STATISTICS OF NATURAL IMAGE DISTORTIONS

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ABSTRACT

Natural scene statistics (NSS) are an active area of research. Although there exist elegant models for NSS, the statistics of natural image distortions have received little attention. In this paper we study distorted image statistics (DIS) for natural scenes. We demonstrate that each distortion affects the statistics of natural images in a characteristic way and it is possible to parameterize this characteristic. We show that not only are DIS different for different distortions, but by such parametrization it is also possible to build a classifier that can classify a given image into a particular distortion category solely on the basis of DIS, with high accuracy. Applications of such categorization are of considerable scope and include DIS-based quality assessment and blind image distortion correction.

***Index Terms*—** Scene statistics, distortion statistics, quality assessment

1. INTRODUCTION

Natural scenes form a small subset of all possible visual signals and over the past few years natural scene statistics (NSS) have received tremendous attention [1, 2]. Apart from the elegant statistical models proposed for NSS, applications of NSS in the field of quality assessment have also been studied and proven successful [3, 4, 5]. In [3], the authors note that the presence of distortion affects the statistics of natural scenes and they attempt to quantify this change using information theoretic measures. If distortions in an image change the statistics of natural scenes, an interesting question is whether we can somehow quantify or parametrize this new distribution in an approach similar to that for NSS. For example, we know that the coefficients from a subband of a scale-space-orientation transformation of a natural image tend to obey a Laplacian distribution (most values concentrated around the origin and heavy tails) [1]. Suppose we distort this image with (say) additive white noise. Will the distribution of subband coefficients be different? The answer according to researchers [3, 5] is that these coefficients are different. However, if one were seeking to quantify distortion statistics, a *systematic* difference for a particular form of distortion is needed. In this paper, we demonstrate that such systematic differences do exist for distorted images of natural scenes.

Even though NSS has been an active area of research, we are not aware of any previous work which seeks to discover the statistics of distorted images. Authors in [3] use NSS for their information theoretic image quality assessment measure, but do not explicitly characterize distorted image statistics (DIS). Similarly, properties of NSS have been used for reduced-reference image quality assessment (IQA) [5], again without explicit characterization of DIS. Our goal in this paper is to explicitly characterize DIS. Specifically, we will show that not only is there a characteristic signature for each distortion, but it is also possible to classify an image into a particular distortion category solely based on its subband statistics with high levels of accuracy.

The major contribution of this paper is distortion identification based on distorted image statistics. Applications of distortion identification range from quality assessment to distortion identification based image distortion correction. For example, present-day blind image quality assessment algorithms assume that the distortion form is know (say JPEG) and then proceed to build models to quantify this distortion. With our technique, it is possible to identify the quality of an image completely blind - i.e., without any knowledge of the distorting source - since we will be able to predict the distortion category with high accuracy. A simple extension of the proposed scheme is as follows. If we pick algorithms for blind IQA designed for each distortion - JPEG [6], JPEG2000 [4] and Blur [7] - we can visualize a system that receives an image as an input, classifies it into one of these distortion categories and then proceeds to assess quality using the cited algorithms. For image distortion correction, one can visualize a similar approach, since there exist distortion specific approaches for this purpose [8]. Even though we have described only two possible scenarios here, DIS may be applied to a wide-range of research areas. Extensions of this technique for multiply distorted images and for videos form another interesting research direction.

In this paper we discuss scene statistics for distorted images and build a model for classifying a given distorted image by its distortion type. For this purpose we choose a large set of images, and four distortion categories with a wide range of distortion severities. Given these distorted images, we will show that each distortion type possess a unique signature. Given that there exists such a signature, we then proceed to build a classifier which is capable of classifying a given image into one of these four distortion classes. We will demonstrate that not only is such an approach feasible, but it can also be performed with high accuracy.

2. STATISTICS OF IMAGE DISTORTIONS

Generating Distorted Images The images used for evaluating statistics were taken from the database proposed in [9]. The database consists of 8 categories of natural scenes: coast, mountain, forests, open country, streets, city, tall buildings and highways. From each category we randomly selected 10 images for training and 10 (different) images for testing. Each image in the training and test sets was distorted using 4 distortion categories: White Noise (WN), Gaussian Blur (GBblur), JPEG compression (JPEG), and JPEG2000 (JP2k) compression. Each category consisted of 30 different distortion levels whose parameter ranges are shown in Table 1. The WN, Gblur and JPEG distortions were created using MATLAB. JP2k distortion

Distortion type & Parameter	Min. Value	Max. Value
WN (σ^2 of filter)	0.001	1
Gblur (σ of filter)	0.5	8
JPEG (quality parameter)	10	75
JP2k (bit-rate)	0.05	1.75

Table 1. Table demonstrating minimum and maximum parameter values used for inducing distortions.

was created using using the Kakadu encoder [10]. The 30 levels for each distortion were equally spaced parameter values between the minimum and maximum values in Table 1 on a logarithmic scale. The parameter values were selected such that the resulting images span a large range of quality so as to cover the space of distortions well. Thus a total of $80 \times 4 \times 30 = 9600$ images were generated for training, and another set of 9600 images were similarly generated for testing. Each distortion category had a total of 2400 images.

Generating Image Statistics Each image created above was subjected to a wavelet transform over 3 scales and 3 orientations (horizontal, vertical and diagonal) using the Daubechies 9/7 wavelet basis [11]. These wavelet bases have been successfully used for image compression [10], texture analysis [12] and for other purposes. For natural images, as we mention in the introduction, the coefficients of each subband are well modeled by a Laplacian distribution. This motivates the question : 'Given that there exists a particular distribution for subband coefficients of natural images from a space-scale-orientation decomposition, does there exist a particular (parameterizable) distribution model for those natural images when distorted with a particular distortion?'. The evidence we have found points to the affirmative. Fig. 1 shows the histogrammed coefficients of an image from the above dataset for a particular subband - the shape appears to agree with a Laplacian distribution. The figure also shows the distributions of coefficients from the same natural image distorted using the above mentioned distortions for the same subband. It is evident that each distortion affects the distribution in a characteristically different way. This is true across subbands and across images. For example WN seems to yield a Gaussian-like distribution while the JP2k histogram is highly peaked. Since we suspect that there exists a characteristic signature for each distortion, our goal is to parametrize these distributions in some fashion so as to retain this signature while reducing dimensionality.

In NSS, there exist many models for the marginal distributions of subband coefficients [1]. One simple model for these coefficients is the generalized Gaussian distribution (GGD). In this paper, we use GGD to model coefficients from each of the wavelet subbands for each distorted image. The GGD is:

$$f_X(x;\mu,\sigma^2,\gamma) = ae^{-[b|x-\mu|]^\gamma} \quad x \in \Re \tag{1}$$

where, μ, σ^2 and γ are the mean, variance and shape-parameter of the distribution and $a = \frac{\beta\gamma}{2\Gamma(1/\gamma)}, b = \frac{1}{\sigma}\sqrt{\frac{\Gamma(3/\gamma)}{\Gamma(1/\gamma)}}$, where $\Gamma(\cdot)$ is the gamma function:

$$\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt \quad x > 0$$

The shape parameter γ controls the 'shape' of the distribution. For example, $\gamma = 2$ yields a Gaussian distribution and $\gamma = 1$ yields a Laplacian distribution. The parameters of the distribution (μ, σ^2 and γ) are estimated using the method proposed in [13]. Since

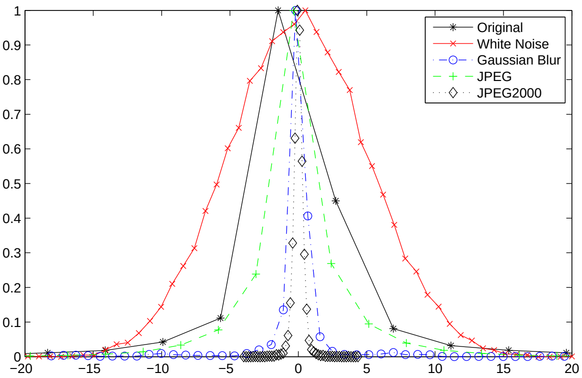

Fig. 1. Histograms of coefficients from one subband for an original image and its distorted versions (normalized).

wavelet bases act as band-pass filters, the responses are zero-mean and we are left with 2 parameters (σ^2 and γ) for each subband. An 18-dimensional vector $\vec{f_i}$ (3 scales $\times$ 3 orientations $\times$ 2 parameters) is formed from these estimated parameters and is the representative feature vector for that image. In order to get a feel for the statistics of these parameters and to visualize the way they vary with each distortion, we also computed these parameters across all contents (80 images) for each distortion type and distortion level. Parameters of the fit are estimated as described. These parameter-vectors are then subjected to a principal component analysis (PCA) [14], in order to reduce the dimensionality of the space to 3. PCA projects the data onto a space such that the newly formed space accounts for maximum variance in the data. The first dimension accounts for the most variance, the second dimension for the next-most variance and so on. We project onto a 3-dimensional space for visualization purposes only. A plot of the 3-dimensional vectors in PCA space is seen in Fig. 2. It is obvious that each distortion follows a particular trend and that the parameter-vectors seem to capture this trend well.

Classifying Image Distortions Before we go further, let us summarize the essence of what we have proposed. A large dataset with varied content was created and each image was subjected to various distortions at various severities. Each image thus created was subjected to a wavelet transform, whose coefficient distributions were parametrized using the generalized Gaussian distribution (GGD). The parameters of this GGD were estimated and stacked to form a 18-dimensional feature vector for each distorted image in the dataset (testing and training) - $\vec{f_i}$, where $i = \{1, 2, \ldots 9600\}$.

Our goal next was to utilize the training vectors to train a classifier such that when the classifier is fed with vectors from the test set, a suitable classification into distortion categories is obtained. For this purpose we use a support vector machine (SVM) [15]. SVMs are popular as classifiers since they perform well in high-dimensional spaces, avoid over-fitting and have good generalization capabilities [15]. We trained a multi-class SVM on the training set consisting of 9600 different feature vectors using the popular LIBSVM package [16]. The radial basis function (RBF) kernel ($K(x_i; x_j) = exp(-\gamma||x_i - x_j||^2), \gamma > 0$) was utilized and its parameters selected using a grid-based 5-fold cross-validation approach on the training set. This trained SVM was then applied as a classifier on the test set

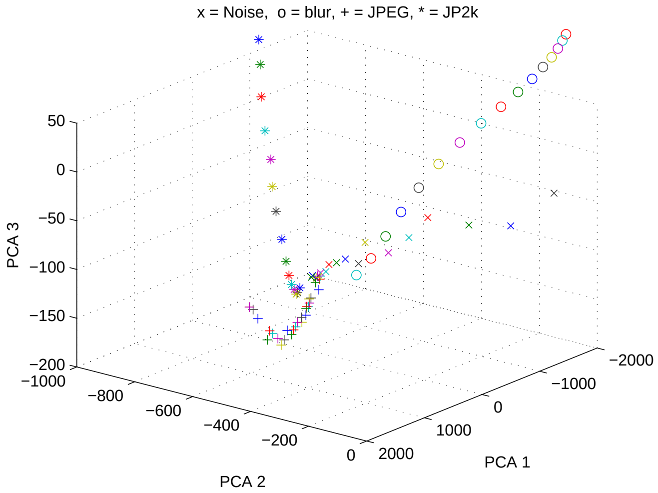

Fig. 2. Distorted Image Statistics. Each point in the figure is the average of statistics of 80 images projected onto a 3-dimensional PCA space. Only a part of the space is shown.

Distortion type	Classification Accuracy
WN	99.17%
Gblur	95.42%
JPEG	74.75%
JP2k	84.67%
Overall	88.5%

Table 2. Classification accuracy on test-set for distortion identification.

consisting of 9600 feature vectors.

3. RESULTS

Parameter section of the SVM during the training phase lead to a cross-validation accuracy of 94.60% with $(c, \gamma) = (128, 0.056)$; where c is a penalty parameter for the error term in the minimization function of the SVM. With this kernel, the classification accuracy of test images is 88.5%. Table 2 shows the classification accuracy per-category of distortion. WN and Gblur are the easiest to classify while JPEG is seemingly the hardest.

We expected that the performance of the classifier should deteriorate with increasing quality of images (reducing distortion severity). In Fig. 3 we plot the performance of the classifier on the test set for five distortion severity levels for each distortion type. For this purpose, each set of 6 distortion levels from each distortion type was clumped into a severity level (to form 5 such quantized 'quality' ranges) and the performance of the classifier was examined for this set of images. Even though the figure groups all distortions on the same *x*-axis - low quality (high distortion severity) to high quality (low distortion severity) - we do not mean to insinuate that these images have the same perceptual quality or that the degradation is the same in any manner. All distortion categories were plotted on the same graph due to space constraints. Figure demonstrates that performance accuracy falls monotonically for increasing quality. In Fig. 4 we plot the 'confusion matrix', that indicates which 2 sets of classes are confused the most for the 'high quality' (most misclassified) images.

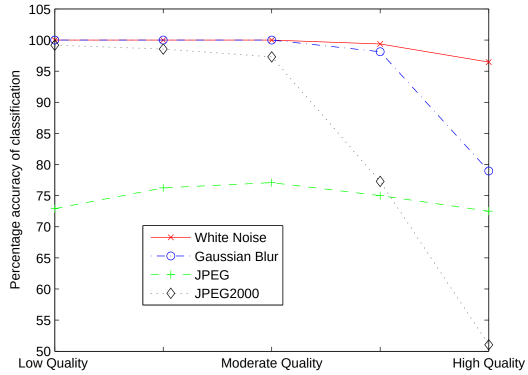

Fig. 3. Figure showing classification accuracy of SVM on the test set as a function of quality/distortion severity.

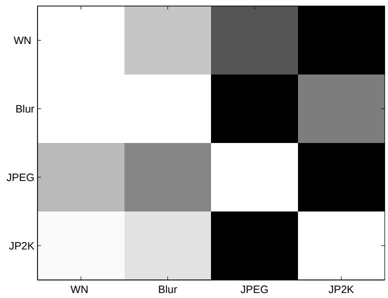

Fig. 4. Confusion Matrix for 'high quality' case - which (row) is confused as which (column) distortion. Darker value indicates greater number of confused images. Each row normalized. For example, Blur is most mis-classified as JPEG - this may be because JPEG compression induces blur as well as blocking distortions in an image.

Given that the overall accuracy of classification is good and that for high-quality images the distortions may not be significant enough to form a characteristic signature, the next question to answer is, 'can we label some images as unclassified'? Based on the confusion matrix in Fig. 4, our hypothesis is that if we create an arbitrary label - unclassified - and based on some criteria place images in this category, our classification accuracy should improve, especially for the high-quality case. In order to do this, we extract the probability estimates of an image belonging to a particular class from the SVM output. We set a threshold on the probability p of an image belonging to the output class. In case p is lesser than the set threshold, we re-label the image as un-classified. We report results of two such probability thresholds of 0.5 and 0.75 in Table 3 along with the total number of images classified after thresholding.

Fig. 5 shows the classification accuracy for each distortion as a function of quality for the $p \geq 0.75$ case. Comparing Figs. 3 and 5 validates our hypothesis that classification performance for high-quality images improves when the criterion for classification is made stricter, since this class of images may not have perceptually

Distortion	Accuracy ($p \geq 0.5$)	Accuracy ($p \geq 0.75$)
WN	99.29%	99.54%
Gblur	95.70%	97.91%
JPEG	76.24%	84.23%
JP2k	85.41%	91.20%
Overall	89.23%	**93.49**%
Total images	9522	9088

Table 3. Classification accuracy on test set for distortion identification with artificial 'un-classified' class and different probability thresholds.

significant distortions.

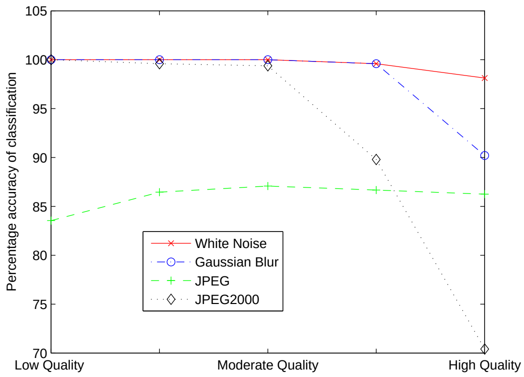

Fig. 5. Figure showing classification accuracy of SVM on the test set as a function of quality/distortion severity for $p \geq 0.75$ with an 'unclassified' category.

Finally, we also tested the possibility of using an alternate classifier - AdaBoost [17]. AdaBoost is a boosting technique used in conjunction with weak classifiers to improve classification performance. In our simulations we used a decision tree as the weak classifier and one-vs-the-rest training since AdaBoost is essentially a 2-class classifier, leading to 4 classifiers - one for each category. We found that with forced categorization into four distortions (based on confidence of returned-class) an overall classification accuracy of 90.41% was achieved for the whole dataset. With the introduction of an artificial 'unclassified' category (where images which each of the four classifiers did not accept as belonging to their 'true' class were placed) accuracy of $\approx 92\%$ was achieved over 9142 'classified' images. Future work will involve exploration of the optimal classifier for this problem.

4. CONCLUSION & FUTURE WORK

In this paper we demonstrated that different distortions exhibit different characteristics which systematically modify natural scene statistics (NSS). We evaluated distorted image statistics (DIS) for natural images in the wavelet-domain and utilized the generalized Gaussian distribution to parameterize these statistics. Further, we built a model for classifying images into specific distortion categories based on their DIS signature, and showed that such a classification may be achieved with high accuracy ($\approx 93.5\%$). We wish to increase the number of distortions to make DIS comprehensive. We are also in the process of creating algorithms for blind image quality assessment that use the frame-work of DIS.

5. REFERENCES

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