Gradient-based Global Features and Its Application to Image Retargeting

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***Abstract*—We propose gradient-based global features and its application to image retargeting. The proposed features are used for an importance map for image retargeting, which represents rough location of salient objects in an image. We focus on areas rather than points and lines to be assigned as an important part. The information about areas in multiple layers provides global features. Experimental results compared to the state-of-the-art salient features for image retargeting demonstrate the effectiveness of the proposed features.**

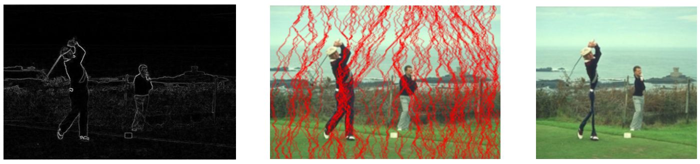
I. Introduction

Image retargeting is to resize an image with different aspect ratio while preserving representative objects, which attracts attention due to a wide variety of digital images and displays [1]. Seam carving is one of the approaches to image retargeting, in which the intensity of gradient is originally used for an importance measure that determines representative objects in an image [2][3]. Achanta and Süsstrunk proposed a saliency map based on global colors and intensity contrast for seam carving [4]. The combination of the saliency map and gradient magnitude was proposed as a balanced energy map [5]. Conger et al. proposed a secondary energy map that prohibits seams from passing through rather than merely defers seams, considering the effect of vertical seam on horizontal gradation [6]. The secondary energy map is very simple but gives exceptional results.

Gradient is widely used in image processing area, such as edge detection and optical flow. Histogram of Oriented Gradients (HOG) [7] and Scale-Invariant Feature Transform (SIFT) [8] are gradient-based local features. The central concept of SIFT and HOG is to use a weighted histogram of gradient as features. The shift describes the features at keypoints, while HOG describes the features of uniformly divided areas.

Salient features have been developed not only for image retargeting but also scene understanding, scene analysis, object recognition. Itti et al. proposed a saliency map in order to guide the selection of attended locations, which is constructed from color contrasts, intensity contrasts, and orientation contrasts built on a second biologically-plausible architecture [9]. T. Liu et al. proposed salient features including multi-scale contrast, center-surround histogram, and color spatial distribution [10]. These saliency features tend to computational expensive for image retargeting.

In the present paper, focusing on areas of salient objects in an image, we propose the variance of weighted gradient orientation as an area feature and global features expressed by the area features in multiple layers. Experimental results demonstrate the effectiveness of the proposed features for seam carving.



(a) Conventional seam carving

(b) Seam carving using the proposed features

Fig. 1. Seam carving. Left, middle, and right columns show the importance map, the seams expressed by red to be removed from the original image, and the resulting image, respectively.

II. Preliminaries

Gradient, gradient-based local features, and seam carving are described. $\mathbb{Z}$ and $\mathbb{R}$ denote the sets of integer numbers and real numbers, respectively.

A. Gradient

Let $g(n_1, n_2)$, $n_1 = 0, 1, \ldots, N_1 - 1$, $n_2 = 0, 1, \ldots, N_2 - 1$, be an image of size $N_1 \times N_2$.

The gradient of $g(n_1, n_2)$ is defined as

$$\nabla g(n_1, n_2) = \begin{bmatrix} \nabla_{\mathrm{n}_1} g(n_1, n_2) \\ \nabla_{\mathrm{n}_2} g(n_1, n_2) \end{bmatrix} \tag{1}$$

where

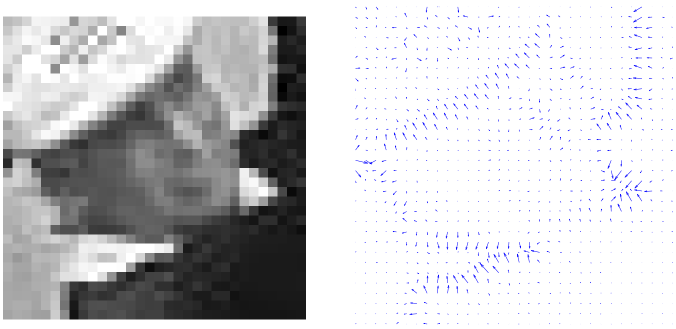
$$\nabla_{\mathrm{n}_1} g(n_1, n_2) = g(n_1, n_2) - g(n_1 - 1, n_2), \tag{2}$$
$$\nabla_{\mathrm{n}_2} g(n_1, n_2) = g(n_1, n_2) - g(n_1, n_2 - 1). \tag{3}$$

The gradient magnitude is defined as

$$||\nabla g(n_1, n_2)|| = \sqrt{\{\nabla_{\mathrm{n}_1} g(n_1, n_2)\}^2 + \{\nabla_{\mathrm{n}_2} g(n_1, n_2)\}^2} \tag{4}$$

which is often approximated by the absolute values as

$$||\nabla g(n_1, n_2)|| \approx |\nabla g(n_1, n_2)| = |\nabla_{\mathrm{n}_1} g(n_1, n_2)| + |\nabla_{\mathrm{n}_2} g(n_1, n_2)|. \tag{5}$$



(a) Original (32 × 32) (b) Gradient vectors

Fig. 2. Gradient vectors of an image. A great magnitude of gradient vectors concentrate on the edge of an object. Gradient vectors on the edge lie in approximately the same direction.

The gradient orientation is defined as

$$\theta(n_1, n_2) = \tan^{-1}\frac{\nabla_{n_2} g(n_1, n_2)}{\nabla_{n_1} g(n_1, n_2)}. \tag{6}$$

where $\theta(n_1, n_2)$ is in the range $[-\pi/2, \pi/2]$.

B. Gradient-based local features

The weighted orientation histogram with a total of N_b bins from 0 to $\Theta \in \mathbb{R}$ is defined as

$$h(b) = \sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1} w(n_1, n_2)\delta(bD, \theta(n_1, n_2)) \quad \text{for} \quad b = 0, 1, \ldots, N_b - 1 \tag{7}$$

where bD ($D = \Theta/N_b = d_1 + d_2$, d_1, $d_2 \in \mathbb{R}$) denotes representative values of bins, $w(n_1, n_2)$ is the weight, and

$$\delta(\phi, x) = \begin{cases} 1, & \phi - d_1 \leq x < \phi + d_2 \\ 0, & \text{otherwise} \end{cases}. \tag{8}$$

The gradient magnitude is used for the weight.

In HOG, the entries of histogram of the a small spatial area called cell is combined to form the vector representation.

C. Seam carving

The energy at a pixel is defined by importance measure in seam carving [2]. A seam, which is an eight-connected path from top to bottom (or from left to right) that contains only one pixel per row (or column), with the minimum energy is removed for resizing the image at a time.

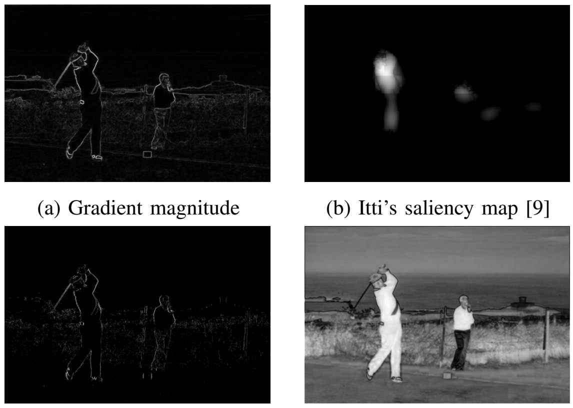
Let us consider reducing the width of image. A vertical seam, s_i, $i = 1, 2, \ldots, N_2$, is a sequence of coordinates and defined as

$$s_i = \{(T(i), i)\} \tag{9}$$
$$\text{s.t} \quad \forall i \quad |T(i) - T(i-1)| \leq 1 \tag{10}$$

where $T(\cdot)$ is a mapping from a location, i, of ordinate $[1, 2, \ldots N_2]$ to the all location of abscissa $[1, 2 \ldots, N_1]$.

The energy, E, of a seam is given as

$$E = \sum_{i=1}^{N_2} e(s_i) \tag{11}$$



(a) Gradient magnitude (b) Itti's saliency map [9]

(c) Secondary energy map [6] (d) Saliency map [4]

Fig. 3. Salient features. Gradient magnitude in (a) and secondary energy map in (b) categorized into point or line feature, while saliency maps in (b) and (d) are area feature.

where $e(\cdot)$ is the energy function that gives the energy at the pixel. A removed seam that has the least energy is effectively calculated by dynamic programming. Figures 1(a) and 1(b) show the seam carving using gradient magnitude and proposed features.

D. Consideration

Generally, accurate salient feature tends to be computational expensive, while gradient magnitude is simple and effective for seam carving to some extent.

When gradient magnitude is used as an importance measure for seam carving, the edge of an object is regarded as the most important part, while the inner part is not, as shown in Fig. 2. Therefore, we focus on areas rather than points or lines.

Figure 3 shows typical and state-of-the-art salient features. Itti's saliency map shown in Fig. 3(b) focuses on *areas*, but important areas are small for seam carving. Secondary energy map for vertical seam shown in Fig. 3(c) focuses on *points* that prohibit seams from passing through. Compared to gradient magnitude shown in Fig. 3(a), the points are restricted by thresholding. Although it is simple and efficient, it cannot completely draw the outline of an important object. Saliency map shown in Fig. 3(d) focuses on *areas* which is based on global color and intensity contrast, but depends on colors of important objects.

The aim of the present paper is to propose area features that hold both the local and global information.

III. Proposed method

We propose the variance of weighted gradient orientation as an area feature and global features expressed by area features in multiple layers.

A. Variance of weighed gradient orientation as area feature

We propose the variance of weighted gradient orientation which is based on the weighted orientation histogram in HOG as an analog. However, unlike HOG, the area feature is not vector but scalar, we no longer need to make a histogram.

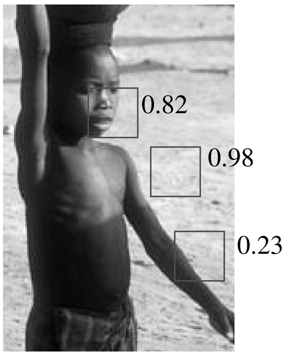


Fig. 4. Variance of weighted gradient orientation of areas. The number in the image denotes the variance of weighted gradient orientation of each area denoted by square.

Let n_1 and n_2 be the horizontal and vertical location of area A, respectively.

The mean of weighted gradient orientation is given as

$$\bar{\theta}_A = \frac{\sum\sum_{n_1,n_2\in A} w(n_1,n_2)\theta(n_1,n_2)}{\sum\sum_{n_1,n_2\in A} w(n_1,n_2)} \tag{12}$$

where $w(n_1,n_2) = ||\nabla g(n_1,n_2)||$.

The variance of weighted gradient orientation in area A is defined as

$$\sigma_A^2 = \frac{\sum\sum_{n_1,n_2\in A} w(n_1,n_2)(\theta(n_1,n_2)-\bar{\theta}_A)^2}{\sum\sum_{n_1,n_2\in A} w(n_1,n_2)}. \tag{13}$$

A small variance of the weighted gradient orientation represents that an edge exists in the area, while a great variance expresses no edges or multiple edges exist as shown in Fig. 4.

B. Block information and its accumulation

To generate global features of an image, the image is divided into blocks and the reciprocal of the variance of weighted gradient orientation is assigned into each block as a block value. Then, block values in multiple layers are accumulated.

Let (m_1,m_2), m_1, $m_2 \in \mathbb{Z}$ be the location of a block. The block value is defined using (13) as

$$B(m_1,m_2) = 1/\sigma^2_{(m_1,m_2)}. \tag{14}$$

The block values are normalized into the range [0, 1].

Let L be the number of layer, and let $(m_1^{(l)},m_2^{(l)})$, $m_1^{(l)},m_2^{(l)} \in \mathbb{Z}$, be the location of a block in the l-th layer. A pixel located at (n_1,n_2) belongs to a total of L blocks as depicted in Fig. 5. The block values over a pixel at (n_1,n_2) are accumulated as

$$\alpha(n_1,n_2) = \sum_{l=1}^{L} B(m_1^{(l)},m_2^{(l)}) \quad \text{for} \quad (n_1,n_2)\in(m_1^{(l)},m_2^{(l)}). \tag{15}$$

Thus, the global features are generated.

FIgure 6 shows the examples of gradient-based global features. We can confirm that the proposed features represent rough location of salient objects in an image.

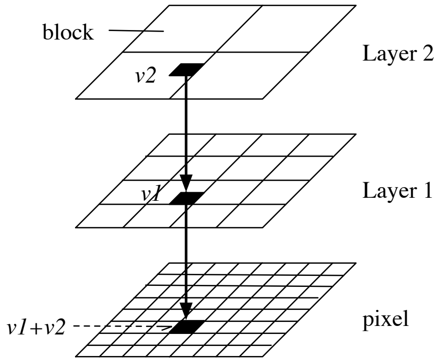
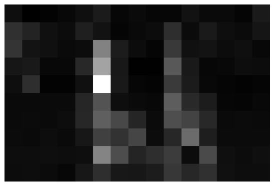
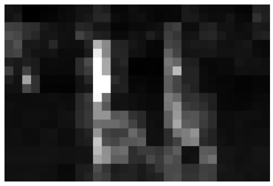


Fig. 5. Proposed features of multiple layers. An image is divided into block in each layer. The information about blocks over a pixel is accumulated.

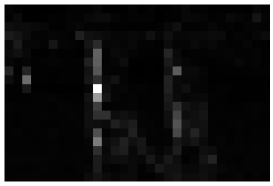
(a) original



(b) Layer 2



(c) Layer 1 + Layer 2



(d) Layer 1

Fig. 6. Examples of proposed features.

C. Gradient-based global feature for seam carving

We can detect the area including an approximately strait line or parallel lines by block value. However, we cannot distinguish no edge area from multiple-edge area by block value. To prevent a seam from passing through the multiple-edge area, the gradient magnitude is required for the importance map in addition to the proposed features.

The energy function in (11) for seams is redefined as

$$e(n_1,n_2) = |\nabla I(n_1,n_2)| + \alpha(n_1,n_2) \tag{16}$$

where $|\nabla I(n_1,n_2)|$ denotes the gradient magnitude of the image.

IV. Simulations

We evaluate the proposed features as an importance measure for seam carving comparing to typical and state-of-the-art features for seam carving.

In typical features, conventional gradient magnitude [3] and the combination of Itti's saliency map [9] with gradient magnitude were used, while in state-of-the-art features balanced energy map (BEM) [5], which is the combination of the saliency map [4] with the gradient magnitude, and secondary energy map (SEM) [6] were used. The color images of size

(a) Original (b) Conventional (f) Itti's + G (d) BEM (e) SEM (c) Proposed

Fig. 7. Comparison of salient features for seam carving with 70 % width of the original.

320×480 with 24 bits at a pixel in Berkeley Segmentation Dataset [11] were used for evaluation[1]. A total of 144 pixels (30 %) of the horizontal width were reduced. In proposed features, the number of layers was 2 with blocks of size 32×32 and 16×16.

Figures 7(a) through 7(f) show the original image, the resulting image by conventional seam carving, by proposed features, by balanced energy map (BEM), by secondary energy map (SEM), and by the combination of Itti's saliency map with gradient magnitude (Itti's + G), respectively. The seam carving using the proposed features gives better results.

V. Conclusion

We have proposed the use of variance of weighted gradient orientation as area features and applied it to an importance map for image retargeting. The importance map as global features is expressed by superimposing area features in multiple layers. We have demonstrated the effectiveness of the proposed features comparing to the typical and state-of-the-art salient features. We can confirm that the gradient vector on a partial edge faces approximately in the same direction and that the homogeneous weight of the block covers the edge is effective for seam carving.

In future work, we plan to find appropriate block shape, size, and weight in each layer.

[1]Except for BEM and Itti's saliency map, the color image was converted into a gray-scale one beforehand by

$$g(n_1, n_2) = 0.2126\, r(n_1, n_2) + 0.7152\, g(n_1, n_2) + 0.0722\, b(n_1, n_2)$$

where $r(n_1, n_2)$, $g(n_1, n_2)$ and $b(n_1, n_2)$ denote 0 to 255 value of the red, green, and blue channels per pixel, respectively.

References

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