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Direction and Scale Preserving Image Analogies

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Abstract Image Analogies is an effective technique for transferring the relationship between the texture features of a source image pair onto a target image for processing. Conventional Image Analogies may fail to preserve the local texture directions or texture scales of the target image if the source image does not have the textures of similar directions or scales. This paper proposes a new technique that involves linking the regions between source image and target image based on texture scale and then rotating the regions in the source image so as to align its texture direction with that of the corresponding region in the target image. This enables the reproduction of textures of the proper directions and scale even when there are no common elements linking the scale and directions of the textures in the source and target images.

Keywords Image Analogies · Texture transferring · Style transferring · Gabor filter

1 Introduction

The Image Analogies [5] approach is one topic of research in the fields of image filtering technology and related texture synthesis. The framework transfers the relationship between the texture features of an example image pair A and A' (called source image pair hereafter) onto an image B (called unfiltered target image) for processing to create an image B' (called filtered target image).

For a filter producing images with directional texture, such as the brush strokes in a painterly filter, preserving the texture direction in the input image is very important. In addition, the scale of texture is also an important feature of a filter. An artist usually changes the size of brush strokes to reflect the local texture size. However, how to preserving the local texture direction and size is not considered in the existing Image Analogies approach either.

To solve such problem, this paper proposes a new method that involves automatically changing the directions of the textures in a source image to match those of the target image. This makes it possible to reproduce textures in the proper directions even when there are no common elements linking the directions of the textures in the source and target images. By automatically identifying the regions with textures of similar scale, the proposed method also maintains the scale of the textures in the resulting image.

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2 Related research

Given a pair of images A and A', the unfiltered and filtered source image pair, along with an unfiltered target image B, Image Analogies synthesizes a new filtered target image B' to complete the analogy $A : A' :: B : B'$. It is achieved by finding the best matching pixels between the source and target images. For the pixel q of B being synthesized, the pixel p in the source image A that having a neighborhood best matches that of q is found. Then, the pixel in the corresponding position of p in A' is copied to the pixel in the corresponding position of q in B'. Multi-scale representations of images are also constructed to match pixels with successive sizes of the neighborhood.

Several research works have been conducted to extend Image analogies or other texture synthesis techniques for preserving the directional or structural features in the resulting image. Xie et al. [12,13] pro-

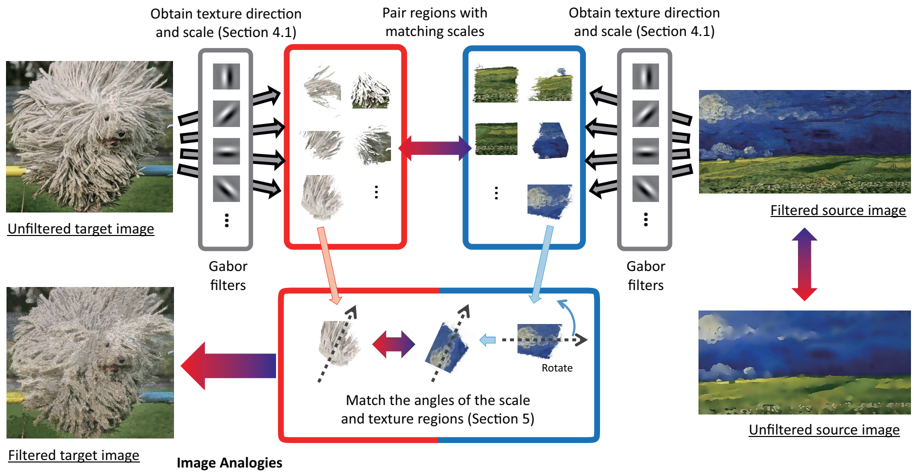


Fig. 1 Framework of the proposed method

posed a technique to better preserve the structure in the synthesized target image by adaptively varying the coherence parameter according to their distance from the structural features such edges and boundaries. Wei-Han Chang et al. [2] proposed to better preserve the structure information of the resulting image by adaptive changing the patch size when performing patch based texture synthesis. Tong-Yee Lee et al. [9] tried to improve the quality of texture synthesis by using the structure information in similarity searching. Johannes Kopf et al. [6] developed a technique for generating directional texture on 3D surface by learning from examples. H. Lee et al. [7,8] extended Ashikhmin's fast texture synthesis technique [1] to generate directional effect in the resulting image. Either in Image analogies or Ashikhmin's algorithm, two different searches are combined to find the best matching pixels. B. Wang et al. [11] and Yan-wen Guo et al. [4] also proposed methods that involved superimposing several user-specified features of an example painting over the brightness gradient of a photograph to synthesize the directions of textures. However, these two methods require the user to specify regions manually.

3 Proposed method

Under the proposed method, the first step involves obtaining information on texture direction and scale from the unfiltered target image and the source image. After dividing the images into regions with the similar texture directions and scales, the method aligns the texture directions of regions of the same scale and then applies Image Analogies approach.

Figure 1 shows the framework of the proposed method. First, a set of Gabor filters are used to obtain the texture direction and texture scale of each pixel in both the filtered source image and unfiltered target image. Next, both images are segmented into multiple texture regions based on the texture directions and scales. Then for each region in the unfiltered target image, a region of filtered source image with the same scale is selected. The selected region is rotated so that its texture direction is aligned with that of the corresponding region in the target image. Finally, Image Analogies framework is applied to transfer the filtering effect across the matching region pairs.

The first step of the algorithm is to detect the directions and scales of local textures in both the filtered source image and the unfiltered target image and divide the images into regions of similar texture directions and scales. We use *K-means* clustering for the segmentation in a high-dimensional feature space defining the texture direction and scale. Response of Gabor filter bank, color in Lab color space and pixel location are used for K-means clustering.

Gabor filter is known to be a powerful texture descriptor[3]. To capture the texture directions and scales, we use a filter bank consisting of Gabor filters given with the following equations [10]:

$$\begin{aligned} &g(x, y : \lambda, \theta, \psi, \sigma, \gamma) = \\ &\qquad exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) cos\left(2\pi \frac{x'}{\lambda} + \psi\right) \qquad (1) \\ &x' = xcos\theta + ysin\theta, y' = ycos\theta - xsin\theta. \end{aligned}$$

Here ψ is the phase shift. γ is the parameter for controlling the aspect ratio of the 2D Gaussian filter kernel. λ is the parameter for controlling the frequency. Varying λ makes it possible to create Gabor filters for capturing the scales of textures. θ is the parameter for controlling orientation. Varying this value makes it possible to create Gabor filters for capturing local texture directions.

Our method use 30 Gabor filters in total with 6 different orientations ranging from 0 degrees to 150 degrees at 30-degree intervals, and 5 different frequencies. The texture descriptor is a 30 dimension feature vector with each dimension being the strength of response to one of the Gabor filter, which is computed as the sum of all pixel values in the filtered image.

Given that regions are essentially groups of pixels with similar color patterns, we also include the color of texture as the feature in clustering. The color of the $n \times n$ neighborhood is used as the color feature for a pixel. *Lab* color space is used from a perspective of being close to human perception. In current implementation, we set $n = 5$ in the current implementation and hence the dimension of color feature is $75(5 \times 5 \times 3)$. Finally, we also include pixel location (x, y) as the feature for clustering so as to deal with the images with multiple texture regions that have similar directions and colors but not adjacent to each other.

Given the segmentation results of the filtered source image A' and unfiltered target image B, we first segment the unfiltered source image A in the same way as A'. Then the filtered target image B' is generated region by region by applying Image Analogies to the matching region pairs between source and target image.

Denoting the representative direction and scale of a region R as $\overrightarrow{v}(R)$ and $S(R)$. For each region $B_i (i = 1, 2, \cdots, n)$ of B, its filtered target region B'_i is generated with the following algorithm.

1. Find a set of regions $\{A'_j\} (j = 1, 2, \cdots, k)$ in A' satisfying $|S(A'_j) - S(B_i)| < \epsilon$.
2. For each A'_j
  2.1 compute $\theta(A'_j, B_i) = arccos \overrightarrow{v}(A_j) \cdot \overrightarrow{v}(B_i)$
  2.2 rotate A_j, A'_j by $\theta(A'_j, B_i)$ to align $\overrightarrow{v}(A_j), \overrightarrow{v}(A'_j)$ with $\overrightarrow{v}(B_j)$
3. Apply Image Analogies with $\{A_j\}, \{A'_j\}$ as the source image pair and B_i as the unfiltered target region.

Here, ϵ is a user given threshold for matching regions between source and target images based on texture scale. Differing from the conventional Image Analogies, here $\{A_j\}$ and $\{A'_j\}$ are a set of regions. Step 3 performs the similarity search in all regions of $\{A_j\}$ and $\{A'_j\}$. The regions of $\{A_j\}, \{A'_j\}$ and B_i are usually no longer in a rectangular shape. However, by taking the advantage of Image Analogies as a pixel based approach, we can perform the similarity and coherence search for each pixel in the same way as the conventional algorithm.

To establish local texture directions and scales in an image, we assign a representative texture direction and scale to each texture region.

Multidirectional Gabor filtering provides directional reaction strength values for six directions. The direction with the strongest reaction strength becomes the texture direction for each region. To determine texture scale, we use multiresolutional Gabor filtering to determine reaction strength values by frequency level. Of the five possible frequency levels, the level with the strongest reaction strength becomes the texture scale for each region.

The proposed method searches for pixels in image regions whose texture scales match those of the regions in the target image. Compared to searching the entire source image, this approach can make it more difficult to reproduce the original intensity of the target unfiltered image with precision. To solve this problem, we add a post processing step which transfers the intensity of the unfiltered target image B to the resulting filtered target image B'. Each pixel $P_{B'}$ in B' is modified via following rule.

$$P'_{B'} \leftarrow P'_{B'} + (m_B - m_{B'}). \tag{2}$$

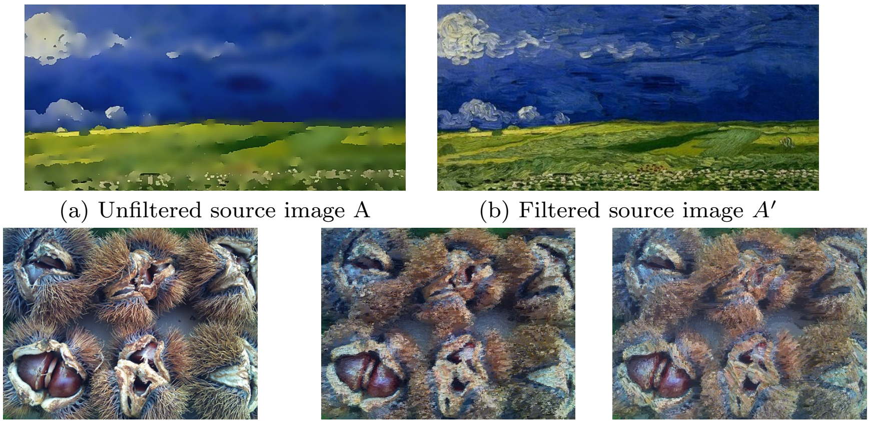
Here, m_B and $m_{B'}$ are the average intensity of B and B'. Such correction makes it possible to retain the texture configuration created by the intensity variance but make the overall brightness closer to that of the original image.

4 Result

For verifying the capability of dealing with directional texture, we used oil paintings with directional stroke texture as the filtered source images. To produce the corresponding unfiltered source images, we applied bilateral filtering to eliminate the characteristic brushwork that emerges in the images as a high-frequency component while retaining the region boundaries.

Figure 2(c) is a photograph of chestnuts in burrs. The photograph shows the burrs growing on cracked chestnut shells, with the spines radiating out in different directions. We applied the source image pair shown in Figure 2(a) and (b) to the target image in Figure 2(c) and then generated images using the two methods. Figure 2(d) shows the result of the conventional method, while Figure 2(e) shows the result of the proposed method. two methods. The results of Figure 2 exhibit the same differences. Whereas the conventional method performs its transfer processing without taking the directional and scale properties of the textures in the photograph, the proposed method retains the photograph's various texture directions and scale better.

Figure 3 shows an example of applying a small painting example (Figure 3(a)) to a target image with textures of varying directions and scales(Figure 3(c)). Fig-



(a) Unfiltered source image A (b) Filtered source image A'

(c) Unfiltered target image B (d) Conventional method (e) Proposed method

Fig. 2 A comparison of the generated images

(a) Unfiltered source image A (b) Filtered source image A' which is a small painting example (c) Unfiltered target image B (d) Conventional method (e) Proposed method

Fig. 3 An example of using a small source image

ure 3(d) shows the results of conventional method, while Figure 3(e) shows the results of the proposed method. Despite having just a small painting example with only one directional property, the proposed method successfully rendered the photograph's texture directions.

5 Concluding remarks

This paper proposed a method that involves find texture regions of similar scale in the source image and rotating the textures to match those of the target image. This enables the reproduction of textures in the proper directions scale even when there are no common elements linking the directions and scale of the textures in the source and target images.

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