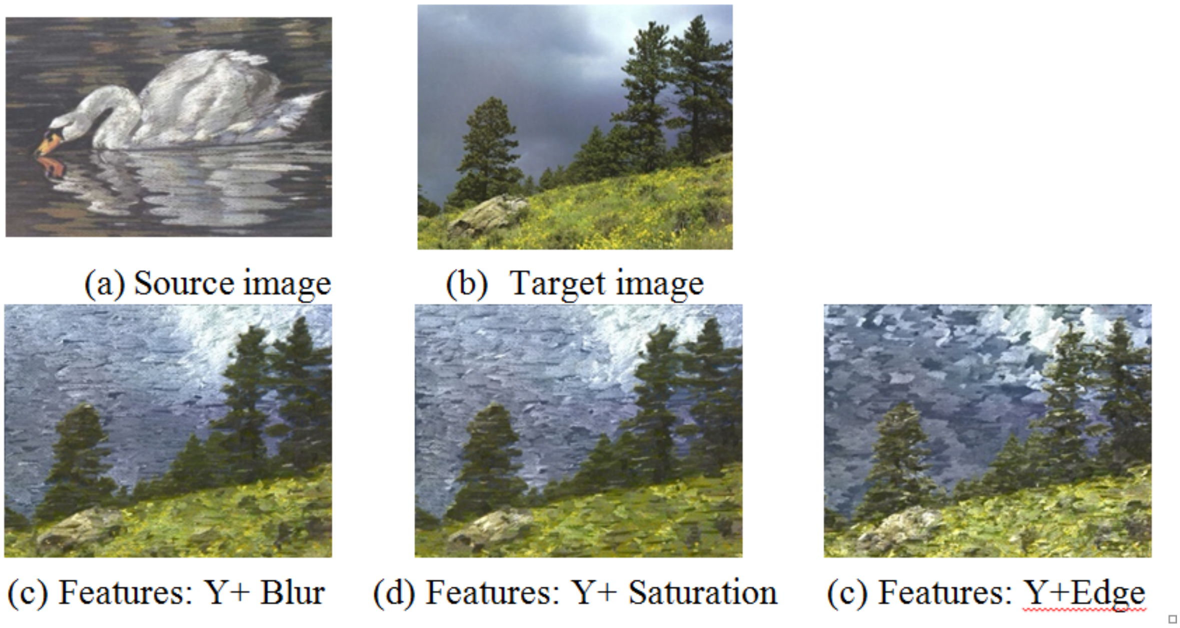


FIGURE 13. The third example for artistic styles transfer comparisons

FIGURE 14. Some results using image analogies and our modified approach for artistic styles transfer

scale features of target image (especially for noise and lip parts), and also with the capability of transferring styles from examples efficiently.

In Figure 15, the apparent abrupt transition and blurring artifacts are marked by red and blue rectangle boxes, respectively. We demonstrate the synthesized textures with more coherent transition as comparing with L. Liang [9] and Efros [8] algorithms. From the hybrid blending approach, it can preserve both advantages of MEBC and feathering and it is perceptually important step for artistic styles transfer procedure.

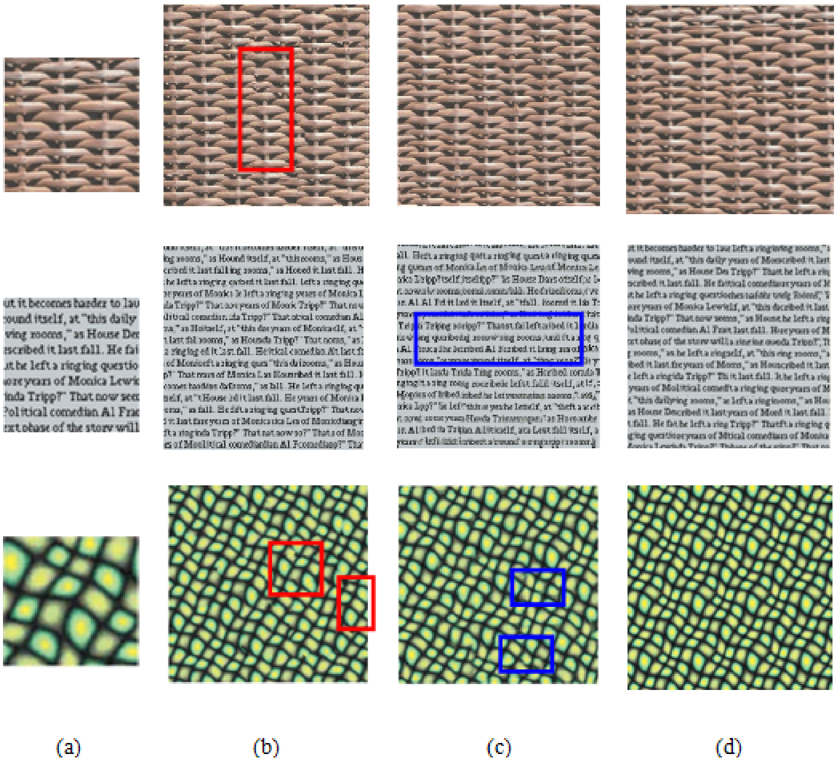


FIGURE 15. Comparisons of our hybrid blending effect with MEBC and feathering approaches (a) Sample texture in 128x128. (b) 256x256 synthesized result by Efros [8] algorithm. (c). 256x256 synthesized result by L. Liang [9] algorithm. (d) 256x256 synthesized result of our hybrid blending approach

6. **Conclusion.** We have proposed an adaptive patch-based artistic styles transfer method which can infuse novel style(high-frequency details) from the styled example and also preserve content in the target image based on activity analysis. Other contributions of this research is that we have proposed a hybrid blending approach which can improve the Coherence Match as compared with MEBC and feathering; Besides, the swarm intelligence approach is mainly aimed at the global sense of users preference for artistic styles transfer. Therefore, the PSO and user-oriented interface are adopted to meet the user needs and make matching degree optimal also. From our experiments, we could find our method provides greater flexibility and better performance for the applications of artistic styles transfer.

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