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Review on Deep CNN-Based Blind Image Quality Prediction Techniques

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Abstract: The images that we take from the various image processing applications usually need to be evaluated with their quality attribute todecide whether they are suitable for specific applications or not. Blind image quality assessment (BIQA) is one of the methods which aim to predict quality of images as observed by humans while not access to reference image victimization Deep CNN. With the increasing demand for image-Processing applications, the efficient and reliable evaluation of image quality has increased in importance. Measuring the image quality is of basic importance for various image processapplications;wherever the goal of image quality assessment (IQA) ways is to mechanicallyevaluatethe standard ofimages in agreement with human quality judgments. Various IQA methods have been proposed over the past years to fulfil this goal. In this paper, a survey of the image quality assessment methods for image processing applications images is presented.

Introduction: Image quality assessment plays vital role in image processing applications such as image compression, image restoration image enhancement and other fields. IQA is also useful for the applications such as image reconstruction and image retrieval. Image quality assessment (IQA) is very important for the image applications because sometime images may contain various types of noise like blur, noise, contrast change etc.IQA dataset gathering is based on complicated and time-consuming psychometric experiments. The cost of generating datasets for IQA is high since it requires supervision of expert. Therefore, the fundamental IQA benchmarks are comprised of solely a few thousands of records. The latter complicates the creation of deep learning models because they require large amounts of training samples to generalize.

Image quality assessment (IQA) classification

Image quality assessment (IQA) can be broadly categorized into *subjective* and *objective* quality assessment (QA). In subjectiveQA, humans are supposed to evaluate the visual quality of content and the average of subjective ratings is termed as Mean Opinion Score (MOS). Subjective QA is most reliable method of quantifying perceptual quality of content because in most cases such content is meant to be viewed by humans. However, subjective QA method is time consuming, expensive, and cannot be embedded in image processing algorithms for optimization purposes. While in case of objective quality assessment automatically predicts the quality of images as perceived by humans. Significant progress has been made in the last two decades in the design of objective QA methods andbased on the IQA three major frameworks are now well-established

1) Full-Reference (FR) IQA, 2) Reduced-Reference (RR)IQA,3) No-Reference (NR) or Blind IQA.

To evaluate the quality of a distorted image, FR methods require thecompleteavailability of its pristine quality version termed as a reference image, while RR methods require access to certainfeatures that have been extracted from the reference image. In many real-world applications, such as image communication systems, the reference image is not available and the quality evaluation is solely based on the test image. NR-IQA is a more difficult task in comparison to RR-IQA and FR-IQA methods. Since the beginning of this century, with the availabilityof subject-rated datasets, a large number of IQA methodsbelonging to all three frameworks (FR, RR, NR) havebeen proposed. These methods are tested on one or moreSubject-rated datasets and claim state-of-the-art performance

To address the above-mentioned challenges, a comprehensivesurvey of the performance of IQA methods, especiallyFR and fused FR methods, is required that showtheir performance on a large and diverse set of subject-ratedIQA datasets. A number of reviews and surveys have beenconducted in the field of IQA over the past decade or so.The performance of ten FR IQA methods was evaluated

Literature Survey

Several researches have been agreed on this image quality. This paper presents a survey on a variety of image qualityassessment. Increases in area of imagequalityassessment have exposed the way for unbelievable raise in widely huge and complete image databases. The images which are existing in these databases, if observed, can supply precious information to the individual clients.

Yezhou Li,1,a Xiang Ye,1,b and Yong Li2,c [1] proposed a method of accurately assessing image quality without a referenceimage by using a deep convolutional neural networkSimone Bianco _ Luigi Celona _ Paolo Napoletano _ RaimondoSchettini[2],"In this work they have investigated the use of deep learning for distortion-generic blind image quality assessment. Arxiv:1602.05531v5 [cs.CV] 4 Apr 2017

Methodologies

Most of the newest algorithms focus on feature learning. As previously stated, the main limitation of these methodologies is that they need large amount of datasets to generalize. Nonetheless, the latest methods focus on hybrid approaches that as a first step automatically learn quality-aware features and secondly an association of such features to a perceived quality score**.**

The main objective of this paper is to introduce three different approaches that have attainedexcessive performanceas compared to previously defined methods. The main objective of first method is based on a deep neural network that is trained to learn an objective error map. The second method based on the concept of multiple pseudo reference images (MPRI) and the extraction of features through high order statistics aggregation, and the third method introduces unsupervised k-means clustering to create an image quality characteristics codebook.

DIQA is an original concept that emphasising s on solving some of the most concerning challenges of applying deep learning to image quality assessment (IQA). The advantages against other methodologies are:

- The model is not limited to work exclusively with Natural Scene Statistics (NSS) images [1].
- Prevents over fitting by splitting the training into two phases (1) feature learning and (2) mapping learned features to subjective scores.

Overall flowchart of DIQA

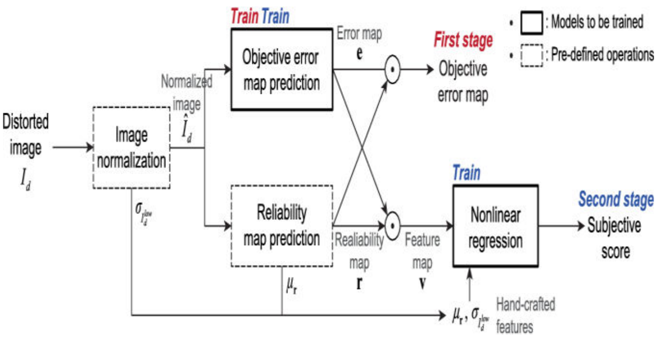

Image Normalization

The first step for DIQA is to pre-process the images. The image is converted into grayscale, and then a low-pass filter is applied. The low-pass filter is defined as:

$$\hat{I} = I_{gray} - I^{low}$$

Where the low-frequency image is the result of the following algorithm:

1. Blur the grayscale image.
2. Downscale it by a factor of 1 / 4.
3. Upscale it back to the original size.

Objective Error Map

For the first model, objective errors are used as a proxy to take advantage of the effect of increasing data

Reliability Map

According to the authors, the model is likely to fail to predict images with homogeneous regions. To prevent it, they propose a reliability function. The assumption is that blurry areas have lower reliability than textured ones. The reliability function is defined as

$$\mathbf{r} = \frac{2}{1 + exp(-\alpha|\hat{I}_d|)} - 1$$

Where α controls the saturation property of the reliability map. The positive part of a sigmoid is used to assign sufficiently large values to pixels with low intensity.

Conclusion: In this work, we carried out a review on performance evaluation study in the field of IQA. This paper presents a systematic survey of various DNNbasedmethods for BIQA .This classification strategy explicitly shows the characteristics, advantages and disadvantages ofdifferent DNN methods for BIQA.I hope this survey of DNN methods can serveas a useful reference towards a better understanding of thisresearch field.

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