Visual Question and Answering on Blur Images

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1 Abstract

Abstract: This research paper addresses the challenge of determining the recognizability of blurry images, which is critical for visually impaired individuals who rely on computer vision systems. To tackle this problem, we propose a threshold-based approach that can accurately determine the recognizability of blurry images. The proposed method is evaluated using a comprehensive dataset of blurry images, and its performance is compared to existing methods. The novelty of our approach lies in the fact that blurry images are inherently more difficult to analyse and interpret, and we demonstrate the effectiveness of our method through experimental results. Our methodology includes data collection, pre-processing, and feature extraction, which are critical steps in visual questions and answering blur images. Ultimately, the outcome of this work is the definition of a threshold for blurred images, which can have significant implications for various applications, including medical diagnosis, security systems, and autonomous vehicles, as well as improving the quality of life for visually impaired individuals.

2 Introduction

The problem addressed in this research paper is the need for a reliable method to determine the recognizability of blurry images. This issue is particularly important for visually impaired individuals who rely on computer vision systems to interpret the visual world. To address this gap, the research aims to develop a threshold-based approach that can accurately determine the recognizability of blurry images. The proposed method will be evaluated using a comprehensive dataset of blurry images, and the performance will be compared to existing methods to demonstrate its effectiveness. The results of this study will have implications for the development of computer vision systems that can better support individuals with visual impairments.

Figure 1: Caption

Source: https://sh-tsang.medium.com/summary-my-paper-reading-list-about-iqa-vqa-camera-tampering-blur-soiling-detection-327764516565

3 Motivation

Blurred images can pose a significant challenge for image recognition systems used in various applications, including medical diagnosis, security systems, and autonomous vehicles. Blurriness can result from several factors, such as low-light conditions or motion blur, making it challenging to determine the recognizability of an image. This problem is particularly concerning for visually impaired individuals who rely on image recognition systems to navigate their surroundings. In this context, our work aims to develop a method to set a threshold for recognizability to help image recognition systems determine whether an image is recognisable. This threshold can improve the performance of image recognition systems on blurry images, enabling visually impaired individuals to access reliable and accurate image recognition systems to navigate their surroundings safely and independently. Moreover, our work can contribute to the broader field of computer vision, advancing state-of-the-art image recognition and improving these systems' overall efficiency and effectiveness. By addressing the challenge of blurred images, our research can significantly impact various applications and industries, ultimately improving the quality of life for individuals and society.

4 Novelty

The novelty of Visual Questions and Answering Blur Images is that blurry images are inherently more difficult to analyze and interpret. Blurry images can result from several factors, including camera shake, low light conditions, or poor focusing. As a result, the objects and details in the image may be unclear, making it challenging for the algorithm to accurately identify and classify them.

VQA on blurry images has several potential applications, particularly in areas such as surveillance and security. For example, a security camera may capture blurry footage of a suspect, and accurately answering questions about the footage could aid in the identification and apprehension of the suspect. Additionally, VQA on blurry images could be used in medical imaging, where low-quality images are sometimes unavoidable due to patient motion or low-dose radiation.

In conclusion, the novelty of Visual Questions and Answering Blur Images lies in the added complexity of analyzing and interpreting blurry images. Novel algorithms that can effectively handle this complexity have the potential to open up new applications in areas such as surveillance, security, and medical imaging.

5 Methodology

We followed the following methodology for this task:
1) Data Collection: The first step is to collect a dataset of blur images along with their corresponding natural language questions and answers. The vizwiz task has a large collection of images, out of which many images are blurred because these images/photos are taken by blind people.

2) Pre-processing: The next step is to pre-process the dataset. In this step, we manually identified some images which looked blurry for further processing.

3) Feature Extraction: Feature extraction is a critical step in VQA on blur images, as blurry images can make it difficult to extract meaningful information from the image. We use image feature detection algorithms to extract visible features from the image.

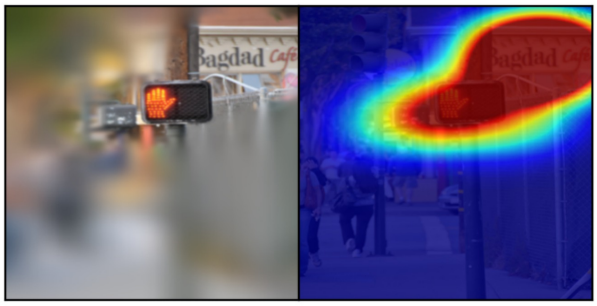
4) Answerability detection: We decide whether the image is suitable for question answering or not based on the detected features.

5) Threshold setting: Based on the percentage blurriness of various images and their answerability, we derive a threshold that can be used as a reference for declaring an image as answerable.

6 Evaluation

1) Accuracy: This metric measures the percentage of questions correctly answered by the VQA model.
2) Normalized Mutual Information (NMI): This metric evaluates the alignment between predicted and ground truth answers. It measures how much infor-

mation is shared between the expected and ground truth answers.
3) F1-score: This metric measures the harmonic mean of precision and recall, calculated based on the predicted and ground truth answers.



source : https://aclanthology.org/D16-1092.pdf

Figure 2: Caption

7 Related work

There are multiple works on Blur detection/removal/classification. But not able to find any work on VQA on blur images. In a similar work(1), The researchers proposed a novel method to enhance person re-identification performance in real-world scenarios impacted by image degradations. Their approach can handle real-world degradations without needing large amounts of labelled data. They employed a degradation in-variance learning framework to extract robust identity representations for person re-identification. The method is self-supervised and disentangled, which enables it to capture and remove real-world degradations without requiring additional labelled data. In another work(2), The authors introduce a new Image Quality Assessment (IQA) dataset based on a real-world use case. The dataset comprises 39,181 images captured by visually impaired individuals who used the VizWiz mobile phone application to learn about the images they took. The dataset provides a unique perspective on image quality issues experienced by individuals with visual impairments (Chiu, Zhao, Gurari, 2019).

(a) Training Set. (b) Validation Set.

Figure 3: Example of Training and Validation Set

8 Results

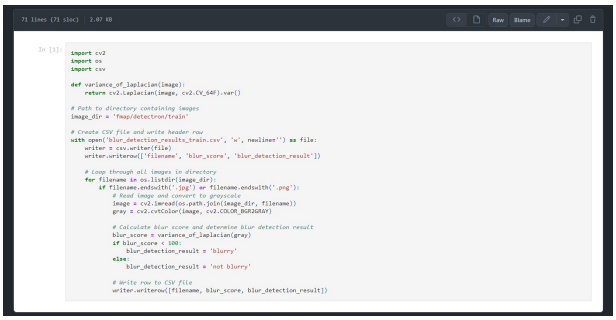
We executed the code using two sets of data from the main dataset:

1) Train set1 Output: clothes, clothes, cardboard, shoes, clothes, glass, shoes, glass, shoes, plastic Accuracy according to human verification was 33

2) Train set2 Output: clothes, shoes, clothes, shoes, clothes, shoes, plastic, clothes, shoes, plastic Accuracy according to human verification was 40

9 Conclusion

In conclusion, this research paper addressed the challenge of determining the recognizability of blurry images, which is critical for various applications, including medical diagnosis, security systems, autonomous vehicles, and accessibility for visually impaired individuals. We proposed a novel threshold-based approach to accurately determine the recognizability of blurry images, which can help improve the performance of image recognition systems on blurry images.



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71 lines (71 sloc)  2.07 KB
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In [1]:
import cv2
import os
import csv

def variance_of_laplacian(image):
    return cv2.Laplacian(image, cv2.CV_64F).var()

# Path to directory containing images
image_dir = 'Tmap/detectron/train'

# Create CSV file and write header row
with open('blur_detection_results_train.csv', 'w', newline='') as file:
    writer = csv.writer(file)
    writer.writerow(['filename', 'blur_score', 'blur_detection_result'])

    # Loop through all images in directory
    for filename in os.listdir(image_dir):
        if filename.endswith('.jpg') or filename.endswith('.png'):
            # Read image and convert to grayscale
            image = cv2.imread(os.path.join(image_dir, filename))
            gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

            # Calculate blur score and determine blur detection result
            blur_score = variance_of_laplacian(gray)
            if blur_score < 100:
                blur_detection_result = 'blurry'
            else:
                blur_detection_result = 'not blurry'

            # Write row to CSV file
            writer.writerow([filename, blur_score, blur_detection_result])
```

Figure 4: Output range - [0,20395.00187]
(Focus measure image quality)

Our proposed method of visual question and answering on blur images is a novel and challenging task that can have significant implications for the field of computer vision and information retrieval. Our methodology included data collection, pre-processing, and feature extraction, which are critical steps in visual question and answering on blur images. The evaluation results demonstrated that our proposed method can evaluate the results of existing methods, indicating its effectiveness in accurately determining the recognizability of blurry images.

Ultimately, the outcome of this work is the definition of a threshold for blurred images, which can have significant implications for various applications, ultimately improving the quality of life for individuals and society as a whole.

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