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WEIBULL DISTRIBUTION BASED MODEL BEHAVIOR IN COLOR INVARIANT SPACE FOR BLIND IMAGE QUALITY EVALUATION

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Abstract. In this paper, we analyze Weibull distribution based fitting using phase congruency components obtained via color invariance approach. Since such model is found suitable for image quality evaluations, we test the effects on different distorted images. Blind or no-reference image quality assessment enables testing without having available subjective ratings. Thus, it is possible to consider additional type of distortions usually neglected in available datasets through data augmentation artificial intelligence tools. The obtained results show that Weibull based modelling using color invariance domain components may be suitable for further experimental analysis. Moreover, data augmentation not used in the training phase, demonstrate the importance of development modern quality evaluator that can be applied even for modified data obtained as a result of augmentation.

Keywords: Probability distribution, fitting, distortion types, image quality assessment, data augmentation.

Introduction. When comparing the effectiveness of different quality evaluations, three approaches are considered, as well as appropriate fine tuning of the parameters. Namely, in addition to subjective image quality assessment (IQA) and personal ratings, there are: full-reference (FR), reduced-reference (RR) and non-reference (NR) evaluation approaches. FR metrics for IQA are expected to give the most satisfying results compared to pristine or original images named as reference [1, 2]. RR approach exploits the attributes of the reference images [3], while the most valuable are NR ones [4, 5]. The purpose is to design a new method for automatic quality assessment of digital images of various types using selected features and low complexity model which do not rely on pristine image content. This is also called blind IQA since no prior information about reference is available.

Recently, there are many blind IQA models and frameworks developed [4, 6-9]. One of the most successful approaches is Naturalness Image Quality Evaluator (NIQE) based on natural scene statistics (NSS) [4, 8]. High correlation with subjective ratings is obtained by block or patch-wise estimations. Typical features are subtracted and contrast normalized (MSCN) coefficients, where local activity is measured and only active patches are treated using Gaussian based fitting. Some of the IQA metrics include supervised model based approaches [9]. Recently, some of the novel unsupervised machine learning models are introduced [6-7]. In [6] unsupervised blind IQA based on joint structure and NSS features, called JSN-NIQE, is employed using thirty eight features per block and per scale (blocks of 96×96 pixels and two scales meaning additionally blocks of 48×48 pixels size). Among MSCN and other statistical features, phase congruency mapping is employed within NIQE-like framework. Such mapping is applied for structural measurement in color invariance domain. Inspired by the results presented in [6], such calculations are tested using different distortion types.

Materials and methods. One of the most applicable benchmarking datasets for IQA is LIVE database [10] applied initially only for FR method development. Five different distortions can be found such the noise, two compressions, blurring and fading. Here, we compare JSN-NIQE measurement results and Weibull fitting results for available distortions and additional images not included in the dataset, but obtained through data augmented approach. Even though, such data may or may not be considered as natural ones structural similarity exists, as well as of importance to observe whether such data may be considered through color invariance domain [11].

The color invariance is calculated using common RGB (Red-Green-Blue) color space, leading to three components: C_1=0.06*R+0.63*G+0.27*B, C_2=0.3*R+0.04*G-0.35*B and C_3=0.34*R-0.6*G+0.17*B. These components represent the result of transforming color values to the Gaussian color model in RGB terms [11]. The color invariance is expected to be robust to material properties, as well as illumination change or any other similar imaging conditions. Weibull fitting is employed for each component in order to observe the behavior of the coefficients representing the local activity of image/patch. In [6] such color space is employed in order to form the feature vector. Structure and attention methods enable to exploit gradient or edge information. Discontinuity found within distorted images is expected to have a crucial impact on subjective based evaluation. By color invariant domain, it is possible to evaluate different types of edge strength while enabling robust content measurements regardless of object reflectance, illumination, noise, highlights, shadows, and similar.

Figure 1 shows an example of pristine image and the three components. They can be interpreted as edge strength measures in order to evaluate the image (or patch) content activity.

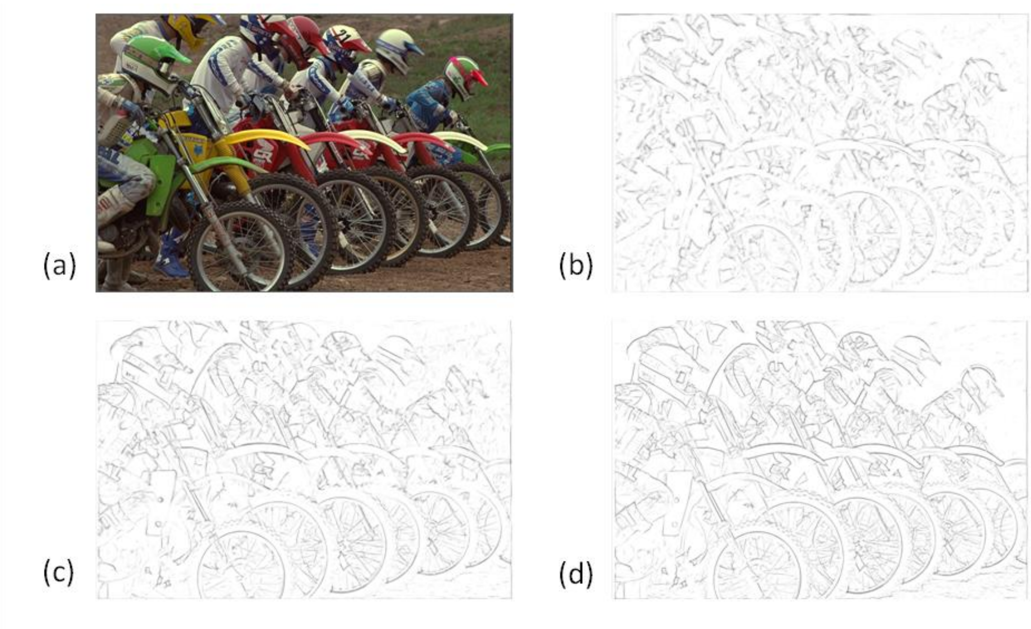

Figure 1. Example of (a) pristine image, and (b)-(d) three color invariance domain components.

Nowadays, the generative AI (artificial intelligence) is applied for content creation. Namely, models and libraries are developed for image generation. Data augmentation can be described as the process of producing new data from available content, primarily for overcoming data lack in learning phase. Even though, the augmented image content may produce biases in the learning step. It can be applied for further experimenting with test images as well, in order to analyze how possible random changes may affect the model, like in the case of quality assessment. There are many ways to perform data augmentation. Some of the typical examples are: by changing brightness, contrast, saturation, color spaces, by adding noise, or cropping, scaling, flipping, translation, rotation, etc. Currently, there are different tools that can be used for enabling data diversity [12]. Some of the Python libraries have been especially designed for this task, like: Albumantations [13], Augmentor [14], Imgaug3 [15], Keras ImageDataGenerator [16] or some other similar tool. In the absence of available subjective scores intended for supervised machine learning evaluations, it is valuable to observe what the effects are obtained using novel generated data. Here, this is done for JSN-NIQE [6] and Weibull color invariance components. For defining data augmentation Albumantations library [13] is applied. In this paper, pipeline consists of horizontal flip and a random selection of brightness and contrast selection using [13].

Results. In order to quantify the differences obtained with augmented data compared to pristine and originally distorted image [12], the selected pipeline is applied primarily to generate additional image data. Depending on the distorted image type, local activity throughout content is changing, which also affects the patch-wise results used in blind measurements. In Figure 2 Jpeg compression distorted image and Fast fading based distorted image are processed with the pipeline for obtaining Data augmentation 1 and Data augmentation 2 samples, respectively. Moreover, obvious discontinuities are presented in the color invariant domain.

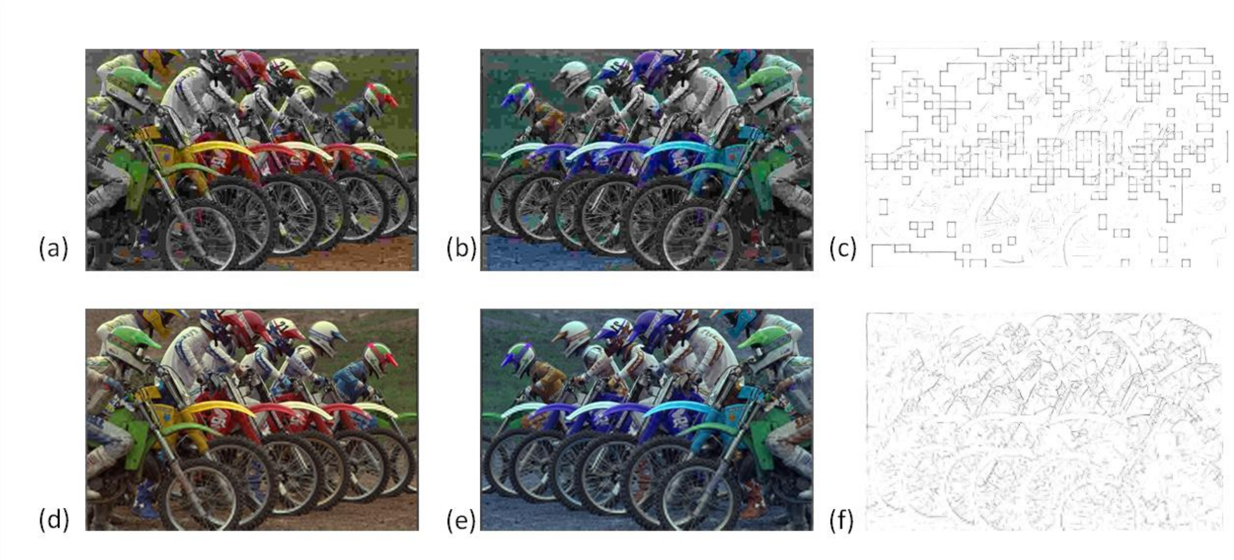

Figure 2. (a) Jpeg distorted image and corresponding (b) result of data augmentation and (c) C1 component; (d) Fast fading (ff) based distorted image and corresponding (e) result of data augmentation and (f) C2 component.

Phase congruency is used to map relevant discontinuities as dimensionless measure. For each color invariant component, histogram of obtained coefficients is approximated using two-parameter Weibull distribution. The two parameters are noted as *a* and *b*, representing scale and shape, respectively. In the case of jpeg compression distortion, for an image produced by augmentation fitting is performed globally here, and the comparison between components is presented in Figure 3.

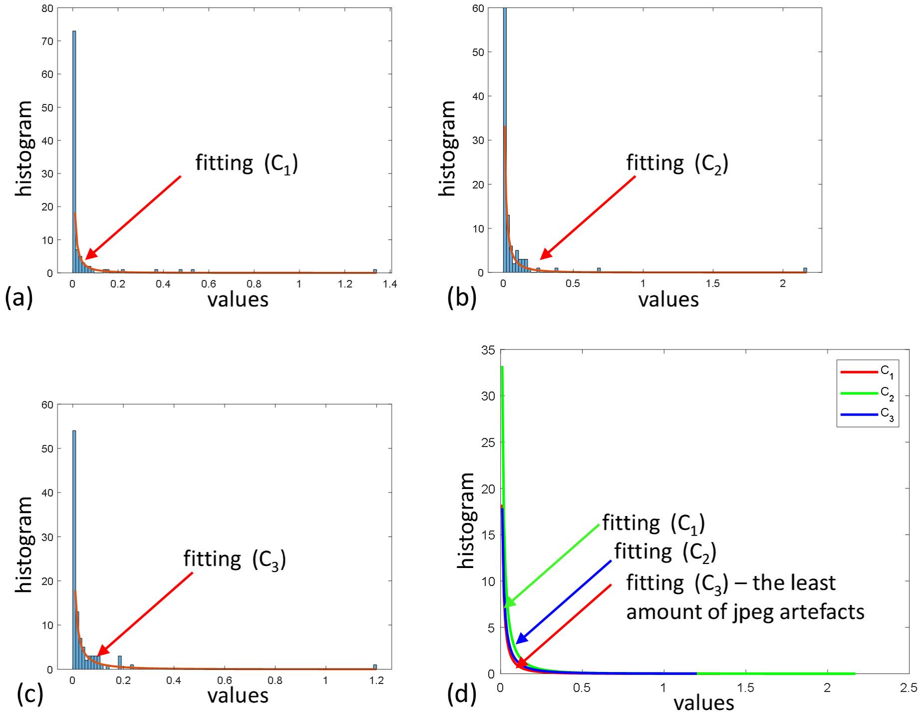

Figure 3. Fitting for (a) C_1, (b) C_2, and (c) C_3 component, and (d) comparison between the curves.

Table 1 shows the relative differences for the two parameters (Δa, Δb) in Data augmentation 1 for jpeg distorted images used as a source. The relative differences are calculated in terms of pristine image, showing C_2 component as the most robust here. On the other hand, absolute shape difference (b_{diff}) found between source and augmented version is less than difference calculated for the scale parameter, a_{diff}.

Table 1. Percentage of Weibull distribution parameter variations in Data augmentation 1 (jpeg)

Component	*Δa [%]*	*Δb [%]*	*a_{diff} [%]*	*b_{diff} [%]*
C_1	-24.5	-12.2	25.8	3.9
C_2	-2.5	0.1	2.5	-0.8
C_3	13.6	5.1	-27.1	-5.2

Table 2 shows the percentage of Weibull distribution parameter variations found in Data augmentation 2, where fast fading (ff) distorted image is treated as a source. Higher variations for fading are found expressed as the relative differences in terms of pristine reference. Nevertheless, the ff parameters are, in general, less affected compared to the jpeg distorted source.

Table 2. Percentage of Weibull distribution parameter variations in Data augmentation 2 (ff)

Component	*Δa [%]*	*Δb [%]*	*a_{diff} [%]*	*b_{diff} [%]*
C_1	32.5	26.4	-0.6	0.4
C_2	62.9	33.3	2.5	0.9
C_3	110	35.1	0.0	-0.2

Having in mind other features, like the NSS based ones, and JSN-NIQE measure, a comparison between measurements is given in Table 3. Distortion effects are evident in both distorted and augmentation cases. It is shown that unsupervised quality evaluation based on augmented data may have different impact based on distortion type used as a source. Here, a decrease in score is obtained in the jpeg case, and metric increase for the fading.

Table 3. Unsupervised quality evaluation based on augmented data and distortion type.

Data	*Score*	*Relative difference [%]*
Original	4.3	/
Distorted 1 (jpeg)	15.8	267
Distorted 2 (ff)	12.9	200
Data augmentation 1 (jpeg)	15.5	260
Data augmentation 2 (ff)	13.2	207

In Figure 4 Weibull parameters are compared for both source distorted images and augmentation data. The parameters are found while distribution fitting for images, and are calculated globally, not for patches as in JSN-NIQE. It is illustrated that some of the parameters may perform weaker grouping, leading to more sparse clusters after the augmentation.

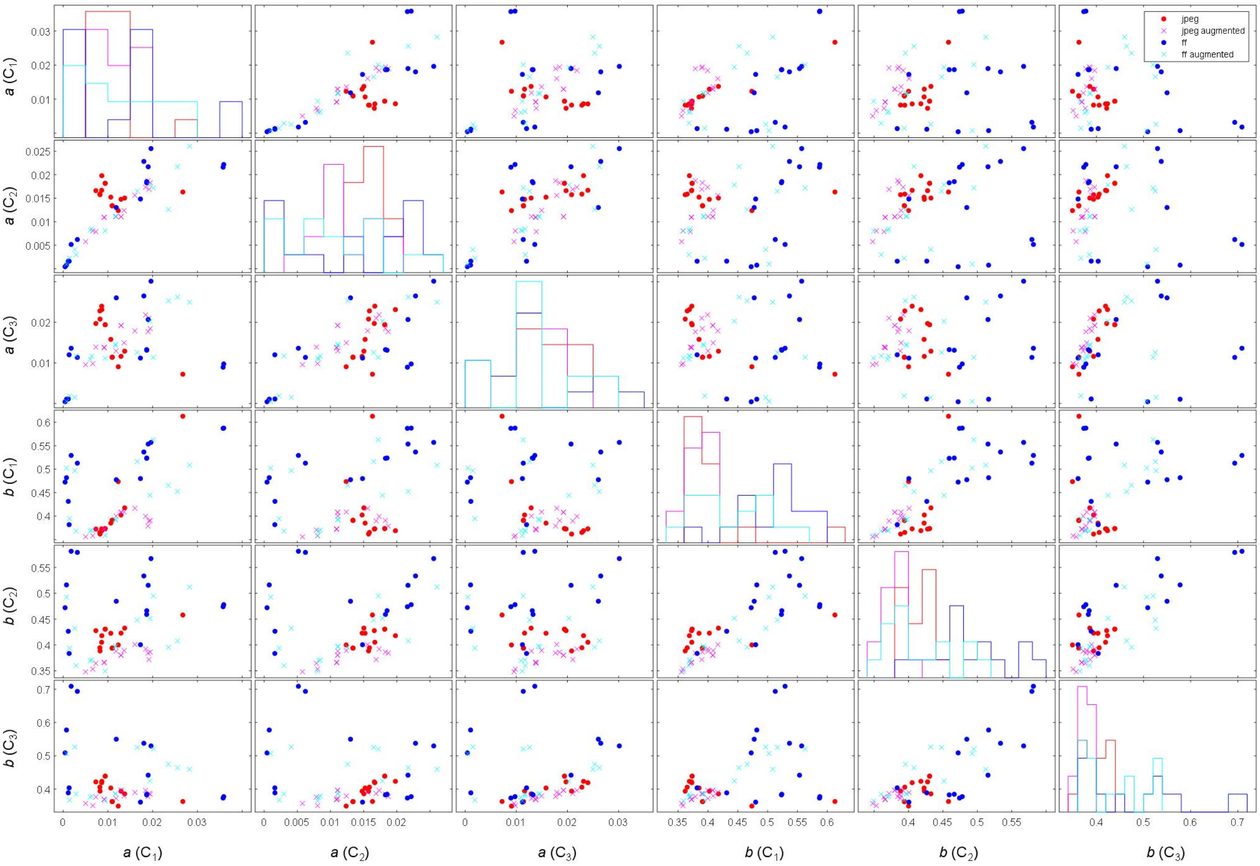

Figure 4. Weibull parameters comparison for jpeg and fast fading (ff) in the case of source and augmented data.

Conclusions. In this paper we analyze an unsupervised metric, and modification of Weibull parameters when applying a simple data augmentation procedure. Depending on the distortion source image, color invariant components are affected in different ways.

Weibull distribution is shown to be adequate for modelling task for each of the component. Even though, it should be noted that the fitting may not be suitable in some cases, like when the amount of distortion is extremely high. The estimation of Weibull parameters in each of the color invariant components represent an efficient and blind insight into existing distortions, and seem to be valuable for further experimental analysis. It is expected that augmented data for big data tasks may be estimated in the similar manner.

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authors' contribution

Ana Gavrovska – led the research on evaluation the quality of tested images.

Andreja Samčović – statement of the research problem, description of the procedure.

Dragi Dujković – describing the data augmentation possibilities.

Yuliya Golub – analysis of quality assessment possibilities.

Valery Starovoitov – statement of the research problem, introducing distribution relevance.

ПОВЕДЕНИЕ МОДЕЛИ НА ОСНОВЕ РАСПРЕДЕЛЕНИЯ ВЕЙБУЛЛА В ЦВЕТОВО-ИНВАРИАНТНОМ ПРОСТРАНСТВЕ ДЛЯ СЛЕПОЙ ОЦЕНКИ КАЧЕСТВА ИЗОБРАЖЕНИЙ

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Аннотация. В этой статье мы анализируем аппроксимацию на основе распределения Вейбулла с использованием компонентов фазовой конгруэнтности, полученных с помощью подхода цветовой инвариантности. Поскольку такая модель признана подходящей для оценки качества изображения, мы проверяем ее влияние на различные искаженные изображения. Слепая оценка качества изображения или без эталонного изображения позволяет проводить тестирование без наличия субъективных оценок. Таким образом, можно учитывать дополнительный тип искажений, обычно игнорируемых в доступных наборах данных, с помощью инструментов искусственного интеллекта для увеличения данных. Полученные результаты показывают, что моделирование на основе Вейбулла с использованием компонентов области цветовой инвариантности может быть пригодным для дальнейшего экспериментального анализа. Более того, пополнение данных, не используемое на этапе обучения, демонстрирует важность разработки современного оценщика качества, который можно применять даже для модифицированных данных, полученных в результате пополнения.

Ключевые слова: Распределение вероятностей, аппроксимация, типы искажений, оценка качества изображения, увеличение данных.