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A Novel Hybrid Classification Technique for Blur Detection

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Abstract— Image, audio and video are the popular entertainment and communication services of internet. Sometime they suffer from many problems, Blur is one of them. Blur is a factor that breakdown the status of image. In this paper, we are going to perform comparison of four different Blur Detection classifiers. This paper introduces our proposed technique (Hybrid Classifier). To verify the accuracy of hybrid Classifier we collect 1000 images from internet and hence results are predicted. From result and discussion, it is clear that Proposed Classifier give 96% accuracy which is 10% more than existing Classifier (SVM).

Keywords— Blur detection, Feature vector, Image enhancement, restoration and segmentation.

I. INTRODUCTION

Internet is a popular media of communication and entertainment. Large number of images and video are present on internet. Mobile phone or digital camera users daily take numbers of photos or video and post or share them online on Facebook, WhatsApp, etc. [1],[4],[5].

Blur is one of the factors that lead to degradation of quality of image as fine details of image loss due to blurriness [14]. A blurred image is needed to be enhanced to improve its quality. For example, in case of real time applications like satellite communication in order to convey the information (that is presented in form of images) correctly, it is necessary to improve quality of images and to detect the blur correctly [5].

A. Cause of Blurriness

On the basis of objective occurrence, blur can be classified into two types: intentional and un-intentional blur. Intentional blur is the blur generated by the photographers to give importance to some objects or to improve appearance of objects [5]. This type of blurriness is also introduced by compression methods to reduce the amount of required time and bandwidth to transmit the captured image. On the other hand, unintentional blur is caused by motion of objects or camera, imperfect image formation process etc. Therefore, this type of blur is difficult to handle.

B. Types of blur

Based on formation of image, blur can be classified as motion blur and out-of-focus or defocus blur.

Fig 1 Defocus blur

Defocus involves movement of object away from correct focus along optical axis [8]. This type of blur produces less sharp and contrast image. Defocus blur is of two types: (1) Fully focal blur (all objects in the scene are not clear) (2) Low Depth of Field (DOF) images or partially blurred photos (only objects with their distance between the cameras falling into the range of depth of field will remain sharp) [10].

Fig 2 Fully focal blur (left) and Partial focal blur (right)

Motion blur caused by movement of camera or objects can be classified into two types: local blur and global blur. When camera is moving but scene is static then blur produced in captured image is called global blur. Whereas Local blur (spatial-varying) is said to be produced when camera is static but some component of scene are moving [11].

Fig 3. Motion blur

Fig 4 Global blur (left) and Local blur (right)

C. Applications

Automatic blur detection will replace most of the human operator work of extracting useful information from blurred image. It is helpful to detect criminals, to analyse road accident reasons, enhancement of satellite images etc. [10].

Detection and Qualitative analysis of blurred region is also required in many other applications like content based image or object retrieval, measurement of quality of received image from internet, object based compression of image, photo editing etc. [7], [13], [14]. Vast applications of blur detection increase the need of research in this topic.

II. LITERATURE REVIEW

Blur detection methods are of two types: direct and indirect. Direct methods only identify the blurred region and segment it from un-blurred one. While indirect methods first detect and then restore the blurred region. We discussed both type of blur detection methods.

Both video based and single image based blur detection methods are also surveyed in this paper. We first review video based methods but our focus is on image based methods.

A. Video-based blur detection methods

Object estimation and restoration in blurred image sequence (i.e. video frames) is difficult. Estimation of the accurate velocity of the moving thing or object leads to restoration of motion blurred videos. L. Bar et al. [2] presented method framework based on Mumford shah to detect moving objects, accurately estimate their velocity/motion and restore that motion blur. However this proposed method is not useful for frames with multiple moving object and dynamic background.

Accurate alignment between frames of video helps in many applications like remove noise content from video and restoration of blurred video. Travis Portz et al. [3] extended the exiting optical flow method (based on classical wrapping method) by taking derivative of blurred frame to represent its variations with regard to the blur induced by flow. There method identify the spatially-varying blur induced by motion and provide consistence flow between sharp and blurred frames.

B. Image-based blur detection method

F. Cauzine-Devy et al. [4] proposed method to estimate and remove both spatially varying motion and out-of-focus blurs. Global minimum is used to estimate global blur. Blur restoration process is based on sparse regularities within non-uniform image.

Elder and Zucker [5] proposed a method for edges detection and blur estimation, which modeled focal blur by a Gaussian blur kernel. It also calculated the response using the first and second order derivative steerable Gaussian basis filters.

Spatially-varying or non-uniform blur is difficult to handle. Renting Liu's et al. [5] as well as [6], [7]. Ayan Chakrabarti et al. proposed method to detect spatially-varying blur with the help of an offered local blur cue that measures the probability of a particular window being blurred by a candidate kernel. Local blur cue is obtained using sub-band decomposition and Gaussian Scale Mixture. Sub-band decomposition involves isolation of local frequency components. Gaussian Scale Mixture (GSM) based image model, in local window of an image, is used to handle the variants in gradient statistics.

J-F. Cai et al. [7] presented redundant tight frame to maximize sparsity or to approximate sparsity that detect blurred region in motion blurred images. Their proposed method efficiently deals with spatially uniform blur.

Bolan Su. et al. [8] proposed technique to detect blurred region as well as to classify the type of blur. The method used to detect blurred region based on SVD that compute singular values for image and arrange them in decreasing order. Firstly, Ratio between few most significant singular values and all singular values is used to form singular value feature that segment blurred region from un-blurred one as singular value feature has large value for blurred region. Secondly, alpha channel feature, which is based on gradient distributions, is used for classification of blur type into either out-of-focus blur or motion blur.

Renting Liu et al. [9] proposed a partial-blur image detection and analysis framework for automatically detect blurred regions and identify type of blur. They utilized image color, gradient, and spectrum information as blur features that detect and classify blurred images.

Zhang et al. [10] for multi-scale blur estimation and edge type classification in scene analysis defined Gaussian Difference Signature that functions similarly to the first-order derivative of Gaussian and measure the degree of diffuseness introduced by out-of-focus objects. Proposed signature also classifies edges into "diffuse" or "sharp".

H. Tong et al. [11] propose new method for blur detection is based on Harr wavelet transformation on sharpness and edge type analysis. Proposed technique used amount of Dirac-Structure/A-Structure to detect blurred region percentage of G step-Structure and Roof-Structure to estimate amount of blurriness.

Pooja Bhor et al. [12] proposed blur detection metric based on CPBD that detects as well as estimate the relative amount of blurriness in image. The proposed metric is used to detect blur when about original image is not present i.e. based on no-reference scheme.

Partial-blur image detection and analysis framework to automatically detect blurred regions and to identify type of blur is proposed by Renting Liu et al. [5]. While to detect fully and partial blur detection, Shi Jianping et al. 14] proposed a new blur feature set in multiple domains that are (1) Frequency Domain (for blurred pixels or regions power spectra falls because of attenuation of high frequency components) (2) Gradient Distribution (blurred pixels has small tail and strong peak) (3) Local filters. They used Naive Bayesian classifier to integrate blur feature set obtained from different domains based on posterior score and to detect the blurred region in image

Zhu et al. [15] proposed new feature vector which is kernel-specific. This feature vector is equal to multiplication of variance of filtered image patch gradient and filtered kernel’s variance. The information provided by feature vector served as guide to train Support Vector Machine (SVM) classifier to distinguish blurred region from un-blurred one and distinguish different blur kernels. Their work improved the results of method used by Shi Jianping et al. [14] (given in table II).

TABLE I

COMPARISON OF ACCURACY OF METHODS IN PAPERS [6], [14], [15]

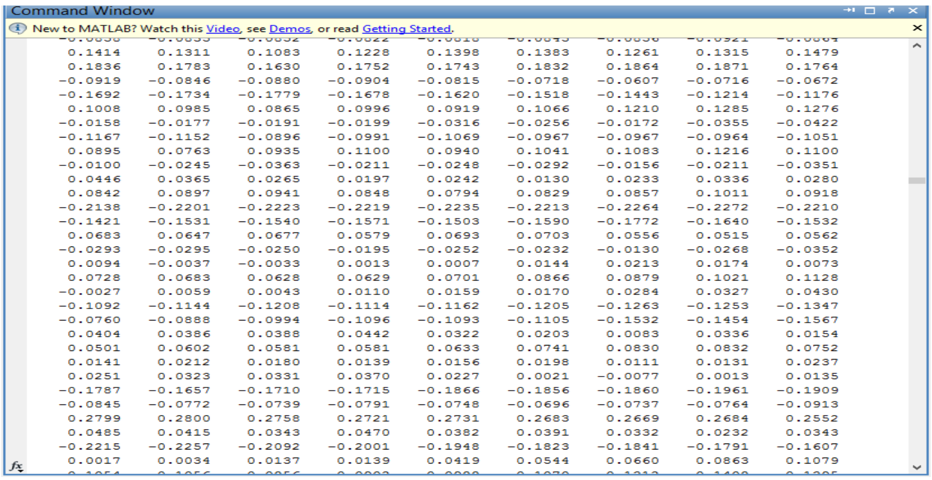
Method	**Images with motion blur**	**Images with defocus blur**	**Images with both type of blur**
DBDF [14][15]	49.8	57.6	54.4
MVV [15]	41.2	53.3	51.1
MVV + Grabcut [6]	56.5	64.2	61.6

III. EXPERIMENTAL RESULTS

The proposed method is evaluated on the public dataset. The testing dataset is composed of 1000 images collected from Internet. The ground-truth blur regions are provided for all the 1000 images. It is found that most of the blurs are either motion blur or defocus blur. We divide the 1000 blurry images into dataset I, mainly due to motion blur. The results are performed on image and the process is start with reading image from Database as shown in Fig 5. After the entire Image is read the DCT feature starts its working for extracting the feature from the database as shown in Fig 6.

Fig 5 Image Reading

The proposed method compares four different Classifiers for detection of blur in images. Training is also provided to train the dataset. The first and very popular Classifier DBDF "discriminative blur detection features" is used to check the blur feature in image. Four discriminative blur detection features and a naïve Bayesian classifier are adopted. In addition, a multiscale inference framework is employed to handle scale variation. The experimental results on dataset shows that DBDF detect 25% blur features in the image as shown in Fig 7.



0.1414	0.1311	0.1083	0.1228	0.1398	0.1383	0.1261	0.1315	0.1479
0.1836	0.1783	0.1630	0.1752	0.1743	0.1832	0.1864	0.1871	0.1764
-0.0919	-0.0846	-0.0880	-0.0904	-0.0815	-0.0718	-0.0607	-0.0716	-0.0672
-0.1692	-0.1734	-0.1779	-0.1678	-0.1620	-0.1518	-0.1443	-0.1214	-0.1176
0.1008	0.0985	0.0865	0.0996	0.0919	0.1066	0.1210	0.1285	0.1276
-0.0158	-0.0177	-0.0191	-0.0199	-0.0316	-0.0256	-0.0172	-0.0355	-0.0422
-0.1167	-0.1152	-0.0896	-0.0991	-0.1069	-0.0967	-0.0967	-0.0964	-0.1051
0.0895	0.0763	0.0935	0.1100	0.0940	0.1041	0.1083	0.1216	0.1100
-0.0100	-0.0245	-0.0363	-0.0211	-0.0248	-0.0292	-0.0156	-0.0211	-0.0351
0.0446	0.0365	0.0265	0.0197	0.0242	0.0130	0.0233	0.0336	0.0280
0.0842	0.0897	0.0941	0.0848	0.0794	0.0829	0.0857	0.1011	0.0918
-0.2138	-0.2201	-0.2223	-0.2219	-0.2235	-0.2213	-0.2264	-0.2272	-0.2210
-0.1421	-0.1531	-0.1540	-0.1571	-0.1503	-0.1590	-0.1772	-0.1640	-0.1532
0.0683	0.0647	0.0677	0.0579	0.0693	0.0703	0.0556	0.0515	0.0562
-0.0293	-0.0295	-0.0250	-0.0195	-0.0252	-0.0232	-0.0130	-0.0268	-0.0352
0.0094	-0.0037	-0.0033	0.0013	0.0007	0.0144	0.0213	0.0174	0.0073
0.0728	0.0683	0.0628	0.0629	0.0701	0.0866	0.0879	0.1021	0.1128
-0.0027	0.0059	0.0043	0.0110	0.0159	0.0170	0.0284	0.0327	0.0430
-0.1092	-0.1144	-0.1208	-0.1114	-0.1162	-0.1205	-0.1263	-0.1253	-0.1347
-0.0760	-0.0888	-0.0994	-0.1096	-0.1093	-0.1105	-0.1532	-0.1454	-0.1567
0.0404	0.0386	0.0388	0.0442	0.0322	0.0203	0.0083	0.0336	0.0154
0.0501	0.0602	0.0581	0.0581	0.0633	0.0741	0.0830	0.0832	0.0752
0.0141	0.0212	0.0180	0.0139	0.0156	0.0198	0.0111	0.0131	0.0237
0.0251	0.0323	0.0331	0.0370	0.0227	0.0021	-0.0077	0.0013	0.0135
-0.1787	-0.1657	-0.1710	-0.1715	-0.1866	-0.1856	-0.1860	-0.1961	-0.1909
-0.0845	-0.0772	-0.0739	-0.0791	-0.0748	-0.0696	-0.0737	-0.0764	-0.0913
0.2799	0.2800	0.2758	0.2721	0.2731	0.2683	0.2669	0.2684	0.2552
0.0485	0.0415	0.0343	0.0470	0.0382	0.0391	0.0332	0.0232	0.0343
-0.2215	-0.2257	-0.2092	-0.2001	-0.1948	-0.1823	-0.1841	-0.1791	-0.1607
0.0017	0.0034	0.0137	0.0139	0.0419	0.0544	0.0660	0.0863	0.1079

Fig 6 DCT Features

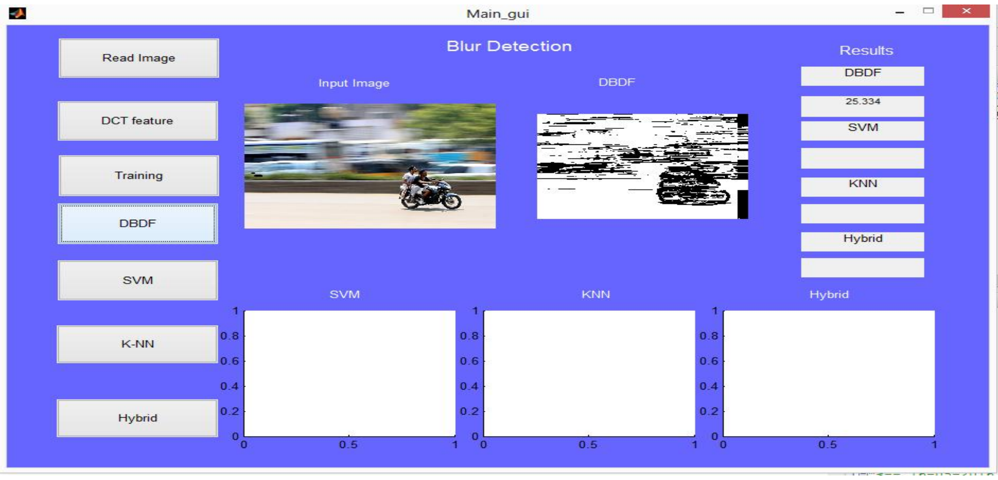


Fig 7 DBDF Classifier

After the result of DBDF Classifier user going to compare other classifiers named SVM "Support vector machine" and K-NN **"**K-nearest neighbours". From the result of SVM, it is clear that SVM gives the result batter then the exciting DBDF which is 39% as shown in Fig 8.

Fig 9 SVM Classifier

The second best classifier after SVM is KNN gives 86% accuracy in results as shown in Fig 10.

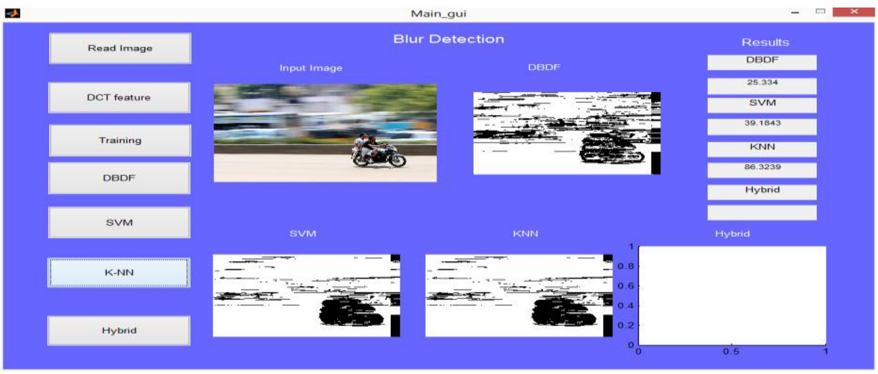


Fig 10 K-NN Classifier

These are the most successful existing methods. Therefore, it is sufficient to compare our method with theses.

The last and the very accurate Classifier is Hybrid Classifier which performs very well and give 96% accurate result as shown in Fig 11.

Fig 11 Hybrid Classifier

The below table III gives the result comparison of these four Classifier. From the below table it is clear that Hybrid Classifier gives best result as compare to all other Classifiers. The comparison in the sense of accuracy is given in Table I. On dataset I, the accuracies of DBDF, KNN, SVM and Hybrid are 25.334, 39.184, 86.323 and 96.881 respectively. The accuracy of Hybrid is 10% higher than that of SVM.

TABLE II

COMPARISION TABLE OF DIFFERENT CLASSIFIERS

Classifiers	**Results**
DBDF	25.334
SVM	39.184
KNN	86.323
Hybrid	96.881

IV. CONCLUSIONS

Detecting blur is one of the major and fascinating problems. As it involve many challenges to resolve like image restoration, segmentation, and enhancement; and object recognition. This paper relates to the comparison of four different classifiers. From the results it is clear that our proposed technique (Hybrid) gives best result as compare to others. Above discussion proved our results that hybrid (SVM or KNN) gives 10% more accuracy than existing classifiers. It is found that there is still a lot of future work need to be done in developing an efficient blur detection algorithm. In future these results can more improved by using other techniques.

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