ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

Face Detection on Distorted Images by Perceptual Quality-Aware Features

Jayashree.A.Mahajan[1], A.N.Paithane[2]

PG Student [DS], Dept. of Electronics, Rajashri Shahu Engineering College, Pune, Maharashtra, India[1]

Associate Professor, Dept. of Electronics, Rajashri Shahu Engineering College , Pune, Maharashtra, India[2]

ABSTRACT: The low-cost digital cameras in mobile was used in automated surveillance networks .we motivated by low-cost digital cameras in mobile devices ,we study the interaction between perceptual image quality and a classic computer vision task of face detection. We quantify the degradation in performance of a popular and effective face detector when human-perceived image quality is degraded by distortions commonly occurring in capture, storage, and transmission of facial images, including noise, blur, and compression. It is observed that, within a certain range of perceived image quality, a modest increase in image quality can drastically improve face detection performance. We introduced , A new set of features, called qualHOG, these new set of feature included face-indicative Histogram of Oriented Gradients (HOG) features with perceptual quality-aware spatial Natural Scene Statistics (NSS) features. Face detectors trained on these new features provide statistically significant improvement in tolerance to image distortions over a strong baseline.

KEYWORDS: Face detection, spatial NSS, surveillance , NIQE.

I. INTRODUCTION

A primary component of many computer vision algorithms is some form of an object detection/ recognition system. Such systems are often prone to performance degradation when the quality of the input images deteriorates. One such task that has resulted in successful commercial embodiment is automatic face detection. Face detection in inexpensive mobile or outdoor devices commonly used for surveillance is often highly unconstrained and subject to quality–destructive distortions, that can adversely affect detection performance. Since face detection is usually a precursor to advanced tasks of recognition, expression tracking, etc., understanding the relationship between face quality and detectability is important. A few distortion–independent approaches to the NR IQA problem have been proposed recently . These models are based on the hypothesis that natural images follow regular statistical properties that are modified by the presence of distortions. Deviations from the regularity of these natural scene statistics (NSS) are indicative of perceptual quality of images. Hence, models based on the quantification of the naturalness of an image are useful for creating distortion–independent measures of perceived quality. Researcher recently developed image quality algorithms (IQA) that aim to accurately predict end–user quality–of–experience. These include Full Reference *(FR)* algorithms, undistorted reference version is evaluated. No Reference *(NR)* algorithms, which do not use any information from reference images, and the intermediate Reduced Reference *(RR)* algorithms ,which use partial information available about reference images. NR algorithms have the greatest potential for many practical settings. In this paper, we are concerned with the latter interpretation of "quality" as it affects face detection performance. In most practical scenarios accurate measures of distortion types and levels is not available. Therefore, we resort to using an easily obtainable proxy for actual distortions, namely, the human visual-quality aware NIQE score. Empirical studies reveal that this proxy yields qualitatively similar results and also retains relative performance results when compared to those provided by using the actual distortion measures .We then show that as with true distortion levels, over a range of objective quality scores delivered by a high–performance NR image quality model.

II. LITERATURE SURVEY

IQA algorithms can be broadly categorized as Full Reference (FR), Reduced Reference (RR) and No Reference (NR) models. in real–life applications FR and RR algorithms are limited in scope as the reference information is generally

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

unavailable at nodes where quality computation is undertaken. NR algorithms have the greatest potential for many practical settings, hence we concentration on NR IQA models. NR IQA models are based on the hypothesis that natural images follow regular statistical properties that are modified by the presence of distortions. This models based on the quantification of the naturalness of an image are useful for creating distortion–independent measures of perceived quality. Recently works by Rouse et. al. in this direction show that perceptual FR IQA algorithms, including VIF and SSIM, correlate strongly with "recognizing thresholds" of human observers. FR algorithms are of limited use in this regard due to the unavailability of reference images in most practical scenarios. We then show that as with true distortion levels, over a range of objective quality scores delivered by a high–performance NR image quality model, moderate improvements in predicted quality can significantly aid face detection performance .Scalable transform–free (spatial) models for NR IQA were recently developed by Mittal et al. They introduced *BRISQUE* and *NIQE* these works operate directly on multiscale spatial pixel data and hence are inexpensive to compute. BRISQUE uses quality–aware spatial features to train a regression model for IQA, while NIQE develops a model for undistorted "pristine" images and measures deviations of the statistics of the test image from the pristine image model.

III. SYSTEM MODEL

The distortions considered are global and hence we cannot use existing face databases that have only face and non-face patches. we require full images which are first distorted by known distortion types and levels and then segmented into face and non–face patches. Thus, as a first step, we created a new Distorted Face Database (DFD) of facial images from images available freely on the internet. To keep the task simple, we chose images with mainly frontal faces. The images were modified in various ways to create distortions. We introduced three distortion type like as additive white guassian noise, gaussianblur, JPEG compressed images at 10 level distorted. The spatial–NSS features have used to accomplish blind IQA and consist of parameters describing the natural scene statistics of spatial components .Image patches is preprocessing using local mean removal and divisive normalization

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C}$$

In next step compute the HOG features, a detection window is divided into dense overlapping blocks of size 16 × 16 with a stride of 8 × 8 pixels. Each block is further divided into 2 × 2 cells and a histogram of gradients in 9 orientations is computed within each cell. All the histograms within a patch are concatenated to form the HOG feature descriptor. This feature descriptor quantifies the gradient structure within a block which characterizes local edge directions. The appearance of an object in a detection window can be largely captured by the edge directions within indexed blocks. Thus, a discriminative classifier trained on histograms of oriented gradients extracted from dense set of local blocks in a detection window is capable of generalizing to other objects.

The quality aware QualHOG descriptor is obtained by simply linked the HOG and spatial–NSS features. The appending perceptually relevant quality– aware features to conventional object detection features is that the optimal decision boundary in the HOG vector space varies non–trivially as a function of input image/video quality. By appending spatial–NSS features to the HOG feature vector and passing this to a linear SVM, we effectively model a quality dependent boundary shift in the space spanned by the HOG features.

Linear support vector machines (SVMs) were trained using QualHOG features from face and non–face patches. we use a soft–margin SVM with a slack penalty that simultaneously maximizes the margin while minimizing the training error. Soft–margin SVM is trained using a set of n annotated samples, $\{(Xi\ ,\ yi\ ) : i = 1, 2, \ldots, n\}$, where Xi are the discriminating features of the training samples, and yi are the class label, +1 for face and −1 for non–face samples. Training a linear SVM involves solving the following optimization problem:

$$\min_{w,b,\{\xi i\}} 1/2\|W\|_2^2 + \lambda \sum_{i=1}^{n} \xi_i$$

$$\text{such that } y_i\left(\langle W, X_i \rangle\right) + b \geq 1 - \xi_i \forall_i$$

where, λ controls the penalty for slack variables {ξi }. For robust face detection, we train linear SVM with the QualHOG features, i.e. Xi = [XHOG i , XNSS I]. The baselines are trained using only {XHOG i }. In the pre–processing step, the features are scaled so that they take values in the range of [−1, 1].

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

IV. EXPERIMENTS

As early discussion we do not use database which are freely available on internet ,first we take image which contain frontal human faces then that image do distorted known distorted type and level and then segmented into face and non–face patches. we created a new Distorted Face Database (DFD) of facial images from images available freely on the internet. A total of 215 images were crawled, each with one or more frontal faces. These images were manually check to be of high quality with no visible distortions. This set of 215 images was divided into 150 training images and 65 test images. we designed a system that detects faces in patches of size 80 × 64. From each of the above sets of training images, the 1231 manually annotated faces were cut out to provide positive samples for each dataset. A random subset set of 1500 negative patches were initially selected from the non–face parts of the images in each training dataset. Soft–margin linear SVM trained using QualHOG features extracted on the positive and negative samples from different combinations of the training datasets . As baselines, analogous classifiers were trained using just the HOG features A face detector trained on QualHOG and HOG features of samples from pristine image. To train the face detectors based on QualHOG and HOG features, implementation of soft–margin linear SVM from LIBLINEAR was used in the experiments.Faces cut on each of the test datasets were cut out to obtain positive test samples and an exhaustive set of 17500 negative samples were extracted from the non–face parts of the test images from the corresponding datasets. extracted from the non–face parts of the test images from the corresponding datasets.

V. RESULT AND DISCUSSION

The spatial–NSS features used to compute NIQE scores are computationally inexpensive as compared to other NR quality scores . NIQE scores as surrogates for perceptual distortion levels. We first assessed the NIQE scores of images against all of the distortion types considered. A strong positive correlation between degree of distortion and NIQE scores is observed for the common distortion types. Of course near–monotonicity against distortion severity is a minimum expectation of a perceptual image quality model. NIQE scores of images distorted by various levels of AWGN are shown in Fig.1

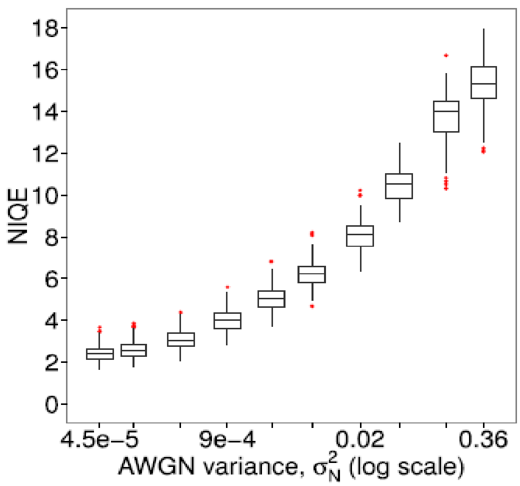

Fig.1. NIQE vs AWGN

NIQE scores of images distorted by various levels of GBlur are shown in Fig.2

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

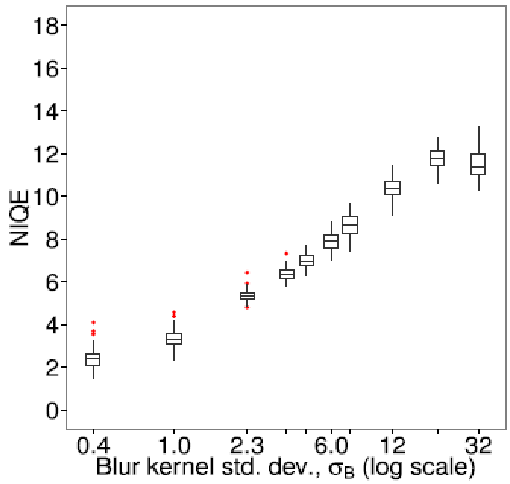

Fig. 2. NIQE vs GBlur

NIQE scores of images distorted by various levels of JPEG compression are shown in Fig.3

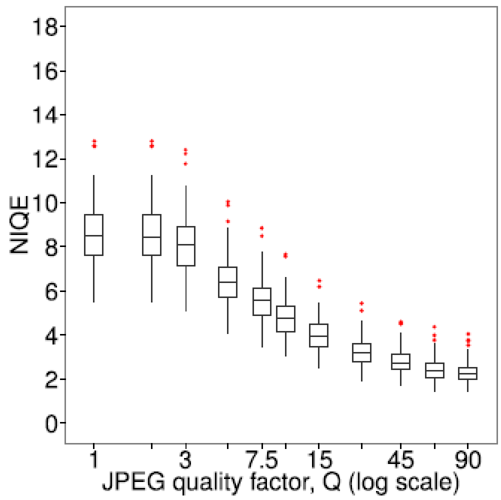

Fig.3. NIQE vs JPEG

we trained distortion–dependent QualHOG and HOG based face detectors using samples with increasing levels of the distortions The face detectors were separately chosen for the HOG and QualHOG based detectors. The distortions levels are represented on a horizontal log–scale. These results compare in Figs. 4, for AWGN distortion. .

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

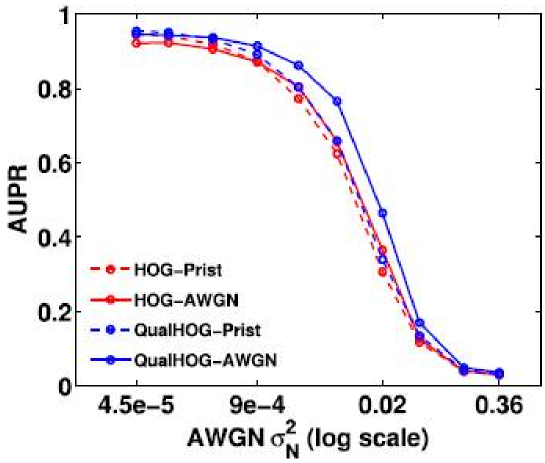

Fig.4. AUPR vs AWGN

AWGN QualHOG face detector show significant improvement in tolerance to quality degradation as compared to the HOG face detector. These results compare HOG and QualHOG based detectors in Figs. 5 for GBlur distortions

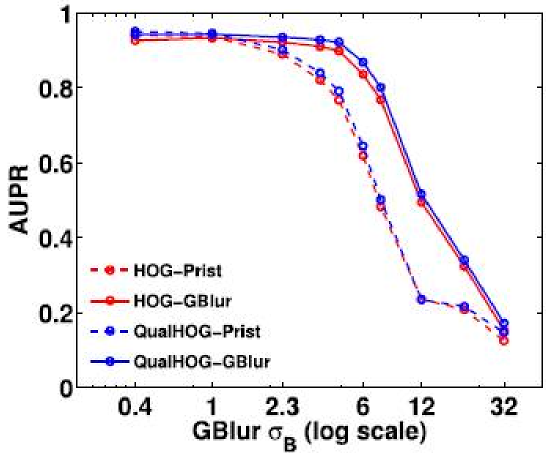

Fig.5. AUPR vs Gaussian blur

For gaussian blur distortions, the improvement is marginal. The results compare HOG and QualHOG based face detectors in Figs.6 for JPEG compression distortions.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

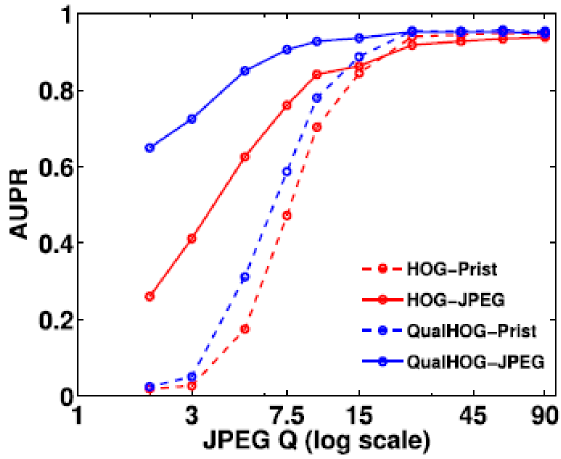

Fig.6. AUPR vs JPEG

JPEG compression QualHOG face detector show significant improvement in tolerance to quality degradation as compared to the HOG face detector. QualHOG based face detectors again show uniformly better robustness as compared to the HOG. QualHOG face detectors are better equipped to learn quality dependent discriminating boundary in the HOG feature space, as compared to learning only the HOG features. AWGN and For gaussian blur distortions, the improvement is marginal.

VI.CONCLUSION

In this paper we first established that the easily computable NR image quality score, NIQE is effective as a proxy for actual distortion levels when evaluating the trade–off between face detection performance against three common distortion types, AWGN, gaussian blur, JPEG. HOG–based face detectors was found to degrade NIQE scores greater than 4. NIQE scores in the 5–8 range, a modest improvement in perceived image quality measures drastically improves face detection performance.
Also we showed that QualHOG features, which combine face indicative HOG features with quality–aware spatial NSS features are more effective at learning a face detector that is robust to common and important image distortions. The QualHOG based face detectors show improvement over their HOG based analogues when trained on distorted images.

REFERENCES

[1] S. A. Karunasekera and N. G. Kingsbury, “A distortion measure for image artifacts based on human visual sensitivity,” in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Apr. 1994, pp. V/117–V/120.
[2] Z. Wang, E. P. Simoncelli, and A. C. Bovik, “Multiscale structural similarity for image quality assessment,” in *Proc. Conf. Rec. 37th Asilomar Conf. Signals, Syst. Comput.*, Nov. 2003, pp. 1398–1402.
[3] P. Ye and D. Doermann, “No-reference image quality assessment using visual codebooks,” *IEEE Trans. Image Process.*, vol. 21, no. 7, pp. 3129–3138, Jul. 2012.
[4] A. K. Moorthy and A. C. Bovik, “Blind image quality assessment: From natural scene statistics to perceptual quality,” *IEEE Trans. Image Process.*, vol. 20, no. 12, pp. 3350–3364, Dec. 2011.
[5] M. A. Saad, A. C. Bovik, and C. Charrier, “Blind image quality assessment: A natural scene statistics approach in the DCT domain,” *IEEE Trans. Image Process.*, vol. 21, no. 8, pp. 3339–3352, Aug. 2012.
[6] A. Mittal, A. K. Moorthy, and A. C. Bovik, “No-reference image quality assessment in the spatial domain,” *IEEE Trans. Image Process.*, vol. 21,no. 12, pp. 4695–4708, Dec. 2012.
[7] Y. Chen, S. C. Dass, and A. K. Jain, “Localized iris image quality using2-D wavelets,” in *Proc. Int. Conf. Adv. Biometrics*, 2006, pp. 373–381.
[8] N. D. Kalka, V. Dorairaj, Y. N. Shah, N. A. Schmid, and B. Cukic ,“Image quality assessment for iris biometric,” *Proc. SPIE Conf. Biometric Technol. Human Identificat. III*, vol. 6202, pp. 61020D-1–62020D-11,2006.
[9] *Information Technology—Biometric Data Interchange Formats—Part 5:Face Image Data*, document ISO/IEC 19794-5, 2005.
[10] C. Zhang and Z. Zhang, “A survey of recent advances in face detection, ”Microsoft Research, Redmond, WA, USA, Tech. Rep. MSR-TR-2010- 66, 2010.
[11] E. Hjelmas and B. K. Low, “Face detection: A survey,” *Comput. Vis. Image Understand.*, vol. 83, no. 3, pp. 236–274, 2001.
[12] D. M. Rouse, R. Pépion, S. S. Hemami, and P. Le Callet, “Image utility assessment and a relationship with image quality assessment,” *Proc. SPIE*, vol. 7240, p. 724010, Feb. 2009.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

[13] D. M. Rouse and S. S. Hemami, “Quantifying the use of structure in cognitive tasks,” *Proc. SPIE*, vol. 6492, p. 64921O, Feb. 2007.

[14] D. M. Rouse and S. S. Hemami, “Analyzing the role of visual structure in the recognition of natural image content with multi-scale SSIM,” *Proc. SPIE*, vol. 6806, p. 680615, Feb. 2008.

[15] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2005, pp. 886–893.