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Blind Image Quality Estimation Using Deep Neural Networks Explicit Image Position

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ABSTRACT

Blind image quality assessment (BIQA) is very challenging problem due to the unavailability of a reference image. State of-the-art BIQA methods usually learn to find the image quality by regression from human subjective scores of the training samples. These methods uses to large number of human scored images for training, and lack an explicit explanation of the image quality is affected by image local features. We propose a family of image quality assessment (IQA) models based on natural scene statistics (NSS) is predict the subjective quality of a distorted image without reference to corresponding distortion less image and without any training results on human opinion scores of distorted images. Different from most deep neural networks (DNN), We take biologically inspired generalized divisive normalization (GDN) instead of rectified linear unit (ReLU) as the activation function. We empirically demonstrate that GDN is effective at reducing model parameters while achieving similar quality prediction results. The proposed model is extensively find the large scale benchmark databases to deliver high performance with state-of-the-art BIQA models as well as with some well-known full reference image quality assessment models. The proposed algorithm uses natural scene statistics in spatial domain for generating wake by distribution statistical model to extract quality aware features. The features are fed to an SVM regression model to predict quality score of input image without any information about the distortions type or reference image.

Keywords: Wake by distribution model, Support vector machine, Blind Image Quality Assessment, Gradient Magnitude, Palladian of Gaussian, Pseudo Distance Technique

I. INTRODUCTION

With the explosion of visual media data huge amounts of digital images are generated stored, processed and transmitted every day. During these different stages, the images can undergo diverse, often multiple distortions, arising from under various blurs, noise corruption, compression artifacts [1]. A present deep learning technique is achieved great successes in solving much image finding and processing problems [2]. The remarkable capability of deep neural networks to learn discriminative features provides a very promising option for addressing the challenging BIQA task [3]. We present a novel solution to BIQA using no human scored images in learning. We propose a quality-aware clustering (QAC) method to learn a set of quality-aware cancroids and use them as the codebook to infer the quality of an image patch so that the quality of the whole image can be determined [4]. We propose a family of such NSS driven blind IQA algorithms. A blind IQA model is opinion unaware if it can successfully predict human subjective judgments of distorted images without the aid of human opinion scores and without the corresponding exemplar reference images [5]. Our system is based on the hypothesis that distorted images have loadings over latent distortion is refer to as latent quality factors(LQFs) that differ from the loadings for natural pristine images [6]. Latent topics are discovered by modeling images as distributions over representative visual words extracted from an assortment of pristine and distorted images [7]. . We empirically show that GDN has the capability of reducing model parameters and meanwhile maintaining similar quality prediction performance [8]. We evaluate the resulting Multi-task End-to-end Optimized Network (MEON) based image quality index on four publicly available IQA databases and demonstrate that it achieves state-of-the-art performance compared with existing BIQA models [9].

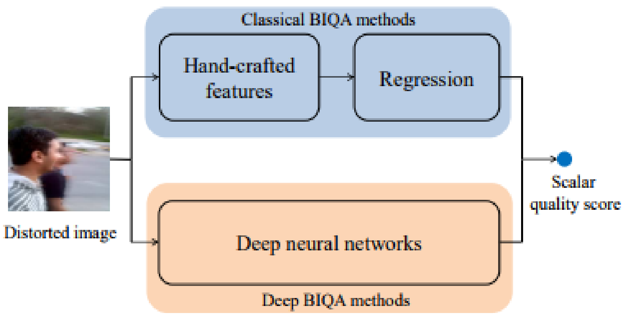

Figure 1. BIQA methods directly train a model to regress the scalar quality scores

II. RELATED WORK

Existing BIQA methods is conveniently divided into two categories: classical regression based models and present deep learning based methods [10]. In classical regression based BIQA methods a set of handcrafted features usually are extracted first to capture quality-related aspects of a set of distorted training images, then, a regression model is learned that maps the image representations onto scalar quality scores [11]. We are aiming at an end to-end solution meaning that feature representation distortion type identification and quality prediction are optimized [12]. Simultaneously estimated image quality and distortion type via a traditional multi-task DNN simultaneous multi-task training requires ground truths of distortion type and subjective quality to be both available which largely limits the total number of valid training samples [13]. Wake by distribution also known as advanced distribution used to modeling the NSS coefficients and extracting quality aware feature vectors. This distribution has a couple of scale and shape parameters which make it more flexible in comparison to the other distribution models used in the state of the art methods [14]. These parameters let us form a feature vector that is very sensitive to changes in an NSS coefficient empirical distribution which causes more accurate model fitting and better prediction of image quality score [15]. Several compression techniques are proposed, some based on general data compression and some on specific file compression [16]. Further improvement of compression gain can be possible when the color table is updated based upon the neighboring pixels. Accordingly Pseudo Distance Transform technique is used in order to avoid equalization errors [17].

III. QUALITY AWARE CLUSTERING

Our method works on image patches and aims to learn a set of quality-aware centric for blind image quality assessment (BIQA). To this end we need some reference and distorted images for training but do not need to know the human subjective scores of the distorted images [18]. Considering that the existing IQA databases will be used to evaluate and compare the different BIQA algorithms. We generate its distorted versions of each type on three quality levels by controlling the noise standard deviation the support of blur kernel the resulted quality level and the compression ratio we obtain a dataset of 120 distorted images and 10 reference images [19]. A choice of the three quality levels should make sure that the quality distribution of the resulted samples in the next section is balanced [20].

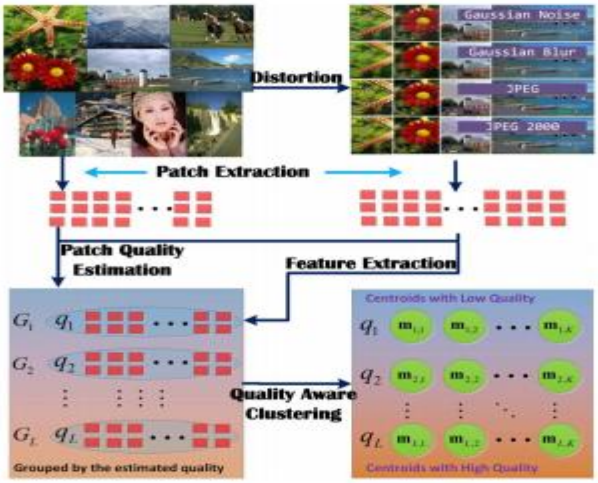

Figure 2. Flowchart of the quality-aware clustering (QAC) scheme

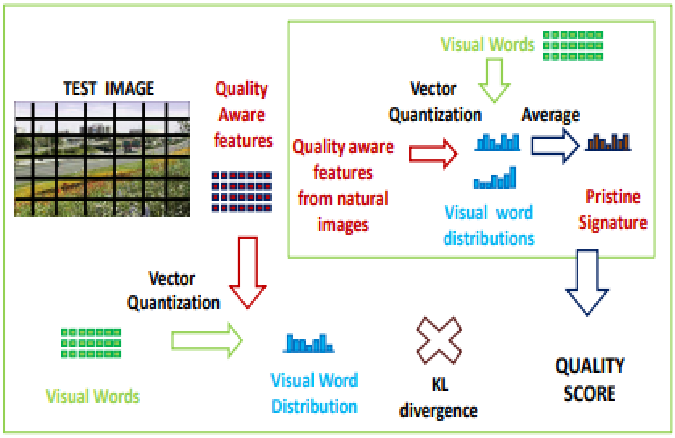

Figure 3. Image quality inference

IV. PROPOSED METHOD

We begin by first briefly outlining the limitations of existing deep BIQA method is motivated and describe the PQR framework. This leads to a probabilistic representation of distorted images and the deep BIQA model training process. We now describe our new completely blind IQA models [21]. Images are decomposed by an energy compacting filter bank and then divisive normalized, yielding responses well-modeled using NSS. LOG and GM operators share common property that they are computed using isotropic different operators without angular favor. LOG deals with center surrounded profile and symmetrically sensitive to intensity changes across all orientation where as GM refers maximum intensity regardless orientation [22]. A novel method to assess quality of natural images based on NSS modeling is proposed in the presented model, the natural features is extracted from input images that to composition of the local mean subtraction and contrast divisive normalization (MSCN) coefficients [23].

A. Quality-Aware Features

While we do not use perceptually relevant human scores to train our model we do rely on natural scene statistic (NSS) features to capture perceptually relevant scene properties. Specifically, we use the NSS features introduced in the Blind Image Spatial QUality Evaluator (BRISQUE) to compute features over every image patch. The principle behind BRISQUE feature design is that natural images obey specific regular statistical properties, which are disrupted by the presence of distortions [24]. Quantifying such deviations from regularity of natural scene statistics is quite useful for assessing the perceptual quality of images [25]. The BRISQUE features also utilize a model for pair-wise products of neighboring (normalized) luminance values. The BRISQUE feature vector computed over each patch is a 36-dimensional vector [26].

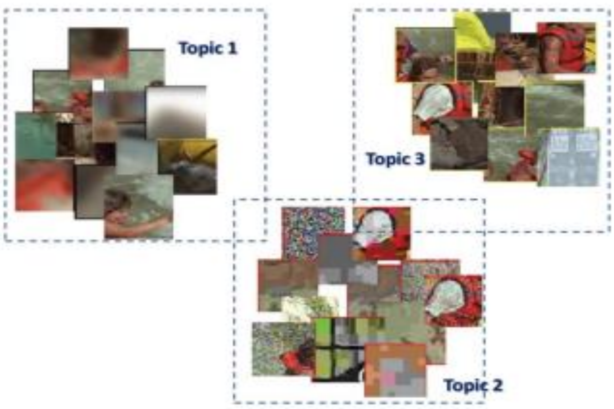

Figure 4. LQFs discovered by the pLSA model.

B. Pseudo Distance Transform Technique

After the BIQA process observed that the image which is obtained has resemblance of the original input image but with the case of compression gain criteria it is poor in it. So in order to improve compression gain without quantization error, color table is updated based on neighboring pixels [27]. The nearest neighbor values the imaginary and the undefined pixel values are considered is encoding and decoding process is considered based upon the imaginary terms.

Consider (x, y, z) are pixel values

1. repeat
2. w PREDICT (x,y,z)
3. u P[w,f]
4. for i 1 to n
5. do if e>P[w,ui]
6. then P[w,ui] P[w,ui] + 1
7. P[w,f] 0
8. If P≠z
9. then e 2 P[z,f]
10. for i 1 to n
11. do if e2 >P[z,ci]
12. then P[z,zi] P[z,zi] + 1
13. P[z,f] 0
14. until All pixels processed
15. return

This algorithm may include uniqueness of entries and repetition of same colors and increasing of zero values.

C. Natural Scene Statistics Extraction

The statistics of natural images have been studied for more than 50 years by vision scientists and television engineers. The idea is simple all natural images share some common statistical behaviors regularities related to the real world [28]. One of the best examples of NSS is MSCN coefficients where its histogram is approximately Gaussian like for a natural image the behavior of these statistics in presence of different distortions is predictable. It helps the reader to have a better imagination of the relation between NSS and severity of distortions [29]. Images are decomposed by an energy compacting filter bank and then divisive normalized, yielding responses well-modeled using NSS. Quality prediction is accomplished by computing the Kull back Lei blur (KL) divergence between the visual word distribution of the distorted image and the signature visual word distribution of the space of exemplar images [30].

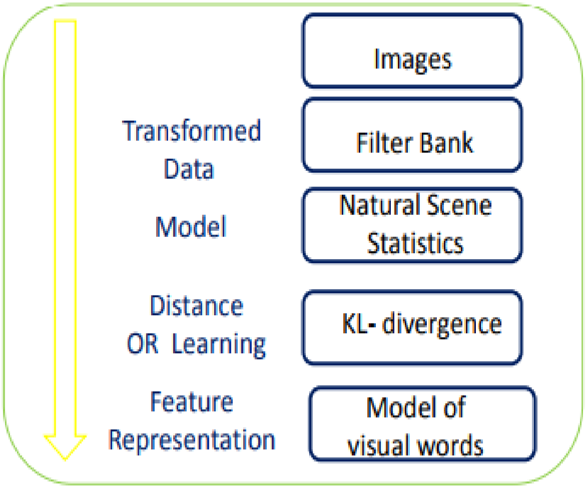

Figure 5. Flow diagram of IQA model

V. EXPERIMENTAL RESULTS

Two commonly used performance metrics, Pearson Linear Correlation Coefficient (PLCC) and Spearman Rank-Order Correlation Coefficient (SRCC) as suggested in [18] are employed to evaluate the proposed algorithm. We made sure there is no content overlap between train and test samples. We conducted performance comparisons between the proposed method and six other state of the art image quality assessment methods. They can be loosely categorized into seven classes: human, animal, plant, landscape, cityscape, still-life, and transportation, with representative images. We partition the reference and distorted images into many overlapped patches. Denote by xi a patch of one reference image and by di the distorted version of it. One key problem in our method is how to assign a perceptual quality to di. To this end, we can first use the similarity function in some state-of-the-art full-reference image quality assessment (FR-IQA) method.

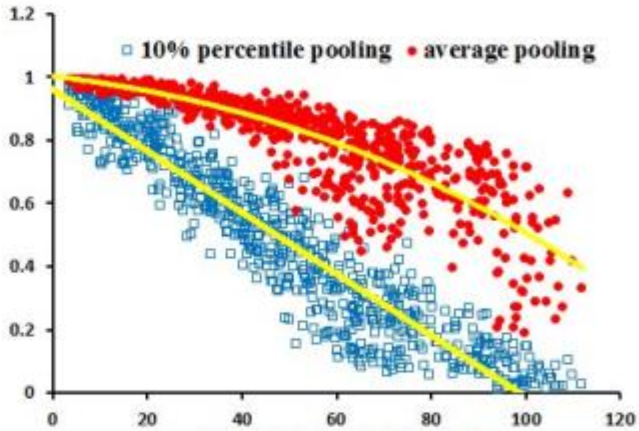

Figure 6. The effect percentile pooling IQA models.

VI. CONCLUSION AND FUTURE WORK

We were able to train deep BIQA models using our probabilistic quality representation (PQR) to accurately predict image quality, while achieving faster convergence with a greater degree of stability. The key of the proposed approach lies in the developed quality-aware clustering (QAC) scheme which could learn a set of quality aware cancroids to act a codebook to estimate the quality levels of image patches. We designed NSS based algorithms by measuring the distance between the visual word distributions of the given distorted image and the space of exemplar images. We believe arises from pre-training for better initializations multi-task learning for mutual regularization, and GDN for biologically inspired feature representations to the scalability of MEON to handle more distortion types and its strong competitiveness against state-of-the-art BIQA approaches. The SVM is trained to predict image quality scores from these feature vectors. We then evaluated performance of the proposed method in terms of correlation with human perception. In future direction is to extend the current work to other problems that involve perceptual attributes of images which casts great challenges to train DNN without over-fitting. a more sophisticated topic model such as Latent Dirichlet Allocation (LDA) [15] but the small size of the dataset led to overfitting of hyperparameters yielding poorer performance than pLSA. Future work would involve learning the framework using LDA on a larger size simulated dataset.

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