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A Literature Survey on Completely Blind Image Quality Evaluator Feature-Enriched

[1]Diya Gavaeikar, [2]Dharna Singhai
[1]M.Tech Scholar, [2]Assistant Professor
[1,2]Department of Computer Science and Engineering, Radharaman Engineering College, Bhopal, Madhya Pradesh, India

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ABSTRACT

Existing blind image quality assessment (BIQA) technique in which are principally opinion-aware. They learn deterioration models from training photos with associated human subjective scores to predict the sensory activity quality of take a look at pictures. Such opinion-aware methods, however, need a bulky amount of training example with associated human prejudiced achieve moreover of a variety of deformation category. The BIQA representation find out through opinion-aware strategies typically have weak generalization capability, herewith limiting their usability in observe. By comparison, opinion-unaware strategies don't require human prejudiced achieve for training, and then have superior possible designed for good quality simplification ability. Unluckily, to the present point no opinion-unaware BIQA technique has shown systematically better quality prediction accuracy than the opinion-aware strategies. Here, we tend to aim to develop an opinionunaware BIQA technique that may compete with, and maybe exceed, the present opinion-aware methods. By integration the options of ordinary picture information consequent as of multiple cues, we have an affinity to discover a multivariate Gaussian structure of representation patches from a set of perfect natural pictures. using the learned multivariate Gaussian form, a Bhattacharyya-like distance is employed to measure the standard of every image patch, and then a generally value score is find by average pooling. The projected BIQA technique doesn't want any distorted sample images or subjective class achieve for training, yet extensive experiment show its better quality-prediction presentation to the situation of the art opinion-aware BIQA strategies.

Keywords : Blind Image Quality Assessment, Natural Image Statistics, Multivariate Gaussian.

I. INTRODUCTION

Algorithms that evaluate perceived picture quality automatically are essential for many image processing applications. This drawback is becoming more and more noticeable as digital photos become increasingly prevalent in our everyday lives. A number of efficient francs goals image quality indicators that favourably correlate with a person's subjective judgement of quality are planned for the full-reference (FR) quality review (QA) problem, which evaluates quality in relation to a likely reference image. This problem has seen major developments in recent years [1]–[11]. At rest, the most popular and efficient quality metrics are the mean square intensity difference (MSE), which is the average square difference between unclear and references picture pixels, and the scaling reverse of mean square error (MSE), also known as peak signal-to-noise ratio (PSNR). However, the MSE, its fluctuation, and subjective quality metrics do not correlate well [12]–[15]. It is indisputable that there is a significantly stronger association between the image data responsibility index [10], the similarity index (MS-SSIM) [2] and its variation [9], and the visual many well-known francs objective measurements. using subjective assessment in place of the MSE, and taking into account the multistage systemic signal-noise magnitude connection [11]. However, in order to do these francium objective measurements, full access to the reference images is necessary. The Video Quality Experts Groups (VQEG) [16] just included RR image/video QA as part of its guidelines for future development. The RR algorithm rule does not include the reference picture, but it does have several options that are not included in the reference icon. When reference materials and an infrequent information measure need to be supplied simultaneously, this can be quite helpful. Up until now, the availability of reference data has proven unlikely in many, if not most, conceivable applications. Examples include pictures from commercial digital cameras, online movies, wireless recordings produced by PDAs and cell phones, and so forth. Often, at least part of the distortion may be predicted in advance, like when watching YouTube videos, for instance. Although most people believe that achieving the true "blind" disadvantage is nearly impossible, a breakthrough in the development of generic comprehensive NR QA is widely desired. Nonetheless, human observers can easily assess the quality of distorted pictures without having to contrast them with any reference image. Our limited understanding of the early and mid-stage processes taking place in the visual cortex and extra-cortical regions will make this problem worse; as a result, it is still unclear who will ultimately benefit from video. If distortions are discovered, significant progress has been achieved, and several efficient distortion-specific objective NR QAs have been put out. As an example, a blind assessment of the feature of pictures compressed using JPEG 2000 is provided in [20] by use of a natural scene statistics (NSS) model. Similar to [21], an algorithmic designed for NR image quality assurance (IQA) targets JPEG 2000 and includes intricate support for edge information as well as pixel aberrations. Blind JPEG QA was considered while using a live spatial action. An further specialised (blur only) NR algorithmic software was developed for JPEG 2000 pictures. A universal NSS-based NR QA algorithmic framework functioning in the discrete cosine transform (DCT) domain was presented for JPEG or MPEG signals. Some algorithmic rules target an artifact type instead of a specific compression technique. Edge blocking is assessed using an NR algorithmic approach that uses the fast Fourier transform. The image cross-correlation of the subsamples is where the darkness metric is formed. A gradient aided computing metric is presented by these authors during. The continued development of blind compression-specific QA procedures in [28] and [29] was based on block-based DCT coding. Recent NR-IQA studies have focused on the blind image quality assessment (BIQA) problem, which arises when prior data on the distortion types are missing. Currently available BIQA algorithms are largely "opinion aware," which means they were trained on a collection of skewed photos and their corresponding subjective assessments.[10]. The fact that their designs are same and [11] are typical instances of belonging to the present class. After feature vectors are eliminated from the training stage because of the fuzzy photos, a regression model is developed to translate the feature vectors to the matching human subjective scores. During the testing step, a feature vector is extracted from the test image and fed into the trained regression model to forecast the model's superiority score. In [11], Moorthy and Bovik presented a two-step BIQA structure that they dubbed BIQI. The specific quality of the adjustment is next evaluated using a similar set of data. In BIQI, view statistics are first retrieved from a distorted image and used to classify the deformed picture into distinct categories, with a focus on one in the middle of n distortions. Using a similar model, Moorthy and Bovik went on to develop BIQI to DIIVINE using a better-off set of conventional prospect features [12]. But this isn't the case in some real-world situations. Both BIQI and DIIVINE assume that the training dataset include representations of the various types of distortion seen in the test images. By training a probabilistic model with contrast and structure choices taken from the DCT domain, Saad et al. [13] projected a BIQA model, called BLIINDS, based on the hypothesis that DCT feature statistics will change in an incredibly predictable manner owing to differences in image quality. Later, Saad et al. [14] extended BLIINDS to become BLIINDS-II. misuse of more sophisticated NSS-based DCT substitutes. In [15], Mittal et al. used scene statistics of domestically normalised luminance coefficients to evaluate the potential loss of naturalness in the image due to the occurrence of distortions. BRISQUE is the name given to the resultant BIQA representation. Three kinds of characteristics are extracted by the prediction algorithm projected in [16] based on the statistics of natural pictures, distortion textures, and blur/noise. After training three regression models for each set of characteristics, the picture quality is evaluated using a weighted combination of these models.

II. LITERATURE SURVEY

Kai Zhao et.al. [1] “Quality-aware Pre-trained Models for Blind Image Quality Assessment” The objective of blind quality of image assessment (BIQA) is to automatically analyse the perceived quality of a single picture. Its efficacy has been recently increased using deep learning-based approaches. However, the absence of labelled data prevents deep learning-based BIQA systems from realising their full potential. Using a pretext task designed specifically for BIQA, we show in this work a self-supervised learning strategy to address the problem that enables learning representations from orders of magnitude more data. We propose a quality-aware contrastive loss to constrain the process of learning, based on a simple premise: the quality of patches from a distorted picture should be comparable but different from patched from the same image with different degradations and patches from other pictures. We also improve the existing degradation process and generate a degradation region of around 2×107. Our method allows for the pre-training of models on Image Net, which leads to much improved performance on downstream BIQA tasks and increased sensitivity to picture quality. Based on experimental results, our method generates significant gains on popular BIQA datasets.

Qi Zheng et.al. [2] “A Completely Blind Video Quality Evaluator” Due to the fact that the majority of video quality models now in use were developed for this enormous volume of material, they were trained on a large number of labelled samples derived from in-depth subjective assessments. Consequently, they often exhibit insufficient generalisation abilities when applied to unknown data. Consequently, it's also ideal to develop "completely blind," opinion-free models of video quality that can compete with existing learning-based models and don't require any training. We now introduce the VIQE (Video Quality Evaluator) model, which we developed after closely studying the patch- and frame-wise video statistics as well as the space-time statistical regularities of movies. The statistical variables required from the study collect complementing predictive properties of perceptual quality, which are used to calculate the final video quality ratings. Extensive testing on recent large-scale video quality datasets has demonstrated that VIQE can even compete with the state-of-the-art opinion-aware algorithms.

Zhengzhong Tu et.al. [3] “UGC-VQA: Benchmarking Blind Video Quality Assessment for User Generated Content” provides a comprehensive analysis and empirical research on the problem of blind video quality assessment for user-generated content (UGC-VQA). Furthermore, we proposed a new fusion-based BVQA model called VIDeo quality EVALuator (VIDEVAL), which employs a feature ensemble and selection procedure to improve upon existing successful BVQA models. After completing a thorough analysis of earlier top video quality models using a consistent and repeatable evaluation approach, we came to this result. We discovered that state-of-the-art, reliable performance may be achieved at a very low computational cost by carefully selecting a mix of straightforward distortion-aware statistical video characteristics and properly specified visual impairment criteria. The promising findings of the baseline CNN models highlight the great potential of using transfer learning techniques to the UGC-VQA problem. We believe that this benchmarking study will support UGC-VQA research by clarifying the current status of BVQA research and the relative efficacy of modern BVQA models.

Lin Zhang et. al. [4] “A Feature-Enriched Completely Blind Image Quality Evaluator” The majority of blind image quality assessment (BIQA) techniques now in use are opinion-based. Regression models are trained with training images and human subjective scores that match the photos in order to predict the sensory activity quality of glance-at photographs. However, a large number of training examples of different distortion classes and the related subjectively human evaluations would prove needed for such opinion-aware systems. Opinion-aware methods typically result in BIQA models that are difficult to generalise, which restricts their use in observation. The majority of blind image quality assessment (BIQA) techniques now in use are opinion-based. Regression models are trained with training images and human subjective scores that match the photos in order to predict the sensory activity quality of glance-at photographs. However, a large number of training examples of different distortion classes and the related subjective human evaluations would be needed for such opinion-aware systems. Opinion-aware methods typically result in BIQA models that are difficult to generalise, which restricts their use in observation. The standard of each image patch is measured using a Bhattacharyya-like distance utilising the learned multivariate Gaussian model, and average pooling is then used to obtain the overall quality score for associations in nursing. Our novel and efficient BIQA approach is founded on the IQA idea that was introduced in. Five distinct types of NSS choices are input into a collection of pristine realistic photographs, which the new model, IL-NIQE, uses to look for a multivariate Gaussian (MVG) model of pristine shots. The quality of the picture patches is anticipated using this model as a reference. The patches in a check picture are examined for quality, and a general quality score is obtained by averaging the patch quality scores.

Zhou Wang et. al.[5] “Blind measurement of blocking artifact in Images” ost annoying artefact in a block transform-coded image or video. For the purpose of event management, optimisation, and image/video coding system assessment, an objective measurement of block artefact is essential. It is also very beneficial for planning and analysing the post-processing algorithms at the decoding side. This study measures block units in cubic pictures using a deterministic method that does not take the primary ones into account as a reference. The new metric is constructed by utilising the second- and third-order applied mathematics options in the picture. The measurement is also modified to account for the visual masking effects of human eyesight. JPEG compressed image testing is used to evaluate the measuring methodologies. The bi-spectrum computing entails a substantial technological load due to the massive volume of picture data. One of the main things that frequently prevents the use of third- or even higher-order statistical approaches in image processing is this. Fortunately, our systems do not need computing the bi-coherence values at certain frequency sites. This keeps our algorithms running quickly. Using the reduced JPEG pictures, we test our prediction methods.

F. Pan et. al. [6] "A locally adaptive algorithmic rule for measuring blocking artifacts in images and videos" Block transform coding is the most used compression technique for photos and movies. The objective measurement of block artefacts is an important consideration in the design, optimisation, and assessment of image and video coding systems. This study presents a unique algorithmic method for assessing the picture quality of films or photos with BDCT coding. It has a number of special and practical characteristics, such as: (1) It uses a one-pass algorithmic rule, requiring only one access to the image; (2) It accounts for flatness in very low bit rate images and blocking artefacts in high bit rate images; (3) It seems at every frame separate in order to determine the degree of block artefacts locally; and (4) The quality measure is well defined within the range of 0–10. Research on a great deal of still photographs and videos show that the new quality measure is very efficient in terms of process complexity and memory use. Consistent block artefact metrics can also be produced by it. This work presents an effective and successful unreferenced technique for lowering measure block artefacts in BDCT coding, especially for low bit-rate settings. What makes the algorithmic rule novel is the adaptive determination of blockings s by block-by-block analysis that takes into account the brightness and spatial masking features of HVS, as well as the influences caused by entirely different quantization steps in neighbouring blocks. It is crucial that the proposed measure captures the BD CT coded image's flatness and blackness, as most existing methods only concentrate on one of these two attributes. The projected measure also has the advantage of having a well-defined range of values and very simple computational.

H. Liu et. al. [7] "A No-Reference Metric for Perceived Ringing Artifacts in Images" A unique no-reference metric for automatically evaluating ringing discomfort in compressed images is presented. To determine which locations are most likely to be impacted by ringing artefacts, a newly created predicted ringing area detection technique is employed. To measure ringing pain in these detected locations, the visibility of ringing artefacts will be assessed and contrasted to the action of the related local backdrop. The local dissatisfaction score for each distinct ringing zone is averaged across all ringing regions to get the overall ringing irritation score for the image. In a psycho visual experiment, ringing annoyance is subjectively quantified and the expected measure is validated. When the performance of our metric is compared with alternative choices from the literature, it shows good agreement with subjective knowledge. A fresh no-reference metric for ringing artefacts in viewed compressed photos was given in this study. Based on the already in use perceived ringing region detection technique, this measure includes ringing annoyance evaluation inside the perceptually relevant regions of a picture [30], [31]. For each unique ringing zone, a ringing annoyance score is calculated by first evaluating the local visibility of ringing artefacts and then contrasting it with the local background activity. An overall score for ringing annoyance was determined by aggregating the local irritant values across each ringing zones. A psycho-visual research was conducted to validate our expected ringing metric and measure ringing annoyance in a subjective manner.

H. R. sheikh et. al. [8] “No-Reference Quality Assessment using Natural Scene Statistics: JPEG2000” Numerous techniques in image processing, such as capture, compression, restoration, augmentation, and duplication, depend on a measurement of the picture or video quality. Image quality assessment (QA) algorithms state that a common way to assess the visual quality is to compare it to a "reference" or "perfect" image. The method's obvious flaw is that the QA algorithms programmer could not access the reference image or video. Most research has not been done in the area of blind, or no-reference, quality assurance, which predicts picture quality but not the reference image or video. In this domain, algorithms only measure blocking artefacts. Modern image and video compression techniques employ a variety of techniques to avoid the dreaded block artefact, but they also produce brand-new types of distortions including ringing and blurring. In this study, we would rather recommend utilising natural scene statistics (NSS) to measure the standard of images compressed by JPEG2000 (or any other wavelet-based) image coder in an unbiased manner. We often claim that compression destroys nonlinear connections present in natural landscapes; these breaks are usually quantified and associated with subjective quality ratings. Typically, we train and test our algorithms systems using data from human participants, and we show that suitably comprehensive NSS models will allow us to generate predictions that are both accurate and of acceptable quality. Because of inter-person heterogeneity, our algorithmic approach delivers near-maximum performance needed for a feasible forecast. In this study, we suggested using NSS to evaluate image quality independently of reference images in pictures and videos. Generally speaking, we contend that since natural pictures and videos come from a tiny subset of all conceivable signals and since distortion mechanisms change the anticipated statistics of them, a signal's divergence from the expected natural statistics may be assessed and associated with its visual quality. We have presented an implementation of this idea for images that have undergone wavelet-based compression, such JPEG2000. The nonlinear connections seen in natural images are broken by JPEG2000 compression. We included quantization distortion modelling into a nonlinear statistical model for natural pictures to provide an algorithmic method for assessing the departure of compressed images from expected natural behaviour. Next, we compared this quantification to subjective assessments of quality.

III. PROBLEM FORMULATION

Predicting human judgements of picture quality digitally is the aim of picture Quality Assessment (IQA). It is well recognised [Teo94] that traditional metrics, such as Root Mean Squared (RMS) error, are insufficient for comparing photos since they do not accurately anticipate how an observer would interpret the differences between the images. Many perceptual Image Quality Metrics (IQM) have been developed to address the issue. The subject of blind/no-reference objective picture quality evaluation is the main emphasis of this thesis. In particular, we suggest developing an algorithm for evaluating the quality of images and videos without reference, based on human perception.

IV. METHOD

A. Probabilistic Latent Semantic Analysis

Firstly, we take a quick look at Hofmann's pLSA model [9], which was first applied to identify latent themes within a corpus of textual data. In this instance, the corpus is made up of an assortment of both perfect and distorted images. Let N be the total number of both perfect and crooked photos in the collection. Based on a "visual word vocabulary," every image in the collection will be shown as an empirical distribution across "visual words." Let W stand for the total number of distinct visual words in the lexicon. For the sake of argument, let us assume that Wj words make up the jth image in the corpus, Ij, and that the ith word is represented by Wij. We also assume that the corpus's photo collection is infused with latent themes, with the kth subject denoted by the indicator variable zk. Typically, an image is represented as a distribution over K topics, where a latent topic zk is connected with each word wij in the image Ij. After the latent themes are marginalised, the contingent chance of perceiving a word wij given an image Ij. zk, i.e.,

$$P(w_{ij} \mid I_j) = \sum_{k=1}^{K} P(z_k \mid I_j) P(w_{ij} \mid z_k) \ .$$

As a result, the kth topic is represented by the W-dimensional vector P (w|zk), and the loadings of pictures across topics are represented by the K-dimensional vector P (zk|Ij). One may infer the themes that are common to the collection of pictures as well as their loadings given a specific image by choosing the model that best matches the probability distribution of the visual words within the photos. This maximum probability estimate of the model parameters may be computed using the expectation-maximization (EM) algorithmic method, as demonstrated in [9]. Remember that because the pLSA framework disregards the spatial order of word occurrences, it uses the "bag of words" approach.

B. Quality-Aware Features

Furthermore, even though we do not use perceptually appropriate human data to train our model, we rely on natural scene statistic (NSS) features to capture perceptually relevant scene properties. More specifically, we use the NSS features first introduced in the Blind-Reference less image Spatial Quality Evaluator (BRISQUE) to compute features over each image patch. BRISQUE superior layout is based on the premise that natural images should follow certain regular statistical patterns, which are disrupted when distortion happens. [12]. Quantifying these departures from the regularity of natural scene statistics is useful for assessing the perceived quality of images. This description is sufficient to categorise the distortion that the photographs have as well as to assess how realistic the images are. The BRISQUE NSS characteristics blend in perfectly with the subject form framework everywhere the inferred topics appear as LQFs that are representative of "pristineness" and of the artefacts brought about by different distortions. Photographic normalised brightness coefficients are statistically represented by the BRISQUE characteristics.[1]. A The BRISQUE features also employ a model for paired products of neighboring (normalised) luminance values. The 36-dimensional BRISQUE function vector for each patch.

V. CONCLUSION

A review paper on a completely new approach to determining perceptual quality of images that supports the application of a subject model on image patches that are shown in an incredibly appropriate quality-aware area, followed by an analysis of the prior approach's analysis of the subject distributions for each image. This solution eliminates the need for the laborious manual process of obtaining DMOS scores. The next task would be to use LDA to learn the structure on a much larger simulated dataset. This should be rather simple to set up, given that our method does not require human opinion ratings.

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