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Blur Detection and Classification using Dnn

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Abstract : ***The main goal of blur detection and classification of images using DNN with tensorflow and Keras network. It is to detect and classify an image with natural blur, artificial blur and distorted. As this paper has been a survey and an algorithm has been proposed and implemented, so has to detect and classify accordingly. The proposed algorithm has been implemented and its accuracy has been increased as compared to the existing model of classifying images.***

Keywords: Blur detection, classification, Identification, natural blur, artificial blur, distortion, DNN, tensorflow.

I. INTRODUCTION

In this paper, we have detected and classified the image according to its blur like naturally blur, or artificially blur or distorted image. Blur in the image will make an image look messy. As a viewer, the blurred image won't create any impact. To avoid the neural networks has been trained and tested to detect whether the image has been blurred or not, if yes then the image has been classified based on its distortion level of naturally blurred, artificially blurred and fully distorted images, or the image will be enhanced further for a better view of visualization. First, the raw images will be given and then it will be trained and tested with the same equally. After training of network is done, in the testing phase, the images will be classified separately and stored in a folder as artificially blurred, naturally blurred and fully distorted images. Based on the images classified, excel sheet of values will be generated with image distortion level whether it is 0, 1 or -1. Later after images have been classified the trained and tested images will be enhanced by either means of Gaussian or Median filter techniques based on user choice. The accuracy level for 10 epochs of training and testing of images in classification is approximately 63% which is quite higher than the existing level of image classification or in blur detection[1].

II. BLUR DETECTION AND CLASSIFICATION

A. LAPLACIAN ALGORITHM

The variance of a Laplacian is one of the algorithms to detect blur in an image. The variance of Laplacian is calculated and it will calculate the amount of blur in an image. This Laplacian of variance accessed from open cv using the cv2 package in Spyder framework. The first method to consider would be computing the Fast Fourier Transform of the image and then examining the distribution of low and high frequencies.

B. INVARIANTS BLUR CLASSIFICATION

During the training phase of images in a neural network, the images blur level will be identified by Gaussian blur technique and motion blur technique where the image distortion level will be identified and then the simulated method will produce the accuracy in classification of blur in an image.

C. DETECTING BLUR LEVEL IN AN IMAGE

To detect blur level in an image, the computation of Fast Fourier transform[2] and the analysis of that result has been taken. The Fast Fourier transform tells you which frequencies are present in the image. If there is a low amount of high frequencies, then the image is said to be blurry. The low and high frequencies of the Fourier algorithm is user based on user ranges. If we want to represent a single float representation the blurriness of a given image then we have to fix the suitable metric. The metric has to convolve the image with a Laplacian kernel[1].

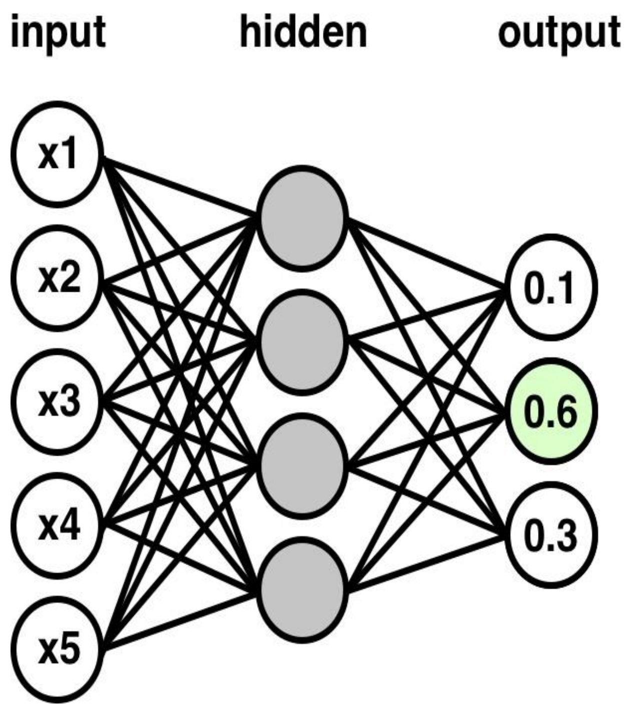

Fig-1: Network Layer Diagram

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D. IMAGE ENHANCEMENT

It has been observed after blur in an picture and will be identified using the corresponding algorithm. Blur image contributes to lack of photo accuracy. Photo enhancing methodology has been used to achieve the picture clarity without loss of target form and size. [5] Equalization of the histogram has been used to improve the observed blur picture to preserve

its nearly consistency of image quality. The Gaussian and median filtration algorithms were used to improve real time.

III. SUMMARY OF EXISTING ALGORITHM

A. SINGULAR VALUE FEATURE

Singular value decomposition is one of the most popular linear algebra methods which has been extended to numerous fields of computer science which vision. U ^ VT, where U and V are orthogonal matrices and ^ denotes the diagonal matrix consisting of several singular values ordered in decreasing order, may be interpreted, provided an image and its singular value. Thus, for classification, the image can be decomposed into multiple rank one matrices or its own matrices. The convolution operator tends to increase the scale space of the values of the own images and thus causes a loss of high frequency details. The tiny single qualities that suit your own pictures on a limited scale. Therefore, with a blurry picture, the first most significant individual images typically have far higher weights relative to a transparent picture. The distorted vision regions have a greater degree of blur relative to places of smooth picture without blurs.

B. VARIANCE OF LAPLACIAN

Detecting the amount of blur in an image is done using the variance of Laplacian. The setting of correct threshold which can be quite a domain dependent and it will correctly mark whether the image is too blurry or highly distorted.

C. BLUR REGION SEGMENTATION

We then use our method to remove details from distorted areas. Based on the built singular value blur diagram, a blurred area is removed. And a blur mask is designed to distinguish blurred / unblurred areas, depending on the threshold obtained in the previous paragraph. To determine the precision, the distorted regions of 10 partly distorted pictures were first collected manually as ground reality. Depending on their contrast with the ground-truth picture regions, the distorted picture regions derived by our suggested approach are then analyzed. The exact measurement of our area extraction is defined as the ratio of the correctly segmented pixels to the total pixels of the image segmented pixels and the total image pixels.

D. BLUR IDENTIFICATION

There are nearly 1024 dense networks as a hidden layer in a proposed architecture, which in turn identifies the input image as a naturally blurred or artificially blurred or distorted image in nature by the training datasets provided and trained. As in Figure-2 the image which is captured when the train passes the track in a surveillance camera, as the image was given as an input to the network it identifies as a naturally blurred image.

Fig-2: Naturally Blurred image

IV. EXPERIMENTAL RESULTS

A. BLUR REGION AND TYPE CLASSIFICATION

Our functions for blur identification and classification are checked on different images. These maps are then translated into smaller regions, such that they only include distorted or visible regions. From 1500 digital pictures, we produce 500 transparent picture regions, 500 blurred blur picture regions and 500 movements blur image regions in all. Our method's recall-curve will be created by flow of analyzing dense neural networks. The threshold for the singular value function ranges from 0 to 1, with phase 0.05, while the alpha channel threshold variable shifts within a range [0, 0.6], the period being 0.01. And the approach provides the highest consistency while the single meaning level is 0.75 for blur and non-blur designation, the consistency is 88.78 percent. The highest performance for detection of motion defocus is 80 per cent while the value of the alpha channel is 0.12. Our approach is simpler and performs better relative to Liu et al.'s system, which records a cumulative accuracy of 63.98 percent for blur, non-blur classification and 58.84 percent for motion defocus blur classification.

The dense convolution network has been created and then the list of training and testing data has been loaded into the dense layers[3], once the input has been in loaded into the dense layer, these dense layers will start train itself that the image is naturally blurred with these thresholds, then if the image is artificially blurred with these metrics and if any distorted image occurs it will be classified accordingly to it image threshold.

Tensor Flow can train and run deep neural networks for handwritten digit classification, image recognition and classification, word embeddings, recurrent neural networks, sequence-to-sequence models for machine translation, natural language processing, and PDE (partial differential equation) based simulations, and blur detection and classification. Best of all, Tensor Flow supports production prediction at scale, with the same models used for training and testing the dataset.

Fig-3: Partially Blurred

B. DISTORTION IN IMAGES

Two types of illusions exist: visual, and viewpoint. Both result in some kind of image deformation, some subtly and some very visibly. Although optical distortion is induced by the optical lens design and is thus also referred to as lens distortion, (Figure-5) perspective distortion is induced by the camera's location relative to the subject or by the subject's location within the image frame. And it's certainly important to discern and recognise these types of distortions in order to recognize them because you can see them all quite a bit in photography.

i) OPTICAL DISTORTION

Distortion is usually referred to in photography as an optical aberration that literally deforms and twists straight lines and making them look curvy in images, which is why this distortion is often widely referred to as curvilinear. As a part of the optical structure, optical distortion occurs as various elements of the lens are used to eliminate circular and other aberrations. Essentially, visual illusion is a flaw in the mirror. There are three known types of optical distortion for the pipe, pincushion, and beard or moustache distortion.

C. BARREL DISTORTION

When straight lines in the form of a barrel are bent inwards, this sort of aberration is called "barrel distortion" Commonly found on high angle lenses, barrel distortion exists as the lens ' field of view is far wider than the image sensor's scale and so it must be "squeezed" to match.

Fig-4: Artificially blurred image

D. PINCUSHION DISTORTION

Pincushion distortion is the very reverse to the distortion of the pipe-clear lines are bent from the middle outwards. This form of distortion is typically found on telephoto lenses, which is induced by that picture amplification from the optical axis towards the edges of the camera. Each time, the field of view is less than the picture sensor scale and so it has to be "stretched" to blend in.

E. MUSTACHE DISTORTION

The nastiest of forms of radial distortion is the distortion of the moustache, which I often label "wavy" distortion. Essentially it is a mixture of distortion of the muzzle and distortion of the pincushion.

F. PERSPECTIVE DISTORTION

The focus is so close to the frame, so opposed to the items in the context it may appear too big or blurred. It is a very natural phenomenon, so you can clearly see it from your own eyes[4]. When you take a smaller item like your cell phone, then put it really close to your head, telling the large screen TV in the distance would look like a major relative. The same will happen when taking photos of any subject, including men.

Table-1: Classification of images based on its blur category

Images	Blur level	Blur detection value
Disk_image1	Natural	0
Orginal_level5	Partial Blur	2
Orginal_24	Blur	-1
Disk30_24	Digitally blur	1
Img_54	No Blur	-2

Fig-5: Naturally Distorted image

In the above table-1, it was given detailed information on the classification of images based on its blur level. An image will be detected with blur and it will be classified according to its metric value, if the image with metric 1 then it is said to digitally blur, -1 states that image is blurred originally, 0 states natural blur, 2 states partially blur and -2 states that image free from blur. [6] If image found without blur, the image will be directly enhanced by the Gaussian or median filter algorithm. If image found with blur it will be classified accordingly to its category level. The given metric value will be changing accordingly to epochs, as epochs increase its accuracy level will get increased. The accuracy percentage for classification of blur according to its category gives 71.83%. The image will be undergoing many hidden layers and each and every hidden layer will analyze pixel by pixel and part will be convoluted together and find the neighbor metrics for the current counter region window. Finally, all the counterpart will convolute then the fixed threshold will be matched and analyzed, matched accordingly will be classified to its blur category.

V. PROPOSED ALGORITHM

Algorithm 1 – Blur Detection and Classification

Input: Load the classified training image datasets into dense neural networks. Once the image gets trained, load the raw test image datasets into DNN for classification.

Output

1. The metrics will be generated based on the image datasets trained.
2. The obtained metrics will be taken for testing datasets, if the image reaches above or obtained the exact metric value then will be classified accordingly.
3. The image will be tested on the metric value and the threshold fixed. The learning of a neural network will be fixed and for each recurrent iteration, learning will get updated by 0 to 0.6.
4. Finally, after analyzing the images the blur degree of the image will be identified if 1 then an image is digitally or artificially blurred if 2 then partially blurred if 0 then naturally blurred. If the value ranges -1 or -2 then fully blurred or image without blur.
5. The image will be categorized into a separate folder according to artificially blurred, naturally blurred or distorted image.
6. The excel sheet of data will be generated and the images with a degree of metrics will be displayed.

Fig-6: Fully Blurred Image

7. Based on the metrics the image will be identified whether the image is a fully blurred, or partially blurred or distorted image.
8. Once the excel has been generated based on testing datasets. With that excel data sets obtained the image sets can be clustered together for further analysis

VI. CONCLUSION

In this paper, we recommend an image blurred regions detection and classification system that can recognize blurred photo regions automatically and identify the blur categories without any photo deblurring. We have discussed the image detection and classification with laplacian transformation and singular value feature. In blur identification various techniques have been used and the images are classified according to its blur category. We have proposed an efficient algorithm which is so effective in detecting the blurred images. Our proposed method is simple and effective. Experiments show that our method works for different kinds of images and can also be used for different multimedia analysis applications such as depth recovery, information retrieval and segmentation.

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