Automatic blur type classification via ensemble SVM

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1. Introduction

Image blur, a form of bandwidth reduction of an ideal image owing to imperfect formation process, is a major source of image degradation. It can be caused by, e.g., blur-incurred point spread function (PSF) in simulated environment, out-of-focus of the imaging system, as well as target motion during the signal capturing process [1]. In addition, natural weather (e.g., haze pictures are blurred images incurred under natural foggy/smoggy weather) interference can also result in blurred images during outdoor imaging [2].

Research regarding blur phenomena in digital image can be roughly categorized into three main branches: blur detection, blur classification, and image restoration. Although the topics of image blur analysis have attracted much attention in recent years, the most focused topic in existing studies is image restoration, i.e., deblurring. In the current literature, various techniques have been developed for restoration of the blurred images. These techniques can be further categorized as non-blind and blind methods. The non-blind methods [3–6] require prior knowledge of the blur kernel parameters, whereas, the blurring operators are assumed to be unknown in advance in the blind methods [7]. In real applications, deblurring a blurred image without the knowledge of its point spread function (PSF) using blind methods is much more common and more challenging. The current literature offers several methods to tackle this challenge. For instance, single-channel blind deconvolution within Bayesian framework is proposed in [8]. Other methods employing either the single scattering model or the multiple scattering model have been attempted to resolve the haze removal problem. These include single scattering model-based guided filtering method in [9] and multiple scattering model-based remote sensing image restoration method in [10].

In addition to the image deblurring problem, blur detection and blur classification which are critical to image deblurring issue have become increasingly attractive in the field of image processing. From articles [11–13], the information of image blur type or blur parameters are necessary for blur image recovery, which are obtained from the blur detection and blur classification. However, though the blur detection and blur classification is significant to the image deblurring, the current research on blur detection and classification is relatively under-explored and the existing results are still far from practical application. On the other hand, automatic image blur detection and classification are not only useful but also critical to learning image information, which are
indispensable in image segmentation, depth recovery, and image retrieval, especially, the restoration of blurred photographs. Between these two topics, blur detection aims at determining whether an image is clear, locally (non-uniform, spatial-varying) blurred, or globally (uniform, spatial-invariant) blurred. For locally blurred images, segmenting the image into blurry and non-blurry areas will be carried out during blur detection as well. However, it can be shown that, without knowing at least the type of the blur, the deblurring filters will not perform up to expectations. Moreover, if an incorrect blur model is assumed during blur classification, the image will be rather distorted than restored after the deblurring operation. Therefore, the objective of blur classification is to determine the type of the blurred areas according to their characteristics extracted from the original digital images. Clearly, blur detection can be viewed as a preparation step for blur classification. For globally blurred/non-blurred images, blur detection can be viewed as a special case of blur classification. This paper is intended to contribute to the area of blur classification.

We know from recent literature that there are several blur detection and classification methods based on the descriptors of blurs. For example, based on the observation that blurry regions are more invariant to low pass filtering, Rugna et al. [14] introduce a learning method to classify blurry or non-blurry regions in a single input image. Unfortunately, this method just segments the blurry region from the whole picture, and no follow-up work is carried out to identify the exact blur types. Another example is the Bayes classifier applied to automatic detection of locally blurred regions in an image and identification of the blur types based on selected blur features (e.g., local power spectrum slope, local autocorrelation congruency) [15]. A similar method based on the alpha channel feature, which has different circularity of blur extension, has been proposed by Su et al. [16]. In addition, some researchers have investigated the application of the neural network architecture to blur type classification and parameter identification. A simple single-layered neural network based on multi-valued neurons is presented by Aizenberg et al. [17] to identify four blur types: defocus, rectangular, motion, and Gaussian. In a recent study, another learning-based method using a pre-trained deep neural network (DNN) and a general regression neural network (GRNN) is developed by Yan and Shao [18] to classify three blur types (Gaussian, motion, and defocus) and then estimate their respective blur parameters. In addition, Gaciono et al. [19] develop a blur assessment algorithm based on multiple weak features to boost the performance of the final feature descriptor, and show that the combined features work better than individual features under most circumstances. As a powerful tool in classification problems with small samples and nonlinearity, Support Vector Machine (SVM) [20] has also been applied to blur image assessment for both artificially-distorted images and naturally-blurred ones by deriving and applying blur features from the power spectrum in the frequency domain [21]. Specifically, in [22], Laplace distribution-based probabilistic SVM classifiers are proposed to detect and localize the blurred regions without using prior knowledge about the image by implementing feature extraction in the discrete wavelet space. In [23], an SVM classifier based on Sobel operator and local variance is developed for blur identification. Experimental results demonstrate the feasibility and validity of the proposed method. Finally, in [24], the spatial features and spectrum features are extracted to train a multi SVM for classifying the degraded images and evaluating the quality of the image degradation.

Inspired by the preponderance of SVM in practical applications [20–24], in this paper, we propose a method, which constructs an SVR-based ensemble SVM classifier by a unique voting weight strategy to identify four kinds of images: motion, defocus, haze, as well as clear images. It should be noted that, while multiple blur types may exist in one picture, in the current paper, we only consider the case where a picture contains no more than one blur type. Extensions of the research to images containing multiple types of blurs will be pursued in future work. Note also that while motion blur can be caused by the movement of either the object (resulting in locally blurred images) or the camera (resulting in globally blurred images), this paper considers the latter. For the former, one can first extract the blurred region and then apply the methods developed in this paper.

Our work contributes to the field of blur image classification techniques in the following three ways:

- To the best of our knowledge, a voting weight-based ensemble SVM classifier is applied to blur image classification for the first time in this paper, and its performance is justified using extensive experiments.
- The Support Vector Rate (SVR)-based SVM-RFE method is adopted for the first time to implement the ranking of multi-characteristic blur features and our experiments prove that SVR can successfully estimate the significance of the extracted blur features.
- Although the haze blur images are very common in real applications, it is considered for the first time in blur image classification.

The rest of the paper is organized as follows. In Section 2, we overview different types of blur features and their extraction; Section 3 details our SVR-based Ensemble SVM classification approach, including a brief review on SVM theory, SVM-RFE-based blur feature selection, and ensemble SVM classifier design. In Section 4, numerical experiments based on simulated datasets and real-world datasets, as well as the comparisons with the state-of-art approaches, are described. Discussions of the numerical experiments are presented in Section 5. Section 6 concludes the paper.

2. Blur feature extraction

Blur feature extraction is the basis for blur image classification and it directly determines whether the classifier can accurately identify the blur images. Except the recent rise of very effective machine learning techniques, such as deep convolutional networks, most other classifiers require manual feature extraction. In general, brainstorming the variables and metrics that might be better features as well as exploring different combinations of variables and metrics are carried out first. The criteria to select 35 features are based on the analyzing the causes of three kinds of blur types. It is found that the fuzzy effect of the motion blurred image mainly exists in the direction of motion, while the blur of the defocus can be regarded as the diffusion effect in all directions, and the attenuation of the edge gradient is larger. As for image blurring caused by haze can be regarded as noise interference caused by atmospheric particles, and the edge details of scenes are reduced, but they are still legible. In this section, we overview and define different types of blur features, including statistical features, texture features and image quality metrics in the spatial domain, and spectrum features as well as local power spectrum features in the frequency domain. These features will be later used in the proposed ensemble-SVM classifier.

- Statistical features

The statistical features extracted from an image measure coarseness, contrast, directionality, etc. In this paper, mean and standard deviation of gray value and dark channel intensity are picked as the statistical features. Specifically, these features are defined as follows:

(1) Mean:

\[
\mu = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} I(i,j)
\]

where \(I(i,j)\) represents the gray value or the dark channel intensity of the image, and \(M \times N\) is the image size.

(2) Standard deviation:

\[
\sigma = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - \mu)^2}
\]

where \(\mu\) is defined in Eq. (1).
It should be noted both gray value and the dark channel value are very effective in handling haze blurred images. Indeed, haze blurred images usually present a gray/white color due to the interference of natural fog, while other types may be rich in color and the distribution of gray values is uneven. As a result, the gray scale distribution scope of a haze blurred image is relative narrower than the other kinds of blurred pictures, whose gray values usually show a more random fluctuation pattern. The dark channel value, proposed by He et al. [25], is defined as follows:

$$J_{dark} = \min_{y \in R} (\min_{c, r, g, b} \{ J'(y) \})$$

(3)

where $J'(y)$ is the color channel map, $Q_x$ is the area of pixel $x$. The dark channel values of clear, motion, and defocus images are shown to be relatively smaller than those of the haze images under the same light condition, and, thus, may be effective in identifying and classifying such blurs.

In addition, the variance of saturation [26] of color image in HSV color space is also extracted as another statistical feature for blur classification. Therefore, a total of 5 statistical features are adopted.

- **Texture features**
  - Texture feature [26], which gives us information about the spatial arrangement of color or intensities in an image, is one of the most commonly used features in computer vision and image processing. Moreover, texture feature can also show the iterative or alternative characteristics of not only the gray level between image pixels but also the image color in space. Therefore, in our work, correlation, inertia, entropy, and energy [27] are extracted through calculating gray level co-occurrence matrix (GLCM) of blur images in $0^\circ$, $45^\circ$, $90^\circ$, and $135^\circ$ directions. This leads to a total $4 \times 4 = 16$ texture features to be used in the proposed ensemble SVM classifier.
  - **Image quality metrics**
    - Image quality metrics are typically used to evaluate the different properties of a picture [28]. Indeed, it can be shown that some objective image quality metrics possess certain correlation with the various image blur types, often appearing as a uniform set of frequencies or some representative marks along special directions in (a certain region of) an image. Taking an example of motion blur images, the blur effect mainly exists only along the motion direction, nevertheless, perpendicular to the motion direction, the blur effect can be negligible. By survey analysis, we discover that the defocus blur can be regarded as the diffusion effect in all direction, and its edge gradient attenuation is relatively larger. Also, as the cause of haze blurred images can be attributed to the disturbance of atmospheric particles, the edges of scene details are decreased (i.e., smoothed) but may still be legible. On the other hand, these edges in clear image are usually sharp over the whole picture. Hence, three features, namely, the gray mean grads, peak signal to noise ratio [29], and image Michelson contrast [30] are selected to characterize the gradient information, noise level, and visual effect of different images. Their computational formulas are as follows:
      
    (1) Image Michelson contrast:
    
    $$\text{contrast}_M = \frac{L_{max} - L_{min}}{L_{max} + L_{min}}$$
    
    (4)
    
    where $L_{max}$ is the maximum pixel gray value of one image and $L_{min}$ is the minimum pixel gray value of the image.

    (2) Gray mean grads (GMG):
    
    $$GMG = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \left( I(i, j+1) - I(i, j) + I(i+1, j) - I(i, j) \right)^2$$
    
    (5)
    
    where $I(i, j)$ is pixel $(i, j)$'s gray value, and $M, N$ indicate the length and width of the image respectively.

    (3) Peak signal to noise ratio (PSNR):
    
    $$\text{PSNR} = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right)$$
    
    (6)

    Here, MSE is mean square error [31] which can be assumed as the standard deviation of a single image.

- **Spectrum and Transform features**
  - Stable spectrum features, which usually describe the intrinsic feature of an image, can indicate the differences of various images in the frequency domain. As an illustration, Fig. 1 shows a set of images and their corresponding spectrum using the pre-processing of Fast Fourier transform (FFT) methods.

  Obviously, there are dramatic differences among the spectral distributions of the four kinds of images. The spectrum of the defocus blurred image appears as a concentric annulus that concentrate at the center of the spectrum (Fig. 1(f)); while the spectrum of the motion blurred image presents parallel stripes with alternating light and shade (Fig. 1(g)); clear image spectrum assumes an irregular quadrilateral pattern in Fig. 1(h). The unique spectrum distribution of hazy blurred image, from a certain perspective, looks like a four-point star. From this knowledge, the spectral parameters of the four types of images can be derived. In our case, we further process these spectral images, which are transformed from the real pictures containing noise, by morphological erosion and Canny edge detection method for a better fit to get the main stripes of various spectrum clusters.

  In order to quantify the differences of the main stripes obtained, the most straightforward way is to apply linear fitting to the spectrums and select the fitting slope, intercept, and fitting error of the fitted line as part of the blur spectrum features. By comparing the four kinds of spectrum fitting curves shown in Fig. 2, we can find that only the slope value of motion blur spectrum may change depending on the motion direction, while other slope values generally remain the same, i.e. almost zero. On the other hand, the value of fitting error displays relatively large differences for different types of spectrum.

  Clearly, linear fitting cannot characterize the behavior of the spectrum of a blurred image very well. Therefore, projection transform tools are necessary to measure the distribution of the spectrum in different directions. To accomplish this, the Radon transform approach is applied to transform the spectrum of $f(x, y)$ in Fig. 1(e)-(h) into the transformed image $H(r, \theta)$ to obtain the distribution of the spectra in the specific direction by computing the line integral along a set of lines characterized by different values of $r, \theta$. The formula of Radon transform can be expressed as follows:

$$H(r, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x - r \cos \theta - y \sin \theta) dx dy$$

(7)

Take the Radon transform diagram of the motion blur image as an example, which is demonstrated in Fig. 3(a). During the Radon transform, Gaussian fitting is conducted along and perpendicular to the fitting line direction, respectively, to estimate the projection distribution of the spectrums from both directions: normal and tangential. The Gaussian fitting results for the four images above are shown in Fig. 3(b)(c).

It can be observed from (b)(c) in Fig. 3 that the fitting curves for the clear and haze images have larger width and amplitude in both normal and tangential directions, while the fitting curves of defocus and motion blur image show narrower width and lower amplitude. Based on this observation, we select the width and amplitude of the Gaussian fitting curve as part of the spectrum features to measure the density degree of spectral distributions.

Finally, note that Hough transformation [32] can be used to detect straight lines and curves in an image. In the case of continuous space, Hough transform can be regarded as a special case of the Radon transform. The basic principle of Hough transformation is to use the duality between point and line to transform a given curve in a binary image under the original space into a point in the parameter space through the curve representation. In this way, the detection problem of the given curve in the original image can be transformed into searching for the corresponding peak pixel point in the parameter space. In our implementation, Hough transformation is utilized to detect the number of straight lines in the spectrum image by counting the number of peak
pixels in the respective parameter space of the diverse spectrums shown as Fig. 1 (e–h). From Fig. 4, it is obvious that the clear image has the largest number of straight lines since its Hough transform spectrum has the most highlight points (peak value).

- Local power spectrum features

Inspired by reference [15], the power spectrum is selected as another blur feature in the frequency domain to further enrich the group of potential features for blur classification. Its expression is given by:

$$S(u,v) = \frac{1}{MN} |F(u,v)|^2$$  \hspace{1cm} (8)

where $F(u,v)$ represents the Fourier transform of the original $M \times N$ image. Let $u = f \cdot \cos \theta$, $v = f \cdot \sin \theta$. Then, the power spectrum $S(f, \theta)$ under two dimensional polar coordinates can be attained. In addition, by calculating the sum of $S(f,\theta)$ in different directions, power spectrum
S (f) as a function of frequency f can be derived [33]:

\[ S(f) = \sum_i S(f, \theta) \approx A/f^a \]  

(9)

where A is an amplitude scaling factor of different orientation and a is the exponent of frequency, which is commonly referred to as the slope of the local power spectrum. The logarithmic form of formula (9) is:

\[ \log S(f) \approx \log A + a \log f \]  

(10)

Clearly, formula (10) shows the linear relationship between the amplitude and the frequency of spectrum images under the logarithmic coordinate. Similar to the method used to define spectrum and transform features, the slope, intercept, and fitting error of linear fitting curves of local power spectrum in the form of expression (10) are selected as features for blur classification.

Summarizing the above discussions, a total of 35 blur features are selected in this paper to characterize the differences between the four types of images described above (i.e., haze, defocus, motion, clear). These features are outlined in Table 1.

On the other hand, it should be noted that selecting more features does not necessarily guarantee higher accuracy in classification tasks. Therefore, an important problem is to identify a subset of most informative features that can best capture the blur behavior in images. In this paper, this will be accomplished by designing an ensemble SVM classifier with support vector rate (SVR)-based feature ranking and selection mechanism, and is detailed next.

3. Design of the ensemble SVM classifier with SVR-based feature ranking and selection

The proposed SVR-based Ensemble SVM classifier consists of two phases; namely, classifier design phase, and blur feature selection and ranking phase. Each of them is discussed below.

3.1. SVM-based classification and overall framework of the ensemble SVM classifier

Support Vector Machine (SVM) is a class of machine learning method developed by Vapnik et al. in the early 1990s [34]. By projecting data into the feature space and then finding the separating hyperplane that maximizes the margin between the data, SVM can transform a nonlinear separable problem into a linear separable problem with different kernel functions [35]. Due to its advantage of enhanced generalization properties and its efficiency without direct dependence on the dimension of the classified entities, SVM-based method is widely used to solve classification problems. However, the original SVM is designed for binary classification tasks, which is not directly applicable to multi-class classification problems. Since the blur classification problem studied in this paper requires identification of four different types of images (haze, defocus, motion, and clear), a modified SVM method should be used. In this paper, we investigate both one-against-one (OAO) and one-against-all (OAA) methods. The implementation of the multi-class SVM classifiers is accomplished using LIBSVM [36], which is an efficient open-source library tool supporting multi-class classification.

Moreover, it should be noted that, if a single classifier is used to solve multi-class classification problems, unbalanced sets, sometimes even rare category, are likely to appear. In addition, applying sophisticated models with high dimensional noise to classification problems using single SVMs may lead to limited reliability of the features. As a result, the prediction accuracy of the SVM classifiers will decrease. Due to these technical barriers, single SVM classifier may fall in tackling complex computer vision problems such as the four-type classification one addressed in this paper. To overcome these challenges and limitations of single classifiers, ensemble-based classifiers have shown strong potential in various domains [37,38]. Therefore, the ensemble SVM approach is employed in our classifier design.

3.1.1. The mathematical principle of SVMs

The method of SVM was initially introduced to solve two-class problems. The core idea is to find an optimized hypothetical hyperplane to distinguish the positive and negative samples. The optimization of hypothetical hyperplane is achieved through the structural risk function:

\[ \min_{\mathbf{W}} (\mathbf{W}) = \frac{1}{2} \| \mathbf{W} \|^2 + C \sum_{i=1}^{N} \xi_i \]  

\[ s.t. \ y_i (\mathbf{W} \cdot \mathbf{x}_i + \mathbf{b}) + \xi_i \geq 1; i = 1, 2, ... , N \]  

where \( \mathbf{W} \) is the weight vector and \( \mathbf{b} \) is the bias, both of which are determined only by the training samples. The regular parameter \( C \) is a penalty factor, which can balance the model complexity and empirical risk. In addition, \( \xi_i \)'s are positive parameters called slack variables, which represent the distance between the misclassified sample and the optimal hyperplane. Function \( K(x_i, x_j) \) is the kernel function, and here \( K(x_i, x_j) \) is the Gaussian radial basis function kernel (RBF) [33], which can be expressed as \( K(x_i, x_j) = \exp(-\| x_i - x_j \|^2 / 2\sigma^2) \).

To enable multi-class classification using binary classifiers, one-against-one (OAO) and one-against-all (OAA) methods [36] are common solutions. Take the four-category classification task as an example: the respective classification model of OAA and OAO are illustrated in Fig. 5.

Note that lines \( L_{11}, L_{12}, L_{13}, L_{14} \) in Fig. 5(a) and \( L_{12}, L_{13}, L_{14}, L_{23}, L_{24}, L_{34} \) in Fig. 5(b) are hyperplanes to distinguish different groups of samples. In this figure, A, B, D, E and F are misclassified regions, referred to as dead zones. As shown in the figure, OAA tends to create larger dead zones than OAO. As far as the computation efficiency is concerned, for a K-category classification problem, while the number of optimal hyperplanes of OAO is \( K(K-1)/2 \), greater than OAA’s K hyperplanes for \( K > 3 \), the computational efforts required by OAO are actually less than the OAA method in model training. Therefore, the OAO method is employed for constructing the proposed SVM classifier in this paper. In the numerical experiments carried out in this paper, such OAO-based multi-class SVMs are implemented using LIBSVM.

Finally, as it follows from expressions (11), the optimization problem of SVM requires a pair of parameters, \( C \) and \( \gamma \). Specifically, penalty factor \( C \) characterizes the tradeoff between the complexity and classification accuracy of the classifier, while kernel width \( \gamma \) controls the radial effect range of the kernel. The commonly used optimization method of
original samples are randomly selected to form the training dataset for each classifier. Specifically, to obtain member classifier SVM-based ensemble learning method [39] will be applied repeatedly to obtain a group of member classifiers. The ensemble and how to fuse the member classifiers to form a strong classifier is cross-validation accompanied with grid-search [36]. In our implementation, a 10-fold cross-validation is adopted to enhance the performance of the proposed SVM classifier.

### 3.1.2. Design of the ensemble SVM classifier

As mentioned above, although the trained single SVM classifier may exhibit great classification performance under some test datasets, it cannot guarantee the same level of performance on other test datasets, especially when the number of samples is significantly increased. Moreover, for applications with feature selection methods based on a single classifier, evaluation results are subject to instability. On the other hand, the ensemble SVM technique can combine a set of single classifiers into a more accurate, stronger one to enhance the generality and robustness of the SVM classifier. The implementation of the ensemble method relies on two factors: How to construct each of the member classifiers in the ensemble and how to fuse the member classifiers to form a strong classifier. This is achieved as follows. First, after calculating the blur features described in Section 2 for all images in the entire training dataset (see Part A of Fig. 6), the bagging-based random sampling method [39] will be applied repeatedly to obtain a group of member classifiers. Specifically, to obtain member classifier SVM-i, \( \frac{N}{i} \) of the original samples are randomly selected to form the training dataset (Tr_i), while the rest is used as the temporary validation dataset (Te_i) to evaluate its performance. Then, without investigating the optimal number of members for an integrated classifier, we directly employ 10 different classifier generated during 10 random sampling of the 10-fold cross-validation SVM Recursive Elimination (SVM-RFE) method as the base learners setting. Thus, an ensemble SVM classifier with 10 member classifiers is constructed in this paper. During this step, the member classifiers will select features based on the Support Vector Rate (SVR)-based ranking criterion (see Section 3.2 for details). Clearly, since the member classifiers are constructed using different random samples of the original dataset, the resulting classifiers may have different personalities and, thus, may have different classification decisions for the same image. Finally, to fuse the classification decisions from all member classifiers and form the ensemble SVM classifier, the outputs of the member classifiers are integrated based on a weighted voting mechanism. The design process of our SVR based ensemble SVM classifier is shown in Part B of Fig. 6. After the ensemble classifier is obtained, it can be used for classification tasks beyond the training dataset, as illustrated in Part C of Fig. 6.

From the Part B of Fig. 6, after a member classifier has been trained, the remaining 1/4 samples in the training dataset are used as a temporary validation dataset (Te_i) to evaluate the performance of this member SVM classifier. In our work, the classification accuracy (CA), defined in Eq. (12), is used to evaluate the performance of a classifier:

\[
CA = \frac{N_{\text{correct}}}{N_{\text{all}}} \times 100\%
\]  

where \( N_{\text{correct}} \) is the number of the correctly classified samples and \( N_{\text{all}} \) is the total number of samples. Thus, the classification accuracy (CA_i) for each of the n member SVM classifiers can be calculated by testing each member classifier on its corresponding validation dataset (Te_i). Furthermore, the voting weight \( A_i \) of each member classifier can be derived by normalizing CA, as follows:

\[
A_i = \frac{C A_i}{\sum C A_i}, i = 1, 2, \ldots, n
\]  

Clearly, since better classifiers (i.e., the ones with greater CA_i) are assigned with greater voting weights A_i, the constructed ensemble classifier can effectively overcome the potential issues of the evenly weighted voting method [40]. The details of constructing the ensemble SVM classifier are summarized in Algorithm 1. In this paper, the ensemble SVM classifier is consisted of \( n = 10 \) member classifiers to ensure the balance between the diversity of the member classifier and the simplicity of the integrated classifier structure.

### Table 1

<table>
<thead>
<tr>
<th>Feature categories</th>
<th>Characteristics description</th>
<th>Corresponding index</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Spatial domain</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Statistical</td>
<td>Mean and variance of gray value and dark channel distribution, and variance of saturation channel.</td>
<td>1-5</td>
</tr>
<tr>
<td>Texture</td>
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<td>Image quality metrics</td>
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<td><strong>Transform domain</strong></td>
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<tr>
<td>Spectrum</td>
<td>Slope, intercept, and fitting error of linear fitting curve of spectrums</td>
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<tr>
<td>Radon transform</td>
<td>Amplitude and width of Gaussian fitting of the Radon transform curve in both normal and tangential directions</td>
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<td>Hough Transform</td>
<td>Number of highlight points in Hough transform parameter space</td>
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<tr>
<td>Local power spectrum</td>
<td>Slope, intercept, and fitting error of linear fitting curve of local power spectrum.</td>
<td>33-35</td>
</tr>
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</table>

- **Fig. 5.** Illustration of multi-class SVM classification methods.
3.2. Feature ranking and selection

In the implementation of the proposed ensemble SVM classifier, a critical part is the selection of a subset of blur features that maximize the performance of each member classifier. As we know, the irrelevant variables in the extracted features will slow down computation during training and prediction processes as well as increase data gathering and storage cost. Moreover, they can even lead to some disrupting effects on the concept to be learned.

To enhance the generalization performance of the SVM-based classifier, we will discuss an effective feature ranking and selection method to eliminate irrelevant variables from 35 extracted features presented in Section 2.

Traditional feature selection algorithms usually fall in the categories of wrapper methods and filter methods [41]. The filter methods are typically computationally less expensive but do not consider the interactions among the features. As a result, the optimality of the selected feature subset cannot be guaranteed. On the contrary, the wrapper methods can evaluate features iteratively and jointly and, thus, are effective in capturing interactions among multiple features. Due to these advantages, the wrapper method is used for feature selection during construction of the proposed ensemble SVM classifier. Among available methods in the literature, the SVM-Recursive Feature Elimination (RFE) approach [42] is regarded as an effective wrapper method for feature selection in single SVM classifier training. In our previous study [43], we have successfully applied SVM-RFE with correlation filter to screening...
features of medical images. In this paper, RFE is accomplished as part of the RBF-SVM classification algorithm using the Support Vector Rate (SVR) metric to rank all 35 extracted features. Here, SVR is defined as follows:

$$SVR = \frac{N_{sv}}{N_{total}} \times 100\%$$ \hspace{1cm} (14)

where, $N_{sv}$ is the number of support vectors (i.e., the samples on the supporting plane) and $N_{total}$ is the number of total training samples. It is commonly known that fewer support vectors can reduce the computational load of SVM and improve training efficiency. In our experiments, it can be learned from Fig. 9 that smaller SVR (i.e., fewer support vectors) also tends to have better classification performance of the SVM classifier.

To better illustrate the ranking process, the flow chart of whole feature ranking is provided in Fig. 7. Initialize feature set $S_w$ with 35 features and assume $R$ is the ranked feature set. Remove one feature in $S_w$ and use the remaining 34 features to train a SVM classifier, which is initialized by empirical parameters to calculate the support vector rate(SVR). This allows us to evaluate the contribution of the removed feature to the SVM classifier. Repeat this for all 35 features, and the feature leading to the biggest SVR after removal is obtained and placed into the ranked set $R$. This feature indicates that it is not a support vector and far away from the hyperplane of SVM classifier and is easy to be classified. After the first feature has been picked out, the selection of second feature is conducted among the remaining 34 features using the same method. Once the second feature is picked out, place it into set $R$ behind the first ranked feature. Repeat the same process, until all 35 features are ranked. The features near front of the ranked set $R$ show a more important rule in classifier construction than the ones towards the end.

After all 35 blur features have been ranked, SVR and CA will be used simultaneously to determine the optimal number of features for training single SVM classifier. Generally speaking, higher CA implies that the classifier possesses better prediction accuracy, while a lower SVR implies stronger property of the classifier. Therefore, the values of SVR and CA can well reflect the classifier’s performance as functions of the number of selected features. During the implementation of this step, one can study the behavior of SVR and CA as functions of the number of selected features, and choose the one that optimizes both criteria simultaneously or achieves the best balance between the two. An example is given in Section 4 through numerical experiments.

4. Experiment results and analysis

4.1. Datasets used in experiments

**Simulated blurred image dataset:** In this paper, we use a dataset with a total of 1188 sample images. Among all samples, 908 are subject to simulated blurs and 280 are blur-free, clear images. In the experiment, the training dataset has 418 blurred images (158 haze blur, 129 defocus blur, and 131 motion blur) and 200 clear images. The remaining 210 blurred images (91 haze blur, 60 defocus blur, and 59 motion blur) and 80 clear images are used as the testing dataset. In the simulated datasets, only the motion blur and defocus blur images were generated by specified blur kernels, the other samples (i.e., haze blur and clear images) were directly downloaded from the same websites as those in natural blurred image datasets.

**Natural blurred image datasets:** The training dataset of natural blurred image dataset consists of 210 haze blur, 190 defocus blur, 190 motion blur, and 213 clear images for a total of 830 samples. The testing dataset of natural blurred images contains 127 haze blur, 80 defocus blur, 86 motion blur, and 16 clear images for a total of 399 samples. These samples are collected from famous national and international websites: Baidu.com, Flickr.com and Pahse.com. A few samples in above datasets are illustrated in Fig. 8. All of aforementioned samples are included in our database denoted as BHBID, which can be found online at http://doip.buaa.edu.cn/info/1092/1073.htm.

4.2. SVM classifier setup

In the numerical experiments, the proposed ensemble SVM classifier is implemented by a 10-member SVM classifiers (see Section 3.1) and integrated through the weighted voting method described in Section 3.2. The feature ranking and selection process discussed in Section 3.2 is carried out as follows. First, we evaluate SVR and CA of the member classifiers as functions of the number of features included based on the simulated training datasets. The results are illustrated in Fig. 9. As one can see from the figure, SVR decreases rapidly when the number of selected features increases from 1 to about 10 and, as the blue elliptical region indicates, reaches the lowest values when 9–20 features are selected and used by the member classifiers. Then, SVR starts to increase slightly, when more than 20 features are used in the member classifiers. Similar observations can be made for CA as well. Specifically, CA shows significant growth when the number of features is under 5. Then, a plateau is reached in the red elliptical region, after which a slight decline occurs for larger number of features. Hence, combining the behavior of both SVR and CA, it can be concluded that including 10–15 features in a member classifier can lead to optimal classification performance for each member SVM classifier under the training sets used in this experiment. In this paper, we choose 13 as the total number of features used in each member classifier and provide the ranked indices of the selected features of each member classifier in Table 2.

From Table 2, we can see that the feature subset selected by each member classifier does not necessarily contain the same features due to the randomized training datasets. However, some features with strong discriminating power, such as the mean of dark channel (feature index 3) and the Gaussian fitting amplitude and width (feature indices 28–31) are selected by all member classifiers. There are also features (feature indices: 18, 22, 30, 31, 35) selected by majority (over 60%) of all member classifiers. Clearly, this observation implies that these are the key features that have the ability to characterize the spatial or frequency domain of an image in blur type identification. After the feature subsets are obtained, 10-fold cross-validation and grid-search
Fig. 8. Parts of blur samples. (a)–(d) come from the simulated blur dataset, (e)–(f) come from the natural blur dataset.

Fig. 9. SVR and CA of member classifiers as functions of the number of features included in each classifier. The bottom four curves are about the relationship between SVR and the number of features while the top four curves are about the relationship between CA and the number of features. Here, CA's are evaluated based on the validation datasets $T_{e_i}$ ($i = 1, 2, \ldots, 10$), which consist of the remaining samples after the $i$th random sampling in the training dataset.

Table 2
The optimal feature subsets and voting weights for each member classifier after training.

<table>
<thead>
<tr>
<th>Member classifiers</th>
<th>Ranked feature indices</th>
<th>Voting weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM-1</td>
<td>30 3 28 21 22 29 35 33 8 19 27 32 7</td>
<td>0.1001</td>
</tr>
<tr>
<td>SVM-2</td>
<td>31 3 21 28 30 35 22 33 20 6 27 32 5</td>
<td>0.0984</td>
</tr>
<tr>
<td>SVM-3</td>
<td>30 3 28 22 9 33 31 35 8 29 18 14 11</td>
<td>0.1004</td>
</tr>
<tr>
<td>SVM-4</td>
<td>30 3 28 21 1 31 35 10 26 33 8 16 12</td>
<td>0.1012</td>
</tr>
<tr>
<td>SVM-5</td>
<td>29 28 3 17 1 35 33 21 23 18 19 16 12</td>
<td>0.1006</td>
</tr>
<tr>
<td>SVM-6</td>
<td>3 30 28 10 22 35 32 31 18 14 11 15 29</td>
<td>0.1029</td>
</tr>
<tr>
<td>SVM-7</td>
<td>3 30 13 28 1 22 8 26 17 6 12 18 33</td>
<td>0.0984</td>
</tr>
<tr>
<td>SVM-8</td>
<td>3 30 28 24 1 34 31 33 18 9 4 25 17</td>
<td>0.0984</td>
</tr>
<tr>
<td>SVM-9</td>
<td>31 3 28 13 22 35 33 32 12 7 25 16 18</td>
<td>0.0978</td>
</tr>
<tr>
<td>SVM-10</td>
<td>30 3 21 28 22 31 35 33 23 2 27 26 16</td>
<td>0.0989</td>
</tr>
</tbody>
</table>

method are applied to optimizing parameter pair $(C, \gamma)$ for each member classifier. Clearly, the unique characteristics of the member classifiers should result in different optimal $(C, \gamma)$ pair as well. In the last column of Table 2, the voting weight $A_i$ of each member SVM classifier is calculated based on Eq. (13) in Section 3.2. The maximum and minimum voting weights are 0.1034 (SVM-3) and 0.0978 (SVM-9), respectively. According to the table, the contribution rate of those members with high voting weights, such as SVM-3, SVM-6, SVM-4, SVM-5 and SVM-1, to the designed ensemble classifier is larger.

5. Results and analysis

As described in Section 3.1.2, classification accuracy, which is defined in formula (12), is utilized as the criterion to evaluate the
The inclusion of the SVR-based SVM-RFE and SVR-based joint feature selection reduces not only increases classification accuracy (0.054s) of that (0.092s) with all 35 features. In other words, the feature ranking and selection in the proposed ensemble SVM classifier is under 70% and its overall accuracy in classifying a certain type of blur and fail dramatically in other cases.

Table 3
Comparison of the ensemble SVM classifiers under different feature sets.

<table>
<thead>
<tr>
<th>Image type</th>
<th>Haze blur</th>
<th>Defocus blur</th>
<th>Motion blur</th>
<th>Clear</th>
<th>Total samples</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Features selected(13)</td>
<td>90.7692%</td>
<td>96.4674%</td>
<td>70%</td>
<td>92.6829%</td>
<td>89.3617%</td>
<td>0.092s</td>
</tr>
<tr>
<td>Features selected(13)</td>
<td>95.3486%</td>
<td>97.3333%</td>
<td>93.3333%</td>
<td>96.3415%</td>
<td>95.7447%</td>
<td>0.054s</td>
</tr>
</tbody>
</table>

It can be observed from Table 4 that the classification accuracy of the methods tested are generally higher on the simulated blurred image dataset than on the natural blurred image dataset. The reason can be attributed to the fact that the simulated blurred images are usually polluted by a single factor, while the natural blurred images may be contaminated by noise and multiple factors. Therefore, the natural blurred images are more difficult to be classified. In addition, our proposed ensemble SVM classifier outperforms the other blur classification approaches based on the numerical experiment results both on the simulated blurred image dataset and natural blurred image dataset and are on-par with the single-layers NN and DNN according to the accuracy reported in [17] and [18]. Furthermore, it should be noted that, while single-layered NN achieves a considerable performance, the Fourier spectrum amplitude is the sole blur feature used in classifier construction, which may lead to poor generalization ability. Moreover, it is widely known that the large-scale training samples and the redundant time consumption of DNN are inevitable for model training, which may lead to impracticability in many applications. On the other hand, our proposed ensemble SVM classifier is constructed based on optimized multi-handcrafted features, and, thus, possesses enhanced generalization ability and remarkable classification accuracy under small-scale blur image datasets. Also, the time and facility costs of model training of the proposed classifier are apparently much lower than DNN method.

6. Conclusions

In this paper, an ensemble SVM classifier is designed to identify four types of images: defocus blur, haze blur, motion blur and clear image. To accomplish this, SVR-based SVM-RFE theory is implemented to rank 35 extracted image features, which include the statistic features, texture features, image quality metrics, spectrum features and local power spectrum features, for blur classification. Based on random sampling and the dual criteria of support vector rate (SVR) and the classification accuracies (CA), 13 most critical features are selected to train each individual member SVM classifier. Then, the ensemble SVM classifier is constructed by integrating a total of 10 trained member classifiers based on appropriate weights assigned according to their respective classification accuracy. By comparison with state-of-the-art blur classification methods, the ensemble classifier demonstrates superior performance to other handcrafted-based methods and is head-to-head with the learned-based Deep Learning method. However, the proposed method requires smaller number of samples, relative lower time consumption and lower computational complexity.
cost of equipment for training than those required by the Deep Learning method. This is due to the fact that SVM is a powerful classification tool, especially for small samples. As shown in the numerical experiments, the generalization and accuracy of SVM classification is influenced by the number of features included and by the ensemble-based methods. The experiment results show that the proposed strong ensemble-SVM classifier has excellent accuracy and stability compared to single SVM classifiers and, thus, can achieve complex computer vision tasks. Using the convolution neural network (CNN) to achieve more stable and accurate blur image classification under the big-sample data is our future research direction.

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References


