Patch-wise Features for Blur Image Classification

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ABSTRACT

Images captured through smartphone cameras often suffer from degradation, blur being one of the major ones, posing a challenge in processing these images for downstream tasks. In this paper we propose low-compute lightweight patch-wise features for image quality assessment. Using our method we can discriminate between blur vs sharp image degradation. To this end, we train a decisiontree-based XGBoost model on various intuitive image features like gray level variance, first and second order gradients, texture features like local binary patterns. Experiments conducted on an open dataset show that the proposed low compute method results in 90.1% mean accuracy on the validation set, which is comparable to the accuracy of a compute-intensive VGG16 network with 94% mean accuracy fine-tuned to this task. To demonstrate the generalizability of our proposed features and model we test the model on BHBID dataset and an internal dataset where we attain accuracy of 98% and 91%, respectively. The proposed method is 10x faster than the VGG16 based model on CPU and scales linearly to the input image size making it suitable to be implemented on low compute edge devices.

KEYWORDS

Classification, Blur Classification, Image Quality Assessment, XG-Boost, Low-compute

1 INTRODUCTION

Images have become ubiquitous with the advent of smartphone devices with advanced camera systems. This explosion in digital image data has been the driving force behind many computer vision applications such as object detection, face recognition [9], medical image classification [2], document recognition, and self-driving cars [3]. These tasks often rely on high quality images with objects in sharp focus and any degradation in image quality leads to adverse performance [15].

Blur is one such undesirable degradation effect that is commonly found in images. This is caused by factors such as lack of focus or due to relative motion between the camera and target. Intuitively, we observe that the degree of blur in an image inversely effects the amount of information within an image. And this poses a challenge to extract semantic level information from it. Thus, blur classification is proposed as a preprocessing step to identify and reject low quality images either at the time of image acquisition or before processing them for downstream tasks. Blur detection, segmentation and image deblurring are areas of active research [4, 7, 13] which help identify and rectify the images affected with blur. The objective of blur detection is to identify the region within an image that is affected with blur. While blur segmentation is posed as a pixel-wise classification task to generate a blur map. Image deblurring restores a sharp image from a given blurred image. Some approaches to image deblurring pose this task as an image filtering problem [12], while some approaches pose this as an image-to-image translation problem [7].

The tasks of image quality assessment and blur classification can be divided into reference-based and non-reference based methods. Non-reference based methods are more challenging since we do not have any access to a sharp reference image which contains accurate information of the scene.

Convolutional neural networks (CNNs) are a well-known approach [5, 6] for image classification, but there exist a few obvious downsides of using CNNs for the task of blur classification. These are data-hungry models and tend to perform best with training on large scale datasets. They have parameters in the order of millions and are trained on optimized GPU-based architectures that take considerably long time to train. Even after training such a large model, in most cases, they cannot be deployed directly on the edge or low compute devices. We generally require sophisticated hardware designed specifically to run these models along with additional optimization steps like distillation, pruning or quantization [8].

For our application we perform blur classification for image quality assessment, to identify and reject images that contain unintentional blur (as shown in Fig. 1). Additionally, we require a model that accurately performs this classification with fast inference times. In this work,

- We propose a method for non-reference based blur classification that utilizes conceptually intuitive features
- We train the proposed set of features using Extreme Gradient Boosting (XGBoost) classifier
- We train convolutional neural networks of varying complexity on the task of blur classification and compare these against our hand-crafted features across metrics like accuracy, roc-auc and benchmark them on inference time

We experimentally demonstrate that our proposed feature sets combined with XGBoost classifier present a model that is accurate and provides fast inference times.



Figure 1: Figure shows the predictions by our best performing model, the rows correspond to samples from BHBID, KBD, Internal Dataset respectively. Columns 1 & 2 correspond to the true positives of blur, columns 3 & 4 correspond to the true positives in sharp, column 5 & 6 correspond to the false positives in blur and sharp respectively

2 RELATED WORKS

We focus on blur detection or classification at the image level to classify the presence of blur in an image.

Feature based methods - Blur classification is a well studied area of research and multiple features like Statistical Features, Texture Features, Image quality metrics, Spectrum and Transform features, and Local power spectrum Features have been used to classify blur [1, 13, 16]. Gradient based methods like Laplacian and Tenengrad capture the regions of rapid changes in intensity, like edges. The presence of high level of edges can be correlated to sharpness of an image. This is extended to capture variance and mean of a laplacian at a global level to represent the amount of blur within an image [14]. The authors of [16] use a combination of 35 features to classify different types of blur within an image by training a SVM in an one against one method and ensemble multiple such SVMs together to classify the type of blur.

Global features do not present an accurate representation of blur around the main object of interest and in [13] the authors propose using both spatial and frequency features to train a naive bayes classifier on local patches. They further extend the concept to multiscale features to create a blur segmentation map. From [1] it is observed that frequency domain features are less robust to noise. Hence, in our work, we draw inspiration from [13] and explore the use of gradient based operations applied at a patch level to images for robust blur classification.

Local binary pattern (LBP) based descriptors have been used to give a robust representation of image texture. In [10] the authors propose a modification to LBP by using only uniform patterns, where the local grid contains only two transitions from zero to one or vice versa. The authors utilize this formulation for the task of defocus blur segmentation.

Deep Learning based methods - Some work has been done to investigate the usefulness of CNNs as a feature extractor and in [14] they replace handcrafted features with a convolutional neural network, however in their comparison the laplacian features perform better. Modern research in deep learning methods has focused on blur segmentation and rectification of various types of blur (defocus, motion, haze etc).

Most of the approaches first detect the focused and out-of-focus regions within an image and subsequently use these segmented regions for deblurring. In [4] the authors use VGG based FCN to extract relevant features from blurred and sharp regions within an image. The benefit of this approach is that it bypasses the need for handcrafted features, while it also comes with a penalty of high computational requirement, limiting the use in edge devices and fast inference situation. In our work we adapt the feature extraction pipeline and fine-tune this for the task of blur classification.

3 PROPOSED METHOD

We propose a method that uses conceptually simple spatial image features, along with their statistical measures such as the mean and the variance. These features rely on the fact that the texture of sharp images is different from that of a blurred image. As the image is subjected to blur the edge details within the scene are reduced. More precisely, the strength and the count of strong edges in blurred images are lower compared to that of a sharp image in other words,



Figure 2: Blurred image from KBD. (a) is the original image and (b) is the same image with a text watermark on the top left. Adding a watermark we observed a 10.7% increase in the mean of the laplacian map, along with an increase of 39.8% in the standard-deviation. Similarly we also observed a 9.5% and 30.2% increase respectively in the mean and standard deviation of the tenengrad map. In (c) we apply patch-wise classification and plot the predictions on each image grid, where each patch depicts the probability-score of an image being blur and the blur prediction. In (d) we can see how the text watermark affects the probability score and the decision of the model.

in blurred images the gradient follows a heavy tailed distribution. Additionally, blur causes a smoothening effect in images which implies that in a neighbourhood the pixel intensities are closer to the central pixel. The features extracted are as follows:

(1) **Normalized gray level variance** This operator is an indication of the overall intensity of the image Eqn. (1). The intensity distribution of a blurred image is relatively packed and on the lower spectrum with an overall uniform distribution of intensity when compared to sharp images.

$$NGLV = \frac{\sum_{(i,j)\in\Omega(x,y)} (I_{i,j} - \mu)^2}{\mu(x,y)}$$
(1)

where $\mu(x, y)$ is the mean value for computed over the neighborhood window $\Omega(x, y)$

(2) **Tenengrad** Sobel is a first order derivative operator and indicates the spatial locations of change in intensity of an image. Locations that tend to have a high change in intensities represent stronger edges. We use the horizontal and vertical Sobel maps to obtain the Tenengrad map Eqn. (2) and use the mean of this operator as our feature.

$$TEN(x,y) = \sum_{(i,j)\in\Omega(x,y)} (S_x(i,j)^2 + S_y(i,j)^2)$$
(2)

where S_x and S_y are the Sobel gradients in x and y direction

(3) Laplacian Laplacian operator is the second-order derivative of the input signal. It is highly sensitive to the noise in the input image when compared to Sobel. Laplacian produces high values where there is a rapid change of intensities. We convolve the input image with a Laplacian operator and obtain the mean of the Laplacian map and also extract the variance from the Laplacian map.

$$Laplacian_{var}(x,y) = \sum_{(i,j)\in\Omega(x,y)} (\Delta I(i,j) - \bar{\Delta I})^2$$
(3)

where $\overline{\Delta I}$ is the mean value of the Laplacian map in a neighbourhood $\Omega(x, y)$

(4) LBP Sharpness Map In [17] the authors propose that the LBP feature descriptor can be leveraged to accurately detect blur within an image patch. For a blurred image, LBP operator relies on the fact that the intensities in a neighbourhood are closer to the central pixel. We use the statistical mean and variance of the LBP descriptor of an image. These features can even help to distinguish between partially blurred images with intended blur from completely unintended blurred images.

$$M_{LBP}(x,y) = \frac{\sum_{i=6}^{9} n(LBP_{8,1}^{riu2}i)}{N}$$
(4)

where $n(LBP_{8,1}^{riu2}i)$ represents the number of rotation-invariant uniform 8-bit LBP patterns of type *i*, and N is the total number of pixels in the neighbourhood

On the whole, we compute the Tenengrad gradient, Laplacian gradient, LBP sharpness map and obtain statistical measures of these maps and the Normalized gray level variance of the input image and stack these together to create a feature vector (Table 1). This descriptor is used for classifying an input image as blur or sharp. We compute the features at a global level, on the entire image. Our experiments (refer experiments 5) reveal that global level features fail to capture finer details of the image and this leads to some obvious misclassifications. We improve upon this by employing the proposed features in a patch-wise manner to capture finer context. We train XGBoost and CNN models using

Table 1: Selected set of features for blur classification. These features are calculated at global or in a patch-wise manner at local level.

Feature	Description	Index
Laplacian	Mean and variance of the laplacian map	1-2
Tenengrad	Mean of the tenengrad map	3
Normalized gray level variance	Combination of variance and mean from the gravscale image	4
LBP Sharpness Map	Mean and variance of the sharpness map	5-6

these features for the task of blur classification and report the metrics on different datasets.

4 DATASET

For the purpose of our experiments, we have used a kaggle dataset¹ for training and validation, which we refer to as Kaggle Blur Dataset (KBD). The dataset contains a total of 1050 images split equally across the 3 categories namely sharp, motion-blur, and defocusblur. Since we do not distinguish between the type of blur in images we have combined the two blur categories into a single category which gives us a total of 700 blur images and 350 sharp images.

To demonstrate the generlizability of our approach, we evaluate our model on the BHBID Dataset from [16]. This dataset contains a total of 1188 sample images. The train split contains 418 blurred images and 200 clear images. While the test split contains the remaining 210 blurred images and 80 sharp images.

We also evaluate the performance of this model on our internal test set. This dataset contains indoor images captured from mobile cameras. This contains a total of 407 images of varying resolution. Among all the samples a total of 202 images are blurred and the rest are sharp.

5 EXPERIMENTS

In order to compare the different methods we use the KBD to train and validate all of our models. We use BHBID and our internal dataset to test the trained models. We choose XGBoost for this task as it perfectly fits our need for a fast and accurate classifier. Additionally, we train several CNN networks for the blur classification task. In the subsequent section, we discuss the improvements in feature selection and compare the performance of our experiments in Table 2.

We train and evaluate the classifiers in a Stratified KFold Crossvalidation manner with K set to 5 and repeat this for 5 random shuffles of the dataset. For each run, we use 25% of the samples as our validation set and 75% of the data is used to train our models. We train the XGBoost model with its parameters (max-depth, learningrate, n-estimators, gamma) set to default values of (6, 0.3, 100, 0) and use the default binary:logistic (binary cross-entropy) as our objective function.

5.1 Global Image Features

In the feature extraction stage, spatial image features - tenengrad mean, laplacian mean and variance, and normalized gray level variance are extracted from grayscale images. With this 4-dimensional feature vector as input, we train a XGBoost model. This model achieves a mean AUC of 0.933 and a mean accuracy of 0.869. On our internal test set we observed missclassification of some blurred images, this was due to a text watermark that is introduced by some smartphones while capturing images. Such artefacts skew the gradients and global features especially mean and variance cannot encapsulate these local features Fig.2.

5.2 Patch-wise Image Features

To investigate the discriminative ability of the features, we isolated the misclassified images, and conduct experiments by cropping the image regions with text. The models classify the watermarked images accurately in this case. Based on this we develop a patchwise voting mechanism for blur classification. We can observe from Figure 2 that the watermarks cause a degradation in prediction confidence.

Rather than employing our classifier in a sliding window fashion on each patch within a single image, we split the image into 3x3 regular size grids and extract features from each of the grid in a single pass. The features are concatenated to produce single feature vector for each image. We refer to these as patch-wise features. With these features, we observe an increase of 1.8% in accuracy and an increase of 1.2 units in AUC.

We conduct ablation on the number of patches, by increasing in number of grids within an image from 3x3 to 5x5 and 7x7 grids. For each we train XGBoost classifiers, and observe an average increase of 2.3% in mean acc and an average increase of 1.67 units in mean auc compared to global features as we move to *smaller grid sizes and a larger number of grids*. This is because high number of patches capture details from the images on a much finer level. We observe that for high resolution images a large number of grids at 7x7 patches are well suited, while for lower resolution images, a smaller number of grids at 3x3 patches perform better. The best results were observed when we use patch-wise features extracted on 7x7 grids, we refer to this as *Grid 7x7* in Table 2.

5.3 LBP Features

We investigate the addition of the global mean and variance of the LBP features to our feature descriptor, resulting in a 6 dimensional feature vector. Training the model on these features we observed a mean increase of 1 unit in AUC and a mean increase of 1.2% in accuracy.

We further conduct ablation on local patch-wise features by adding global LBP features and patch-wise LBP features. We observe similar trends (Figure 3) in the increase of AUC and accuracy. We achieve the best performance, an average AUC of 0.956 and average accuracy of 90.1%, using *LBP Grid 7x7* features.

We compare all these methods on the validation sets, plot the metrics in Figure 3 and report them for comparison in Table 2

¹Kaggle Blur Dataset - https://www.kaggle.com/datasets/kwentar/blur-dataset



Figure 3: Figure shows the mean accuracy and mean auc plots for the XGB models trained on different features, it can be observed that the metrics increase as we move to finer and more detailed features

5.4 Comparison with convolutional neural networks

To present an effective benchmark of performance, we compare our proposed features with various CNNs. We train two CNN classifiers which have a vgg16 backbone. These networks were finetuned from different tasks, one was used as an encoder in a defocus segmentation task, we refer to this as *vgg-defocus* and the other was trained on imagenet for classification, we refer to this as *vggimagenet*. VGG16 is a heavy and memory hungry network that is orders of magnitude complex compared to our handcrafted features, with this complexity in mind, we also train a simple cnn network with 6 layers (4 conv + 2 linear). We also fine-tune a Mobilenet [11] network which is preferable for low-latency and low-power systems. We compare these over evaluation criteria such as AUC, accuracy.

KBD contains images of varying resolution. In order to train the networks, we follow the method laid out in [6] and resize the shorter side of the image to 224 while preserving the aspect ratio. We then perform a center crop of 224x224 from the resized image. For fine-tuning, we freeze the convolutional layers in the networks and modify the structure of the final layers for binary classification. We use data augmentation, which includes a random horizontal and random vertical flip with a probability of 0.6. We fine tune the network using an Adam optimizer with a learning rate set to 1e-3, a batch size of 256, and binary cross entropy loss as our objective function. Similar to the XGBoost setup, we train these networks in a Stratified KFold Cross Validation manner with 25% of the data being used as validation set in each run. To prevent overfitting, we train the vgg networks for 5 epochs each and the other networks for 10 epochs each.

We report metrics on the original image resolution and also on images downscaled to 224x224. The adaptive average pooling layer handles the variable input size in the case of original image Table 2: Improvements observed by introducing more features and local features. We report the average accuracy and auc score of different the methods across all the validation sets of the KFold cross validation. For the CNN networks we report metrics on input resolution and downsampled images to 224x224.

Feature Type		Accuracy	AUC
Global Features	Global Feature	86.9 ± 3	0.933 ± 0.02
	Global Feature + LBP	88.1 ± 2	0.943 ± 0.01
Patch-wise Features (No LBP)	Grid 3x3	88.7 ± 2	0.945 ± 0.02
	Grid 5x5	89.3 ± 2	0.951 ± 0.01
	Grid 7x7	89.6 ± 1	0.953 ± 0.01
Patch-wise Features + Global LBP	Grid 3x3 + Global LBP	89 ± 1	0.949 ± 0.01
	Grid 5x5 + Global LBP	89.3 ± 2	0.952 ± 0.01
	Grid 7x7 + Global LBP	89.6 ± 2	0.955 ± 0.01
Patch-wise Features	LBP Grid 3x3	89 ± 2	0.95 ± 0.01
	LBP Grid 5x5	89.4 ± 2	0.953 ± 0.01
	LBP Grid 7x7	90.1 ± 1	0.956 ± 0.01
CNN Methods	vgg – defocus*	94.2 ± 1.6	0.985 ± 0.01
	vgg – imagenet*	93.1 ± 1.6	0.971 ± 0.02
	vgg-defocus	83.2 ± 2	0.894 ± 0.04
	vgg-imagenet	78.3 ± 2	0.883 ± 0.04

* The metrics were calculated on downscaled images

resolution. We report the mean AUC and mean accuracy metrics on the validation splits in Table 2.

Table 3: Comparison of CNN methods - we measure the inference time on images of size 1000x1000

Network	Param Count	Inference Time	Accuracy
VGG16 *	138M	16.4s	93.1
MobileNetv2 *	2.3M	4.3s	90.8
Simple CNN Classifier *	0.96M	0.94s	80.5

* Accuracy calculated on downscaled images



Figure 4: Comparison of runtimes across different methods. We take 5 different images from KBD, resize it to different sizes and record the time required to run inference on these. It can be seen that the best performing feature *LBP Grid* 7x7 is 10 times faster than VGG

 Table 4: Performance of our best feature set (LBP Grid 7x7)
 on two different test sets.

Dataset	Accuracy	AUC	F1 Score	
			Blur	Sharp
BHBID (TestSet)	98	0.98	0.98	0.96
Internal Dataset	91	0.96	0.89	0.91

5.5 Results

We benchmark the inference time required to classify an image across all the methods. All the models are run on a computer with an Intel i5-8250U CPU running at 1800 MHz using 8GB RAM, running Ubuntu 20.04.3 LTS and Python 3.8.10, no other compiler optimizations are used. For the XGBoost model, we measure the time required to extract the features and perform the classification. For vgg16 we set the batch size to 1 and record the time elapsed for the forward pass. For all the algorithms, we measure the time required to process 5 different images, we repeat this experiment for 10 runs and report the mean of the 10 runs in Fig. 4.

We also test our extracted features using support vector machines (SVM) classifiers and compare the performance to XGBoost classifier. They perform 3, 3.4, 3.4 percentage points (accuracy) lower than XGBoost in case of Grid 7x7, Grid 7x7 + Global LBP, LBP Grid 7x7. This shows that the extracted features are discriminative across various classifiers.

When discussing CNN classifiers, it is worth noting that the VGG network provides the best performance but is very large and

requires a lot of memory. In contrast, the lightweight Mobilenet is reasonably fast and accurate but does not compare well in speed with our selected features. Simple CNN is very fast but it performs worse than Mobilenet Table 3

To demonstrate the generalization of our method we test our methods on two additional datasets. We train our model on the training split of BHBID Dataset and report the results achieved by our best model *LBP Grid 7x7*. We also report the metrics on our internal test set, we use the XGBoost model that was trained on KBD out-of-the-box and perform classification using our best model *LBP Grid 7x7*. The results are summarized in Table 4.

A drawback of this approach is that this fails when none of the patches in the image contain features in other words a plain image with no noticeable difference in intensity, in such cases the images are classified as blur.

6 CONCLUSION

In this work, we address the task of blur classification for image quality assessment. We extract various spatial and statistical image features to classify an input image as blurred or sharp. And empirically demonstrate how extracting features at a global level fails to capture the intricate details in an image. We propose a patch-wise method for feature extraction and show its effectiveness for blur classification on multiple datasets. We also apply this method to our internal dataset without any further tweaks after training on KBD. We train XGBoost models and show the superiority of our features both in terms of inference time and classification metrics. Our best performing feature is the LBP Grid 7x7 that has an AUC of **0.95** on KBD and an AUC of **0.98** on the BHBID Dataset. We compare our features against pretrained as well as lightweight CNN models, and find that they are 6.9 percentage points better than the VGG model (at original image resolution) and are twice as fast when compared to the low-latency Mobilenet.

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