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Image Blur Classification and Unintentional Blur Removal

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ABSTRACT Blur is a general image degradation caused by low-quality cameras or intentional photographing for highlighting moving or salient objects. However, most blur classifiers just classify images into blur and sharp, which cannot distinguish the intentional blurred images from the unintentional blurred ones. Some unintentional blurred images are too valuable to discard directly. In this paper, we propose a robust image blur classifier to classify images into sharp, intentional blur, and unintentional blur. The basic idea of identifying the blur of a pixel being intentional or unintentional is that whether the blur occurs on a salient and semantic meaningful object. This inspired us to employ cues of blur, saliency, and semantic segmentation. We use spatial pyramid pooling to extract global features. Then, a random forest is used to conduct classification. We further detect the unintentional blur pixels by incorporating the cues into a conditional random field (CRF). The intentional blur image can be generated by pasting the deblurred unintentional blur regions back to the blur image. We conduct image blur classification on UBICD dataset and unintentional blur removal on different types of unintentional blur images. The experimental results show superior performance of image blur classification and the promising results of unintentional blur removal of our method.

INDEX TERMS Blur detection, blur classification, deblurring, blur removal.

I. INTRODUCTION

Blur is a very common image degradation problem when capturing the photos. The main reasons caused image blur are camera shaking, object movement, out-of-focus and low-quality cameras. Delicate photographers intentionally blur the background to highlight the salient foreground objects or blur the moving objects to exhibit dynamic effect. Thus, the stories of the images are vividly. On the contrary, ordinary users are easier to blur the whole images because of the camera movements caused by pushing shutters. Obviously, this kind of blur is unintentional. However, some unintentional blur images are very valuable for recording important moments, which need to be recovered.

To better understand the concepts of *intentional* and *unintentional*, we give two examples of unintentional blur images and the corresponding recovered intentional blur images in Fig. 1. The main objects (i.e., the man and the cows) of the unintentional blur images are blurred, which makes unintentional blur images lacking of themes and artistic conceptions. However, most of the people want the intentional images shown in the rightmost column of Fig. 1. In intentional blur images, the blur only occurs on the unimportant objects and backgrounds; the most parts of the main objects are sharp. Compared with sharp images, intentional blur images can filter out the secondary information and catch the readers' attentions. In contrast to blur images, intentional blur images have highlighted themes and artistic conceptions. Thus, intentional blur is very useful.

However, on the one hand, the state-of-the-art image blur classification pays more attention on classifying images into blur and sharp [1]–[3], and ignores the intentional blur and the unintentional blur. Recent works [4], [5] further classify the blur into motion and out-of-focus. The major

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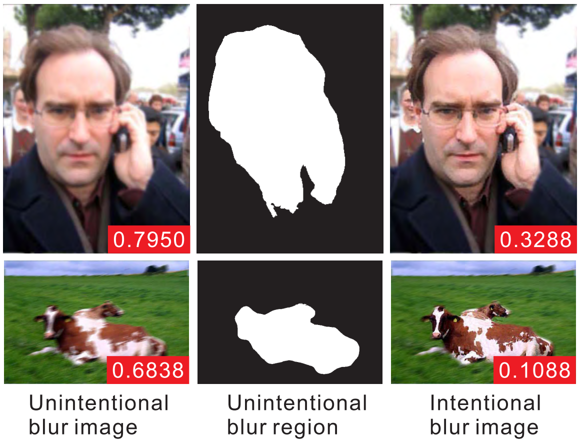

FIGURE 1. Examples of unintentional blur images and recovered intentional blur images. The blur useless scores are highlighted by the red rectangles. Smaller useless blur score means better perception.

obstacles and difficulties of classifying the blur images into intentional or unintentional blur are lacking of the definite definition of unintentional blur and effective semantic features. On the other hand, there are no existing methods for removing unintentional blur. Although traditional deblurring methods [6], [7] can remove the blur, they recovery the whole blur image to generate a sharp image. Directly deblurring image may not obtain promising deblurred result with the blur kernel that estimated on the whole image, let alone retain the artistic conception of the image. For most unintentional blur images, we just want to remove the unintentional blur and keep the backgrounds to be blurred.

In this paper, one of our aims is to classify the images into sharp, intentional blur and unintentional blur. The final objective is to detect and remove unintentional blur. The main difficulty is that how to define the unintentional blur pixels. By observing the captured images, we find that the intentional blur and the unintentional blur are tightly related to the position of blur occurring. Generally speaking, if blur occurs on the background, then the blur is intentional; Else if the blur occurs on the foreground object, then the blur is unintentional. The most related works of finding foreground objects and backgrounds are salient object detection and semantic segmentation. Thus, we use probability maps of blur classification, saliency detection and semantic segmentation as cues for intentional and unintentional blur identification. The saliency detector identifies the salient object. And semantic segmentation method distinguishes the foreground object and background. The basic rationale is that the object having high saliency value and in same semantic region should be sharp in blur image. We employ spatial pyramid pooling method on the probability maps of blur, saliency and semantic segmentation to formulate global features. This kind of features can capture the relation and distribution of blur, saliency and semantic segmentation. Based on this discriminative features, a simple classifier has been trained to conduct classification. The byproduct of the cues is pixel-level unintentional blur region detection. A conditional random field (CRF) is used to generate the unintentional blur pixels by incorporating blur, saliency and semantic segmentation cues. We employ the state-of-the-art deblurring method to generate a sharp image. Then pasting the recovered sharp regions back to the corresponding unintentional blur image to generate the intentional blur image. The experimental results of image blur classification on UBICD dataset and unintentional blur removal on five different types of unintentional blur images verify the effectiveness of our method. The contributions of this paper are three-fold:

- We propose to subdivide blur into two novel blur types, i.e., intentional blur and unintentional blur. We also propose an image blur classifier by classifying images into sharp, intentional blur and unintentional blur.
- We propose a method to detect unintentional blur regions by incorporating the probability maps of blur, saliency and semantic segmentation.
- We propose two strategies for recovering unintentional blur regions and removing unintentional blur with the state-of-the art deblurring methods.

II. RELATED WORK

A. BLUR CLASSIFICATION & DEBLURRING

Two-type image blur classifiers are proposed by [1]–[3], which only partition the image into sharp and blur. In recent works [4], [5], the blur types are further classified into motion and out-of-focus. Low-level statics features, such as multi-directional gradient statistics [8], singular value [9], local power spectrum slope [10], sub-band decomposition [11] are favorite for blur classification. Specifically, Hsu and Chen [4] propose a SVM based classifier that classifies images into sharp and blur at first, and further classify the blur kernels into motion blur and out-of-focus blur. The blur extent can also be obtained by SVM confidence. Sun *et al.* [2] propose image blur classification based on adaptive dictionary. Beyond handcraft features and simple classifiers, deep networks are also introduced in blur classification and blur detection. Yan and Shao [5] propose a two-stage system using deep belief networks to classify the blur type first and then identify its parameters. The latest work [12] proposes a six-layer deep convolutional neural networks to conduct patch-level blur classification.

The purpose of image deblurring is estimating the sharp image and the corresponding blur kernel from a blurry image. General deblurring methods can be classified into uniform deblurring and non-uniform deblurring. Uniform deblurring methods [13], [14] assume the blurry image is blurred by a single blur kernel in a whole image extent, which is more easier than non-uniform deblurring [15], [16]. Deblurring is highly ill-posed problem, which always needs additional priors and iterative optimization. General priors, such as heavy-tailed gradient distributions [13], sparsity [17], low-rank [14] and extreme Channels [18] are used to constrain the image or blur kernel. Our purpose is to classify image blur, to detect and remove unintentional blur, not to deblur. Thus, in this paper, we utilize the state-of-the-art deblurring

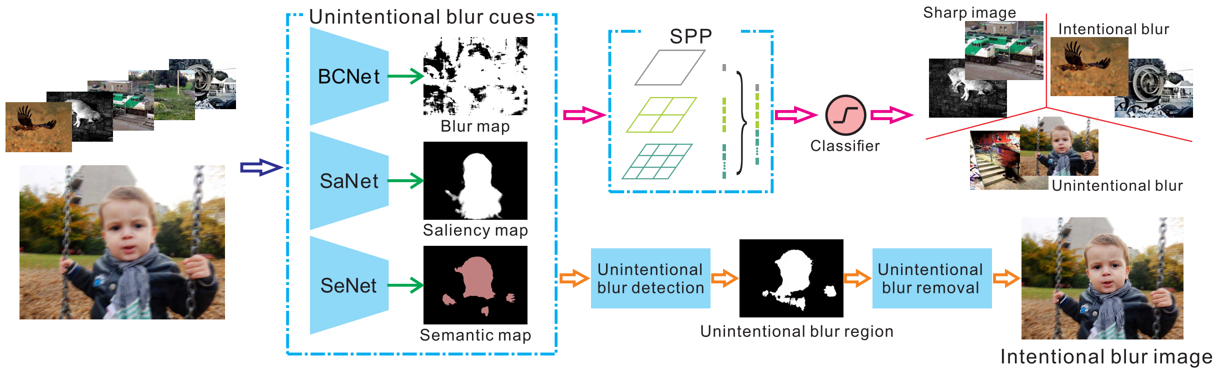

FIGURE 2. The frameworks of image blur classification and unintentional blur detection and removal. SPP denotes Spatial pyramid pooling. BCNet, SaNet and SeNet are blur detection, saliency detection and semantic segmentation networks, respectively.

methods to achieve sharp images, while not to study a novel deblurring method.

B. SALIENCY DETECTION

Saliency detection aims at detecting the conspicuous foreground objects in an image. Thus, the results can indicate the position of an image where the photographers want readers to read. The existing saliency detection can be divided into top-down models and bottom-up models. Top-down models are task-driven methods that aim at detecting specific objects. While bottom-up models simulate the perception of the human eyes to detect any salient objects in an image. A representative work of contrast based saliency detection [19] simultaneously compute region-level global contrast and spatial coherence. Because of the simplicity, contrast based models are always computation efficient. However, this kind of methods do not consider the neighborhood relationships and salient priors, which makes them fail in some complex scenes. Later works [20]–[22] employ boundary and connectivity priors and propose geodesic saliency measure based on superpixel graph.

After the huge success of CNN for object recognition, most of the state-of-the-art saliency detectors are designed based on CNN. Li and Yu [23] use a two-layer neural network to classify a superpixel into salient or non-salient with concatenated multiscale deep features of that suerpixel. Liu and Han [24] propose an end-to-end deep hierarchical saliency network, which learns global saliency and then progressively refines the local details with recurrent CNN. Li and Yu [25] design a two stream saliency detection method, wherein, one stream is a fully CNN that is responsible for end-to-end pixel-level saliency detection, another is a network with two fully connected layers that is responsible for segment-level contrast evaluation. The saliency predictions of the two streams are fused by an element-wise addition layer to generate final saliency prediction. In this paper, we use a deep learning based saliency detector [26] to generate the features for image blur classification and unintentional blur detection.

C. SEMANTIC SEGMENTATION

Unlike the saliency detection focuses on conspicuous objects, semantic segmentation tries to segment the images into semantic consistent regions like background, people, cars, buildings and so on. Previous semantic segmentation primarily adopt hand-crafted features and simple classifiers to classify each pixel (or superpixel) in accordance with their corresponding labels [27], [28]. One representative work [27] proposes to use 1708D superpixel features that consists of shape, location, texture/sift, color and appearance for local superpixel labeling. Most contemporary semantic segmentation methods use CNNs to extract adaptive features and classify pixels into different semantic labels [29]–[31]. To improve the results of semantic segmentation, CRF can be incorporated in CNNs [32] or added as postprocessing step [33], [34] because of the efficient inference of dense CRF [35]. From our experiments, we find that objects generated by semantic segmentation are more complete than the objects produced by saliency detection. Thus, semantic segmentation can help us find complete and salient foreground objects.

III. METHOD

Fig. 2 shows the main framework of the proposed method. Given an image, we first classify it into sharp, intentional blur and unintentional blur. If the image is classified into unintentional blur, then our method can further detect the unintentional blur regions and remove the unintentional blur.

A. UNINTENTIONAL BLUR IMAGE CLASSIFICATION

Unintentional blur image classification aiming to evaluate the quality of an image that is highly relate to people's cognition is different from image classification. Whether the blur is intentional or unintentional, it is decided by the position of blur occurring. Specifically, if the blur happens on the background, it is intentional; If the blur happens on the foreground objects, it is unintentional. Thus, the main task for classifying an image into sharp, intentional blur and unintentional blur is finding effective features. Since lacking of data, in this paper, we use hand-crafted features, i.e., the probability maps of blur, saliency and semantic segmentation. Blur map indicates where the blur happens. Saliency map gives the cues of where the blur should not exist. Semantic segmentation helps to complete the saliency detection to achieve accurate object boundaries. Firstly, we introduce how to extract image-level unintentional blur features. Then we describe the details of our image blur classifier.

1) IMAGE-LEVEL UNINTENTIONAL BLUR FEATURE EXTRACTION

The state-of-the-art deep learning based saliency detector (SaNet) [26] and semantic segmentation method (SeNet) [36] are used to generate saliency maps and semantic segmentation results. Note that all estimated semantic objects are treated as foreground. Thus we only have foreground and background maps. For generating blur map, we propose a six-layer convolutional neural network, named BCNet. BCNet has similar architecture with the network of [37]. It takes a 48×48 image patch as input and outputs the probabilities of sharp, motion blur and out-of-focus blur. Here, we consider the blur type of motion and out-of-focus because some move objects have motion blur to highlight the movements. Although the blur happens on the foreground objects, it belongs to intentional blur. BCNet has three convolutional layers with 64, 128 and 256 filters of sizes 11×11, 5×5 and 3×3, respectively. And three fully connected layers with 1024, 256 and 3 nodes for classification. Please refer to [37] for the details of BCNet training. We use dilation filters [38] to convert the BCNet to an end-to-end network.

As mentioned before, sharp, intentional blur and unintentional blur classification is highly related to the blur types, image content and the position that blur occurs. The probability maps of blur detection, saliency detection and semantic segmentation are used as our basic intentional blur features. Given an image, we use spatial pyramid pooling (SPP) to extract image-level unintentional blur features. SPP can capture distribution of blur, saliency and semantic segmentation feature, which coincides with the blur judgment of human. Specially, in kth pyramid, we partition the maps into $k \times k$ cells, and use average pooling in each cell to obtain the corresponding features. From BCnet, we obtain 3D blur features (sharp, motion blur, out-of-focus blur). From SaNet and SeNet, we get 1D saliency feature and 1D semantic segmentation feature (the probability of foreground), respectively. Finally, for each cell, we concatenate 3D blur features, 1D saliency features and 1D semantic segmentation features to obtain a 5D (sharp, motion blur, out-of-focus blur, saliency and semantic) unintentional blur related features. The features of all cells are concatenated together to generate image-level unintentional blur features. When using pyramid level K, we can obtain a $n_{dim} = 5 * \sum_{k=1}^{K} k^2$ dimensional features for each image. According to the experiment of previous work [37], we set K to 5.

FIGURE 3. An example of the deblurred result of a state-of-the-art deblurring method. There are serious ring artifacts at the boundaries of the deblurred image.

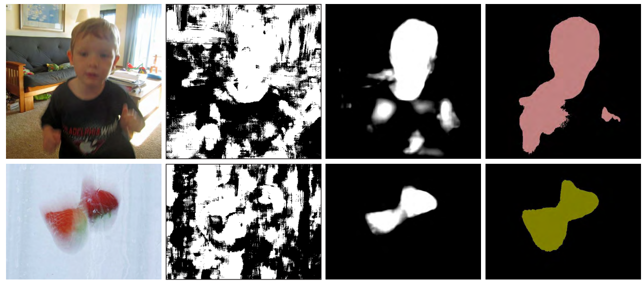

FIGURE 4. Two images (a) with blur detection (b), saliency detection (c) and semantic segmentation (d).

2) IMAGE BLUR CLASSIFICATION

Given a training image set $\mathbb{I} = \{I_1, I_2, \ldots, I_N\}$, where N is image number. Let $\mathbb{F} = \{F_1, F_2, \ldots, F_N\}$ denotes the feature set, where $F_i \in \Re^{1\times n_{dim}}$. The corresponding label set is $\mathbb{L} = \{l_1, l_2, \ldots, l_N\}$, where $l_i \in \{-1, 0, +1\}$, -1 means sharp, 0 means intentional blur and $+1$ means unintentional blur. We train a RandomForest [39] with 1000 trees to classify the image. The confidence score of unintentional blur is used as the blur usefulness score of an image. Note that one can also use SVM [40] classifier provided by LIBLINEAR [41].

B. UNINTENTIONAL BLUR DETECTION AND REMOVAL

The purpose of unintentional blur removal is to remove the unintentional blur while keeping the intentional blur. This is different from traditional deblurring methods which deblur the whole image. Fig. 3 shows a deblurring results of state-of-the-art deblurring method. Although the blur has been removed from the car, there are rings on the image boundaries. Actually, the blur of the backgrounds are useful, which should be kept. To remove the unintentional blur, we should detect the unintentional blur regions at first, then conduct deblurring algorithm on the corresponding regions.

1) UNINTENTIONAL BLUR DETECTION

Only using one of the results of blur detection, saliency detection or semantic segmentation could not capture the real unintentional blur regions. Fig. 4 shows the blur detection, saliency detection and semantic segmentation results of two images. The results of the saliency are easily affected by the blur boundaries of the objects. To conquer this problem and obtain accurate unintentional blur region, we conduct image segmentation with blur, saliency and semantic segmentation probability maps. We use the summation of the motion blur probability and out-of-focus probability that obtained from BCnet to generate blur probability map P_{Bl}. The saliency probability map P_{Sa} and semantic segmentation probability map P_{Se} can be obtained by the SaNet and SeNet, respectively. Then we compute the unintentional blur probability by weighted sum of probability maps of the blur, saliency and semantic segmentation by

$$P = \omega_1 P_{\mathrm{Bl}} + \omega_2 P_{\mathrm{Sa}} + \omega_3 P_{\mathrm{Se}}, \tag{1}$$

where $\sum \omega_i = 1$. In the experiments, we set $\omega_1 = \omega_2 = \omega_3 = \frac{1}{3}$. However, one can adaptively adjust the weights by observing the quality of the blur detection, saliency detection and semantic segmentation.

With the unintentional blur probability map P, we compute the unintentional blur regions by dense conditional random field (CRF) [35]. The energy function of CRF is defined as

$$\mathrm{E}(l) = \sum_p \phi_p(l_p) + \sum_{pq} \psi_{pq}(l_p, l_q), \tag{2}$$

where l is pixel label, $\phi_p(l_p)$ is unary potential, $\psi_{pq}(l_p, l_q)$ is pairwise potential, p and q are pixel positions. We define the unary potential $\phi_p(l_p) = -\log \mathrm{P}(p)$, where $\mathrm{P}(p)$ is unintentional blur probability. The pairwise potential $\psi_{pq}(l_p, l_q)$ considers the distance and the appearance smoothness of the neighbor pixels, which is defined by

$$\psi_{pq}(l_p, l_q) = \mu(l_p, l_q) k(p, q), \tag{3}$$

where, $\mu(l_p, l_q) = [l_p \neq l_q]$ is indication function, kernel $k(p, q)$ is defined as

$$k(p, q) = \omega_1 \exp\left(-\frac{\|p - q\|^2}{2\sigma_\alpha^2} - \frac{\|I_p - I_q\|^2}{2\sigma_\beta^2}\right) + \omega_2 \exp\left(-\frac{\|p - q\|^2}{2\sigma_\gamma^2}\right), \tag{4}$$

where σ_α is set to 20, σ_β is set to 3, σ_γ is set to 3, ω_1 is set to 5, ω_2 is set to 3. The first term encourages that the pixels with similar features have same labels. The second term removes isolated pixels.

2) UNINTENTIONAL BLUR REMOVAL

After we obtain the unintentional blur region, we can remove the blur of the corresponding region by the state-of-the-art deblurring methods [6], [7], [15]. Note that there is no omnipotent deblurring method for all kinds of blur images. Thus, one should select deblurring methods adaptively according to the image. There are two different strategies for recovering unintentional blur regions. The first one is deblurring the whole image and segment the unintentional blur regions, which can be formulated by

$$I = (B \otimes K^{-1}) \odot M + B \odot \bar{M}, \tag{5}$$

where M is unintentional bur mask; $\bar{M} = 1 - M$ is intentional blur mask. The second strategy is directly deblurring the unintentional blur region by

$$I = (B \odot M) \otimes K^{-1} + B \odot \bar{M}, \tag{6}$$

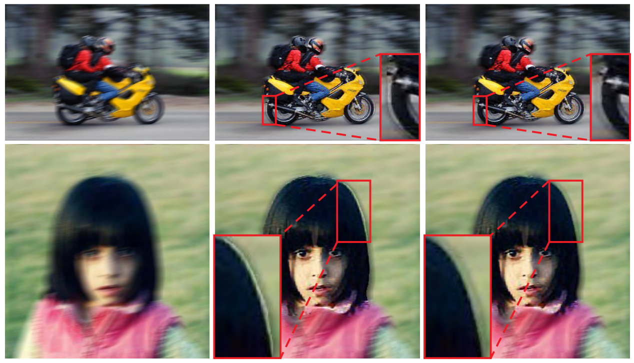

FIGURE 5. Two examples of unintentional blur removal with/without the proposed contour smoothed combination.

In the experiments, we use the first strategy for the uniform blur images and use the second one for the non-uniform blur images.

3) CONTOUR SMOOTHED COMBINATION

As shown in the 2nd column of Fig. 5, directly combining the restored unintentional blur region to the original blur image would result in unpleasant artifacts in the junction of the restored regions. To solve this problem, we propose contour smoothed combination. Specifically, we blur the boundary pixels of restored unintentional blur region by a Gaussian blur with kernel size of 3×3. The width of the boundary pixels are set to 10. Then we paste the restored region back to the original useless blur image and obtain the recovered useful blur image. This strategy can smooth the junction of the unintentional blur regions. As shown in the 3rd column of Fig. 5, the recovered intentional blur images have less artifacts in the connection areas.

IV. EXPERIMENT

In this section, we first show the results of the proposed image blur classification method. Then we demonstrate unintentional blur detection and removal for the unintentional blur images.

A. UNINTENTIONAL BLUR IMAGE CLASSIFICATION

1) DATASET

We use UBICD [37] for unintentional blur image classification. UBICD has 2000 images, including 1000 sharp images and 1000 blur images. There are 500 intentional blur images and 500 unintentional blur images.

2) BASELINE

Since the proposed image blur classification method aims at classifying the images into sharp, intentional blur and unintentional blur, the previous two-class blur classification methods (e.g., BIQI [42], BRI [43], JNB [44], CPBD [45] and MDWE [46]) are not suitable for comparison. In this paper, we use BICUBA [37] as the baseline with the pyramid level set to 5. BICUBA tries to classify the images

TABLE 1. Comparison of accuracies of the image blur classification method and baseline BICUBA [37] for sharp, intentional blur and unintentional blur image classification.

Criteria	Ours	BICUBA [37]
Accuracy	0.9	0.8675

into sharp, useful and useless. The concepts of *useful* and *useless* are similar to the proposed concepts of *intentional* and *unintentional*. However, BICUBA conducts two steps for classification. In the first step, the images are classified into sharp and blur. In the second step, the blur images are further classified into intentional and unintentional.

3) RESULTS AND ANALYSIS

Table 1 shows the accuracies of the proposed method and BICUBA [37] for sharp, intentional blur and unintentional blur image classification. On UBICD [37], BICUBA [37] achieves 0.8675 accuracy for three types classification. And our image blur classification method reaches the accuracy of 0.9, which achieves 3.7% relative improvement. The proposed method takes 7.91s to process an image of size 640 × 480, which is faster than BICUBA [37] whose processing time is 8.96s. Both the accuracy and the speed of the proposed are superior than the baseline.

B. UNINTENTIONAL BLUR DETECTION AND REMOVAL

1) DATASET

To quantitatively evaluate the performance of the proposed blur removal method, we manually collect 100 unintentional blur images from 5 different themes. There are 26 animal images, 7 food images, 38 person images, 24 traffic images and 5 other images. The blur images may have motion blur, out-of-focus blur or both.

2) RESULTS AND ANALYSIS

Fig. 6 shows the average useless blur scores of different types of images before and after our unintentional bur removal. From the figure, we can find that for all types of the images, the images generated by our unintentional blur removal have lower useless blur scores. Specifically, compared with the original blur images, the average useless score of recovered intentional blur images is lower about 0.2382 on whole set. For animal, food, person, traffic and other images, our recovered intentional blur images obtains about 0.2802, 0.2682, 0.2893, 0.0906 and 0.32 improvements, respectively.

Fig. 7 shows some typical unintentional blur detection and removal examples. We can find that directly deblurring the images with general deblurring methods may cause *ring* artifices, even losing the focus effect to highlight the salient object. This states the necessities of the proposed unintentional blur removal. As shown in Fig. 7, our method detects the relatively complete unintentional blur regions (e.g., the running car in the 1st row and the driver in 4th row). Deblurring on the unintentional blur region can remove the unintentional blur and make the gist of image more clear. And the retained blur in background region can suppress less important image content. Therefore the recovered intentional blur image has ability in highlighting the salient object in an image and making the image has more artistic conception, which is coincident with photography. We also give the useless blur score of each image at the right-bottom of the image in Fig. 7. The generated intentional blur images always have lower useless blur scores, which shows the effectiveness of our unintentional blur removal.

V. DISCUSSION

The performance of unintentional blur detection and removal relies on the quality of blur map, saliency map and semantic segmentation. Bad result of blur detection, saliency detection or semantic segmentation will generate bad unintentional blur detection, which further results in unsatisfactory unintentional blur removal. Fig. 8 shows some failure cases of unintentional blur detection. The failure of the first row of Fig. 8 is caused by misclassifying the pixels of the bear into sharp and missing the salient object in saliency map. The bad semantic segmentation of the second image results in unsatisfactory unintentional blur region. One can change the weights of Eq. 1 to endow large weights on saliency or semantic segmentation. However, in the third row, both of the saliency map and semantic segmentation are incorrect, which results in bad unintentional blur region detection.

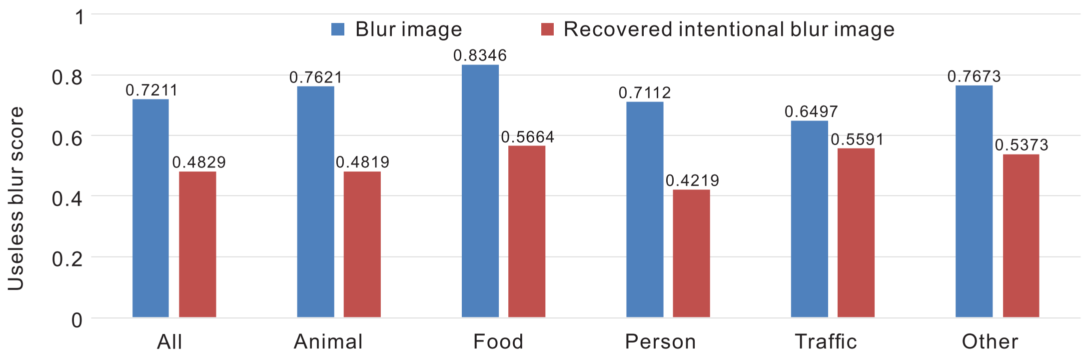

FIGURE 6. The comparison of average useless score of the different types of images before and after the unintentional blur removal.

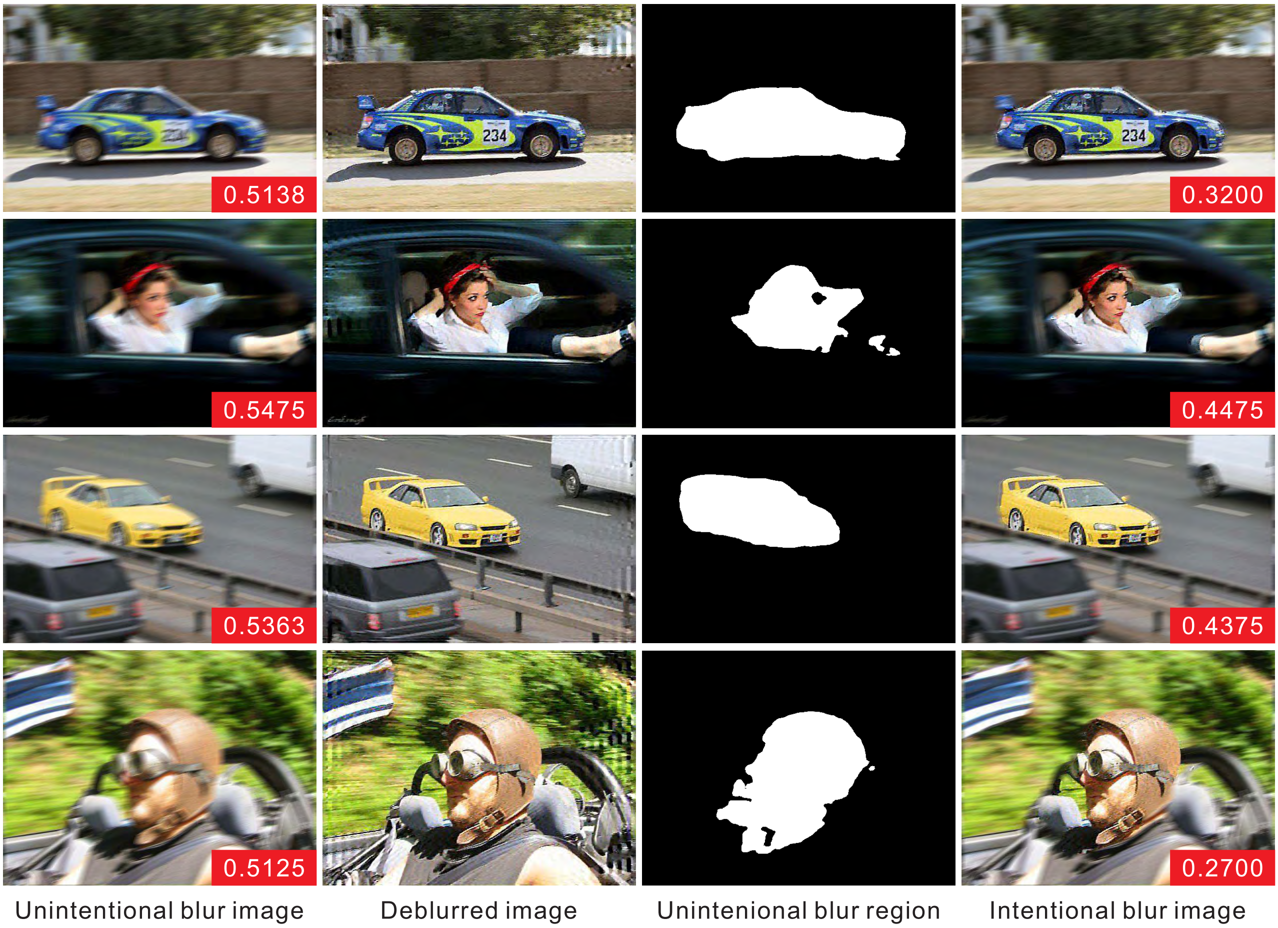

FIGURE 7. **Examples of unintentional blur detection and removal. From left column to right column are unintentional blur images, deblurred images, unintentional blur regions and recovered intentional blur images. The useless blur scores are highlighted by the red rectangles. Smaller useless blur score means better perception.**

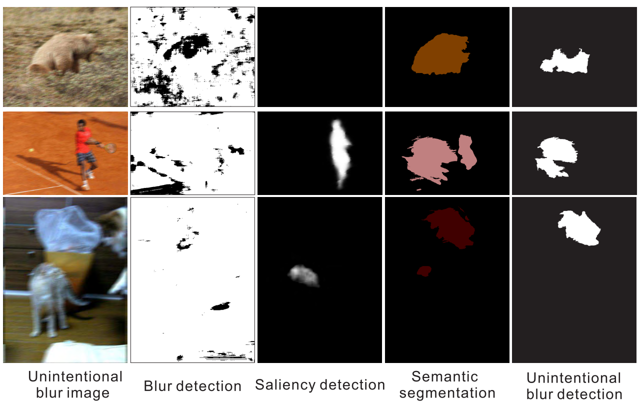

FIGURE 8. **Failure cases of unintentional blur detection caused by different reasons.**

Different from image deblurring that removes the blur of whole image, the proposed unintentional blur detection and removal aim to find the unwanted blur and remove it. Actually, intentional and unintentional blur are subjective and hard to be formalized mathematically. To make the data unbiased, we classify the blur images into intentional and unintentional blur images by five people. According to the voting results, we select 500 intentional and 500 unintentional blur images. The details of building the dataset can be found in our previous work [37]. A possible way to formalized unintentional blur removal is nonuniform deblur, which will be studied in our future work.

Unintentional blur detection can be treated as saliency detection or semantic segmentation, which can be solved by training a convolutional neural network. However, due to lacking of data, end-to-end models cannot be easily learned. In our future work, we will try to build a large dataset for facilitating intentional and unintentional blur classification, detection and removal.

VI. CONCLUSION

In this paper, we have proposed a novel image blur classification to classify the images into sharp, intentional blur and unintentional blur. The proposed classifier explores the cues of blur detection, saliency detection and semantic segmentation based on the assumption that unintentional bur always occurs on the salient and semantic complete objects. Although our image blur classification achieves 90% accuracy on UBICD [37], there is still much space to improve intentional blur and unintentional blur classification. Besides image blur classification, we further propose to detect and remove the unintentional blur for unintentional bur images. The unintentional blur removal is not simple deblurring and pasting back. To generate pleased intentional blur images, we propose two different strategies for deblurring and a Gaussian blur based contour smoothed combination to reduce the unpleasant artifacts in the junction of the restored regions. The experimental results show the promising performance of unintentional blur detection and removal.

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