Impact of Deblurring on Image Matching Algorithms

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Abstract

Motion blur can have a significant impact on the performance of image matching tasks, particularly when using feature-based matching algorithms like SIFT (Scale-Invariant Feature Transform) or SURF (Speeded Up Robust Features). In this work we explore the impact of image deblurring on image matching algorithms. For our work we chose one classical algorithm SIFT and one Neural network model D2NET. For deblurring the images we used the state of the art deblurGAN model. It is observed that Image matching has significantly improved on the deblurred images compared to the blurred images as observed from the precision recall curves.

Keywords: *DeblurGAN, SIFT, D2NET, Image matching, Neural Network, Computer Vision*

1. Introduction

In vision-based navigation systems cameras mounted on moving and vibrating platforms like UAV's causes blurring in the images which reduces the visual perception quality and also severely degrade the performance of image matching tasks [1]. Image matching involves finding correspondences between two or more images. This can be used for tasks like image registration, object recognition, and 3D reconstruction.

Feature-based matching algorithms like SIFT [2] and SURF [3] identify distinctive keypoints in images and match them based on their descriptors. When images are affected by motion blur, the distinctive keypoints can become difficult to detect and match accurately, leading to errors in feature matching. Motion blur causes objects in the image to appear blurred or smeared, which can change the appearance and location of keypoints. This can result in a lower number of matched keypoints and a higher rate of false matches, which can reduce the accuracy of image matching.

Most of the literature available on image matching have tested the performance of image matching algorithms on Gaussian blur with varied sigma [4], However most of the work in literature ignore the effects on motion blur on image matching algorithms. In this work we tested the degradation of image matching performance because of different kinds of motion blur.

To mitigate the effects of motion blur on image matching tasks, it is important to use appropriate preprocessing techniques to reduce or remove the blur. This can include image deblurring, motion estimation, and motion compensation techniques. In this work we have explored the impact of deblurring on image matching, we have used the state of the art DeblurGan [5] model to deblur the blurred images and have studied the performance of image matching on the deblurred images.

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2. Literature Review

Deblurring images can have a significant impact on matching techniques. Juncai Peng et al [6] proposed a joint image deblurring and matching method unlike the traditional method of deblurring the image first and then applying the image matching techniques.. By combining image deblurring and matching tasks, their approach could obtain significant improvements over the state-of-the-art image matching algorithms. However the blur kernels used are gaussian blur kernels and the work has not been tested on images with motion blur. T. Sieberth et al [7] used an approach of using Fourier transformation to obtain good deblurred results and improved feature matching . Jian W et al [8] compared different variants of SIFT and have tested the performance of SIFT variants under different blur conditions and have found that color invariant scale invariant feature transform CSIFT has improved performance on blurred images compared to sift, however the improvement is not very high compared to sift. In all these works the blur used to corrupt the images are Gaussian blur and none of them have used motion blur for testing.

3. Research Methodology and Proposed Method

We first generate motion blur on the INRIA Graffiti dataset [8] and find the precision recall curves for both sift and D2Net [9]. Next we deblur the images using deblurGAN and find the precision recall curves and compare the results.

Motion Blur Generation: We introduce synthetic blur on the images by convolving clean natural images with one out of 73 possible linear motion kernels [10].

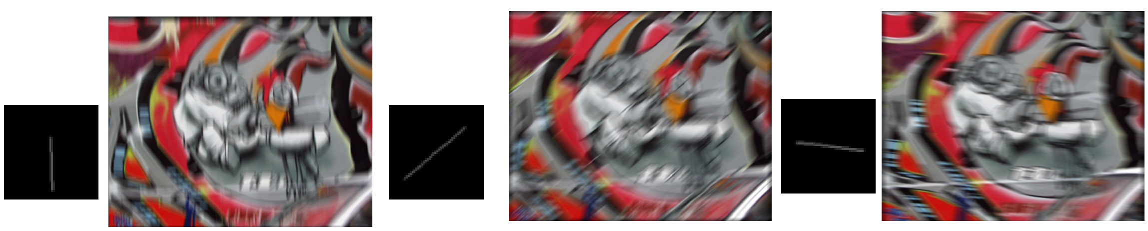

Figure 1: Figure shows the kernel and the corresponding blurred image. Kernel size chosen to generate the blur is 50x50

Feature extraction

Scale-Invariant Feature Transform (SIFT) is a computer vision algorithm used for object recognition and image matching. It was introduced by David Lowe in 1999 and has since become one of the most widely used methods for feature detection and extraction in computer vision.

The SIFT algorithm identifies local key points in an image that are invariant to scale and rotation. It does this by first constructing a scale space representation of the image, which involves repeatedly applying Gaussian blurring and downsampling to create a set of progressively lower-resolution images.

Next, the algorithm identifies potential key points at various scales by looking for local extrema in the difference-of-Gaussian (DoG) images, which are obtained by subtracting adjacent scales of the Gaussian pyramid. These potential key points are then filtered based on their contrast and edge response, and a gradient orientation is assigned to each key point.

Finally, SIFT constructs a descriptor for each key point based on the gradient orientations and magnitudes in its local neighborhood. The resulting descriptors are highly distinctive and invariant to scale, rotation, and illumination changes, making them ideal for image matching and object recognition tasks.

SIFT has been widely used in applications such as image retrieval, 3D reconstruction, and robot navigation.

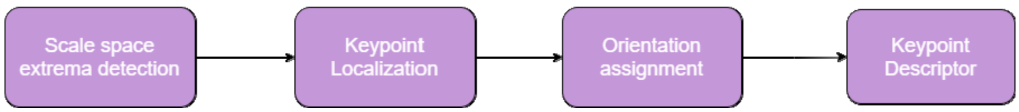

Figure 2: SIFT algorithm

Figure 3: Result of SIFT on original images

D2-Net is a deep learning-based algorithm for feature detection and description in computer vision. It was introduced by Rocco et al. in 2019 as an improvement over existing methods such as SIFT and SURF.

The name "D2-Net" comes from the fact that the algorithm is built around a deep neural network that predicts two types of features: keypoints and their descriptors. The network is trained on a large dataset of image pairs with ground truth correspondences, using a loss function that encourages the predicted keypoints and descriptors to match those in the ground truth.

One of the key advantages of D2-Net over previous methods is its ability to handle large scale changes and viewpoint variations in images. This is achieved through a multi-scale architecture that generates feature maps at different resolutions, allowing the network to capture both fine and coarse image structures.

Another strength of D2-Net is its speed and efficiency. Unlike SIFT and SURF, which require multiple steps of filtering and matching, D2-Net performs feature detection and description in a single forward pass of the neural network. This makes it much faster and more scalable, especially for large-scale applications.

D2-Net has shown state-of-the-art performance on several benchmark datasets for feature detection and description, and has been used in applications such as image matching, 3D reconstruction, and object recognition.

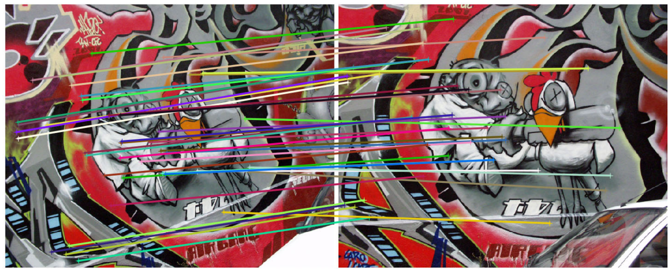

Figure 4: Result of D2NET on original images

DEBLURRING

DeblurGAN is a deep learning-based algorithm for image deblurring, introduced by Kupyn et al. in 2018. It uses a generative adversarial network (GAN) to restore sharp images from blurry ones.

The DeblurGAN architecture consists of two neural networks: a generator and a discriminator. The generator takes a blurry image as input and produces a sharp image as output. The discriminator is trained to distinguish between the sharp output images and the original, unblurred images.

The generator is trained using a loss function that combines two components: a content loss and an adversarial loss. The content loss measures the difference between the generated sharp image and the original unblurred image. The adversarial loss encourages the generator to produce images that are indistinguishable from real, sharp images, according to the discriminator.

DeblurGAN can handle a wide range of blur types, including motion blur and defocus blur, and has shown state-of-the-art performance on several benchmark datasets for image deblurring. It has also been used in real-world applications such as restoring blurry images in surveillance footage and medical imaging.

Figure 5: Results of DeblurGan on blurred images

5. Results and Discussions

We have tested SIFT and D2NET on blurred images and the deblurred images. Below figures summarizes the results

Figure 6: Result of SIFT on blurred and deblurred image

Figure 7: Result of D2NET on blurred and deblurred image

ISBN - 978-93-95038-50-8

As seen in the above figures the matching has improved on the deblurred images compared to the blurred images, we quantify these results below.

Precison Recall Curves: We use the same evaluation metrics as discussed in [4]. The first step in finding precision recall curves is to find all the keypoints for all of the images in the dataset. Euclidean distance between the descriptors for all pairs of keypoints between the reference image and all other images in the dataset are found. If the Euclidean distance between the descriptors for a particular pair of keypoints falls below the chosen threshold *t*, these keypoints are termed as a match. A correct-positive is a match where the two keypoints correspond to the same physical location. A false-positive is a match where the two keypoints come from different physical locations. This information is verified by utilizing the homography between the two images. The total number of positives value mentioned is known apriori. From these numbers, we can determine recall and 1−precision [12]:

$$recall = \frac{\text{number of } \textit{correct-positives}}{\text{total number of positives}}$$

$$1-precision = \frac{\text{number of } \textit{false-positives}}{\text{total number of matches (correct or false)}}.$$

We generate the recall vs. 1−precision graphs by varying the threshold *t*.

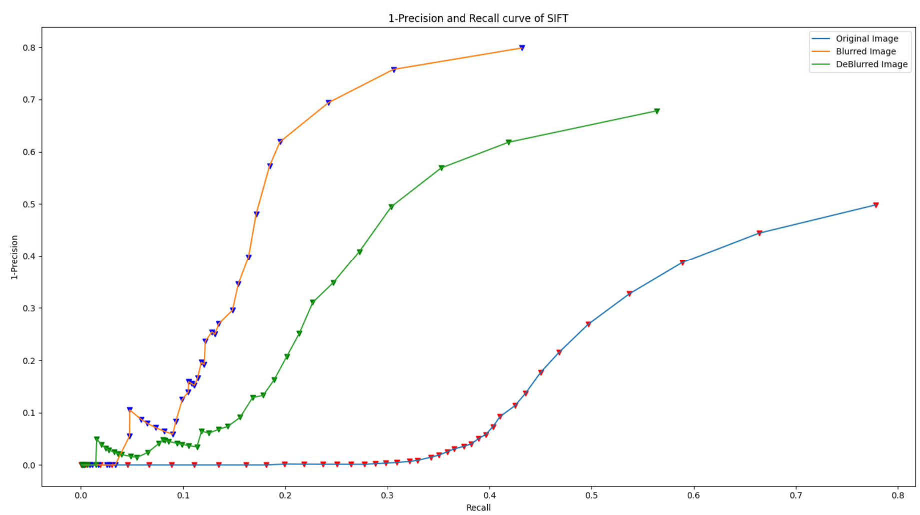

Figure 8: Figure shows 1-precision recall curve for sift on original, blurred and deblurred images

We now discuss the interpretation of these curves. An ideal detector should have recall close to 1, and 1-precision close to zero. We can see that from Fig 8, for the same value of 1-precision the recall value for deblurred image is greater than recall for the blurred image, proving that deblurring the image has significantly improved the true positive rate. Similar observations are made for D2Net from Fig 9. However D2Net has lower 1-precision compared to SIFT, and the curve for deblurred image is very close to the curve for original sharp image, indicating that deblurring as a pre-processing stage for D2Net is very effective.

ISBN - 978-93-95038-50-8

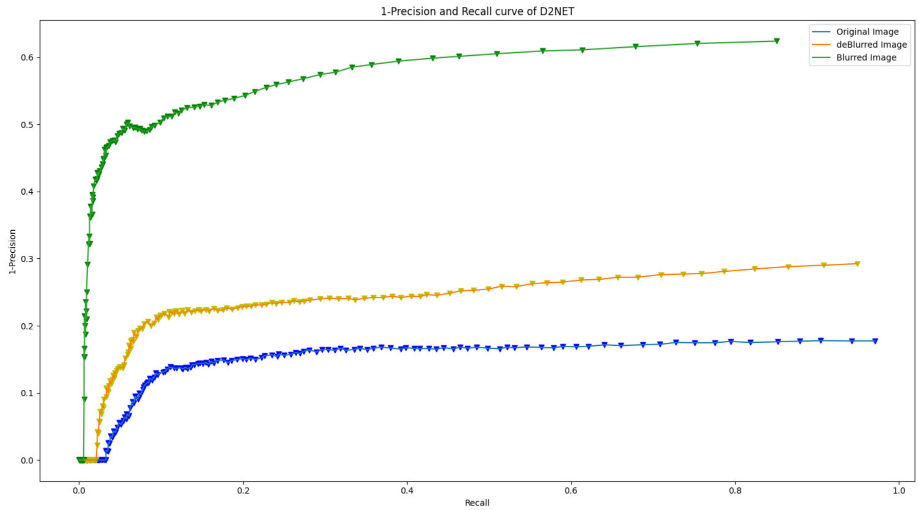

Figure 9: Figure shows 1-precision recall curve for D2NET on original, blurred and deblurred images

6. Conclusions

We have successfully demonstrated how removing the blur from images improves the accuracy of image matching. 1-precision vs recall curves showed improvement for both SIFT and D2NET on deblurred images compared to blurred images. The results also show that D2NET curve for deblurred images is very close to the original image, showing that deblurring is very effective while using D2NET as image matching technique, and D2Net is a better technique for image matching compared to SIFT because of very less false positives as indicated by very low values of 1-precision.

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