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Convolutional Neural Network for No Reference and Full Reference using Image Quality Assessment

S. Sathyamoorthy[1] and M. Dharmalingam[2]
[1]Research Scholar, Department of Computer Science,
Bharathiar University Arts & Science College, Modakkurichi, Erode, Tamilnadu, India.
[2]Assistant professor, Department of Computer Science,
Bharathiar University Arts & Science College, Modakkurichi, Erode, Tamilnadu, India.

(Corresponding author: S. Sathyamoorthy)
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ABSTRACT: Image Quality Assessment tasks done on No Reference Image Quality Assessment (NR-IQA), which evaluates the visual quality of digital images without access to reference images and without prior knowledge of the types of distortions present. Full Reference Image Quality Assessment (FR-IQA) uses both distorted and reference image. The advantage of full reference image quality assessment is that it can quantify visual sensitivity on the basis of the difference between the distorted and reference images .We evaluate LIVE, CISQ and TID 2013 databases as well as the LIVE in the wild image quality challenge database and show higher performance of NR and FR IQA methods. Number of images and videos are captured displayed and transmitted are intended to be viewed by humans. This paper focuses on the most challenging category of objective image using Deep learning of Convolutional Neural Network. In deep learning a CNN is a class of deep neural networks, most commonly applied to analyzing visual imagery. Deep Neural Network architechers generate compositional model where the object is expressed as a layered composition of primitives. DNNs are typically feed forward networks in which data flows from the input layer to the output layer without looping back.

Keywords: Image Quality Assessment, No reference image quality assessment, Full reference image quality assessment, Distortion, Convolutional Neural Network, Deep Neural Network.

I. INTRODUCTION

Full reference image quality assessment and no reference image quality assessment approaches to image quality prediction differ significantly. To improve FR-IQA different kind of computational models of the HVS (Human Visual System) have been introduced. Depending on these analyses on HVS a number of FR-IQA metrics have been developed. In contrast to FR-IQA, NR-IQA covers on improving decision accuracy more brilliantly i.e., similar to an image recognition task rather than the HVS [2]. Objective image quality metrics can be categorized according to the availability of an original image which the distorted image is to be compared. Existing approaches are known as full reference. The meaning of full reference that a complete reference image is assumed to be known. In many practical application however the reference image is not available and a no reference or blind quality assessment approach is desirable [3].

Deep neural network, each layer of nodes trains on a distinct set of features based on the previous layer's output. The further advance into the neural net, the more complex the features nodes can recognize, since they aggregate and recombine features from the previous layer [21]. The effectiveness of these models reduces significantly when applied to an asset of image originating from different reference image and including a type of distortions. Deep neutral networkers contain multiple non linear hidden layers and this makes them expressive models that can learn very complicated relationships between their inputs and outputs with limited training data. However many of these complicated relationships will be the result of sampling noise, so they will exist in the training set but not in real test data even if it is drawn from the same distribution. This leads to over fitting and many methods have been developed for reducing it [4]. A deep neural network is a neural network with a certain level of complexity, a neural with more than two layers. Deep neural networks use revealing mathematical modeling to process data in complex ways. Neural networks are a set of algorithms, modeled loosely after the human brain, that are designed to recognize patterns. Neural networks help us cluster and classify. Neural network is a base for artificial neural network, convolutional neural network and deep neural network. Today neural network is used in lot of areas in games, voice recognizion, finger print and weather forecasting and etc. Artificial Neural Network has been effectively applied to various recognition and classification problems and games. ANNs are classified under the broad umbrella of Artificial Intelligence techniques that attempts to imitate the way a human brain works. Among ANNs, the Back-Propagation Neural Network (BPNN) is commonly used architecture, normally trained by a supervised learning method [25].

The neural networks are based on non-linear activation function approximations which make them appropriate for most of the applications specifically games. The number of tricks to be taken by a one pair of bridge players is called double dummy bridge problem. The bridge game is one of the well-known card games played in the worldwide. The bridge game with randomly dealt cards, which are makes it is also a game of chance. In which, it is more accurately, a tactical game with inherent uncertainty, imperfect information and classified communication [24]. Games, Voice recognizing, finger prints, and Weather forecasting.

II. RELATED WORK

Image Quality Assessment (IQA) algorithms take an arbitrary image as input and output a quality score as output. A whole variety of models for image quality assessment has been proposed and is commonly classified as full reference reduced reference or no reference IQMS, depending on how much information from the reference image is available to IQA algorithm. No reference image quality assessment target at a general solution to the IQA problem it may not be feasible for all applications [7]. Usually this is performed using database of test image for the Mean Opinion Scores (MOS) of image quality has been experimentally collected. The methodology of database creation and experimental tests carrying out directly influences accuracy of quantitative analysis [8]. A field of image processing which deals with recovering original an original image and sharp image from a degraded image with the use of restoration model is known as image restoration. The purpose of image restoration is to recover the original image from the degraded image which is blurred by same degraded function [23].

A. NR-IQA

No Reference (NR) Image Quality Assessment (IQA) algorithm is capable of measuring the quality of distorted images without referencing the original images. This property is of great importance in image processing, compression, and transmission. The goal of an objective No Reference Image Quality Assessment model is as follows given an image i.e., possibly distorted and no other additional information, automatically and accurately predict its perceptual Quality. Given that the ultimate receivers of these images are humans the only reliable way to understand and predict the effect of distortion on a typical person's viewing experience is to capture options**.** In a no-reference method is explained on object detection and training a radial neural network. The method can be summarized in two steps, 1) an object detection algorithm is applied to an image; 2) the spectrum distribution of a detected object is compared with an empirical method to determine a quality score for the detected object. The signal features that are used for object/region detection are chosen to reject overlap with those features that are used for quality assessment.

There were works applying neural networks to qualify assessment [9], [10], where shallow models with only one or hidden layers were used. Recently a few NR-IQA metrics have updated the deep learning technique to support prediction accuracy. Ghadiyaram and Bosvik attempted to capture plentiful NSS features using multiple transforms and then used Deep Belief Network (DBN) to predict the subjective score [11].Hoe et al. adopted a DBN based framework where extracted in the wavelet domain [12]. Although they enhanced the performances of the NR-IQA metrics, these still lie on the second category. Kang *et al.* applied a CNN to the NR-IQA framework by regressing images on the target subjective scores without hand crafted features [13]. The method employed in this work is closest to the fully deep NR-IQA framework. However an equal Mean Opinion Score, which cannot represent pixel wise quality variation over the spatial domain, was used for all patches in images.

B. FR-IQA

In FR IQA the distorted image is compares with the original or an undistorted version of that image in Fig.1. Here the perfect quality reference image is fully available for quality prediction process. Now a day there is lot of IQA metrics available for the image quality evaluation process. In order to evaluate the performance of existing IQA metrics, you need to conduct experiments on the available image databases. Normally, in such a database, there are a lot of reference images and for each image, there exit several distorted images. For each distorted image, there are several subjective evaluations by human beings. Many Full Reference databases that take into specific features of human visual system have been already proposed. To adequateness and performance of these metrics database of color images with certain types and levels of distortions have been used including the databases LIVE, TID 2013 etc. To sufficiently modify and to add types of distortion which are important from technical and practical view points. All these consideration we have decided to introduce 7 new types of distortions to get the total number of distortions types equal to 24 with five levels distortions, there are 120 distorted versions of each reference color image [26].

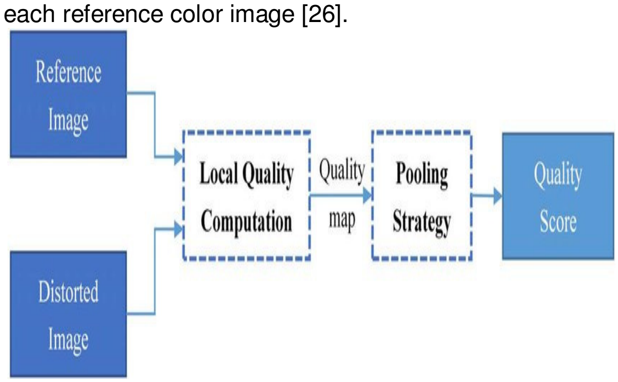

Fig. 1. Flow chart of Full reference image quality assessment.

III. DATA SETS

Experiments are performed on the LIVE, TID2013 and CISQ image quality databases, the NR IQA approach is also evaluated on the LIVE In the Wild Image Quality Challenge Database.

A. LIVE database

The LIVE database comprises 779 quality annotated images based on 29 source reference images that are subject to 5 different types of distortions at different distortion levels. Distortion types are JP2K compression, JPEG compression, additive white Gaussian noise, Gaussian blur and a simulated fast fading Rayleigh channel. Quality ratings were collected using a single-stimulus methodology; scores from different test sessions were aligned. Resulting DMOS quality ratings lie in the range of (0, 100), where a lower score indicates better Visual image quality. The LIVE in the Wild Image Quality Challenge Database (CLIVE) comprises 1162 images taken under real life conditions with a large variety of objects and scenes captured under varying luminance Conditions using different cameras.
The result of new resources is called LIVE in the Wild Image Quality Challenge database. We have included into our database the images compressed by JPEG or JPEG 2000 and decoded with errors in data transmission channels. We have added into database images for which mean shift and contract change distortion image has been designed [17]. The LIVE database contains 5 different distortion categories including JPEG 2000, JPEG, additive white Gaussian noise, Gaussian blur and bit errors due to transmission of JPEG 2000 images over a fast fading channel [18]. There are a number of tested images available in image quality assessment algorithm using the LIVE database which includes 344 JPEG and JPEG 2000 compressed image. The range of bit rate from 0.028 to 3.150 bits/ pixel which allows the test image to cover a wide quality range from in distinguishable from original image to highly distorted [5]. Image Quality Assessment databases are the evaluation of the performance of an IQM is conducted on the LIVE database. The reliability of the LIVE database is widely recognized in the image quality community. Per image the database also gives a Difference in Mean Opinion Score (DMOS) derived from an extensive subjective quality assessment study [6].

B. CISQ database

The CISQ image quality database contains 866 quality annotated images. 30 reference images are distorted by JPEG compression, JP2K compression, Gaussian blur, Gaussian white noise, Gaussian pink noise or contrast change. For quality assessment, subjects were asked to position distorted images horizontally on a monitor according to its visual quality. After alignment and normalization resulting DMOS values span the range (0, 1), where a lower value indicates better visual quality. In novel approach to learn and prediction of image quality on local region. The experimental model result with no reference Image quality Assessment method and full reference image quality assessment method.

C. TID 2013 database

The TID2013 image quality database is an extension of the earlier published TID2008 image quality database containing 3000 quality annotated images based on 25 source reference images distorted by 24 different distortion types at 5 distortion levels each. The distortion types cover a wide range from simple Gaussian noise or blur over compression distortions such as JPEG to more exotic distortion types such as non-eccentricity pattern noise. This makes the TID2013 a more challenging database for the evaluation of IQMs. The rating procedure differs from the one used for the construction of LIVE, as it employed a competition-like double stimulus procedure. The obtained mean opinion score (MOS) values lie in the range (0, 9), where larger MOS indicate better visual quality [19].
At the moment TID 2008 is the largest database of distorted images intended for verification of full reference quality metrics architecture.
Estimates marked by * in Table1, are obtained as the result of experiments described.

Table 1. Comparison characteristics of LIVE database and TID 2008 database.

S. No	Main characteristics	Test image database	
		LIVE Database	TID 2008
1	Number of distorted images	779	1700
2	Number of different types of distortions	5	17
3	Number of experiments carried out	161	Totally 838
4	Methodology of visual quality evaluation	Evaluation using five level scale	Pair-wise sorting
5	Number of elementary evaluation of image visual quality in experiments	25000	256428
6	Scale of obtained estimates of MOS	0..100	0.9
7	Variance of estimates of MOS	250*	0.63
8	Normalized variance of estimates of MOS	0.083*	0.031

For evaluation, the networks are trained either on LIVE or TID 2013 database in Table 2.

Table 2. Types of distortion used in database.

S. No	Type of distortion (four levels of each distortion)	Corresponde-nce to practical situation	Accounted HVS peculiarities
1	Additive Gaussian noise	Image acquisition	Adaptivity, robustness
2	Additive Gaussian noise in color components is more intensive than additive noise in the luminance component	Image acquisition	Color sensitivity
3	Spatially correlated noise	Digital photography	Spatial frequency sensitivity
4	Masked noise	Image compression, watermarking	Local contrast sensitivity
5	High frequency	Image	Spatial

	noise	compression, watermarking	frequency sensitivity
6	Impulse noise	Image acquisition	Robustness
7	Quantization noise	Image registration, gamma correction	Color, local contrast, spatial frequency
8	Gaussian blur	Image registration	Spatial frequency sensitivity
9	Image denoising	Image denoising	Spatial frequency, local contrast
10	JPEG compression	JPEG compression	Color, spatial frequency sensitivity
11	JPEG 2000 compression	JPEG 2000 compression	Spatial frequency sensitivity
12	JPEG transmission errors	Data transmission	Eccentricity
13	JPEG 2000 transmission errors	Data transmission	Eccentricity
14	Non Eccentricity pattern noise	Image compression, watermarking	Eccentricity
15	Local block wise distortions of different intensity	In painting, Image acquisition	Evenness of distortions
16	Mean shift	Image acquisition	Light level sensitivity
17	Contrast change	Image acquisition, gamma correction	Light level, local contrast frequency

IV. CONVOLUTIONAL NEURAL NETWORK FOR IMAGE QUALITY ASSESSMENT

A convolution is the simple application of a filter to an input that results in activation. Repeated application of the same filter to an input result in a map of activations called a feature map, indicating the locations and strength of a detected feature in an input, such as an image. The innovation of convolutional neural networks is the ability to automatically learn a large number of filters in parallel specific to a training dataset under the constraints of a specific predictive modeling problem, such as image classification. The result is highly specific features that can be detected anywhere on input images. Convolutional neural networks are neural networks used primarily to classify images, cluster images by similarity, and perform object recognition within scenes. For example, convolutional neural networks are used to identify faces, individuals, street signs, tumors, platypuses and other aspects of visual data. The convolutional layers serve as feature extractors, and thus they learn the feature representations of their input images. The neurons in the convolutional layers are arranged into feature maps. Each neuron in a feature map has a receptive field, which is connected to a neighborhood of neurons in the previous layer via a set of trainable weights, sometimes referred to as a filter bank. Artificial Neural Network consists of several dispensation units which are interconnected according to some topology to accomplish a pattern classification task or data classification through learning process [27]. Inputs are convolved with the learned weights in order to compute a new feature map, and the convolved results are sent through a nonlinear activation function.

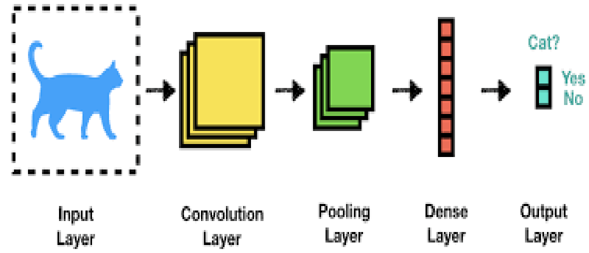

Fig. 2. Deep Convolutional Neural Network.

Deep CNNs have dominated image classification because they are able to automatically learn high-level feature representations in Fig.2. It seems counter-intuitive to extract high-level features for IQA and so far NR IQA systems have used low-level features or relatively shallow neural networks. Nevertheless, we show that extracting high-level features through deep neural networks can lead to superior performance in NR IQA.A deep Convolutional Neural Network to the issue of NR IQA and the some related task of blind QP estimation. For the NR IQA task, the proposed CNN achieved the best LCC among all evaluated NR and FR IQA methods. This encourages continuing working on a good understanding of the features driving the perception of image quality [14]. This result is opposite as IQA is commonly believed to rely, in contrast to image classification tasks on rather low level features. In future studies should further address local distortion sensitivity in order to take it into account for the IQA problem. As CNNs achieve high performance for FR IQA [15]. The CNN approach offers an excellent framework to explore the domain of reduced reference IQA [16], living between NR and FR IQA.

A. System Architecture

The boxed branch of the network indicates an optional regression of the feature vector to a patch wise weight estimate that allows for pooling by weighted average patch aggregation show in Fig. 3 [22].

B. Neural Network Based FR- IQA

Siamese networks have been used to learn similarity relations between two inputs. For this, the inputs are processed in parallel by two networks sharing their synaptic connection weights. This approach has been used for signature and face verification tasks, where the inputs are binarily classified as being of the same category or not. For FR IQA we employ a Siamese network for feature extraction. In order to use the extracted features for the regression problem of IQA, feature extraction is followed by a feature fusion step. The fused features are input to the regression part of the network.

Features are extracted from the distorted patch and the reference patch by a CNN and fused as difference, concatenation or concatenation supplementary with the difference vector. The fused feature vector is regressed to a patch wise quality estimate.

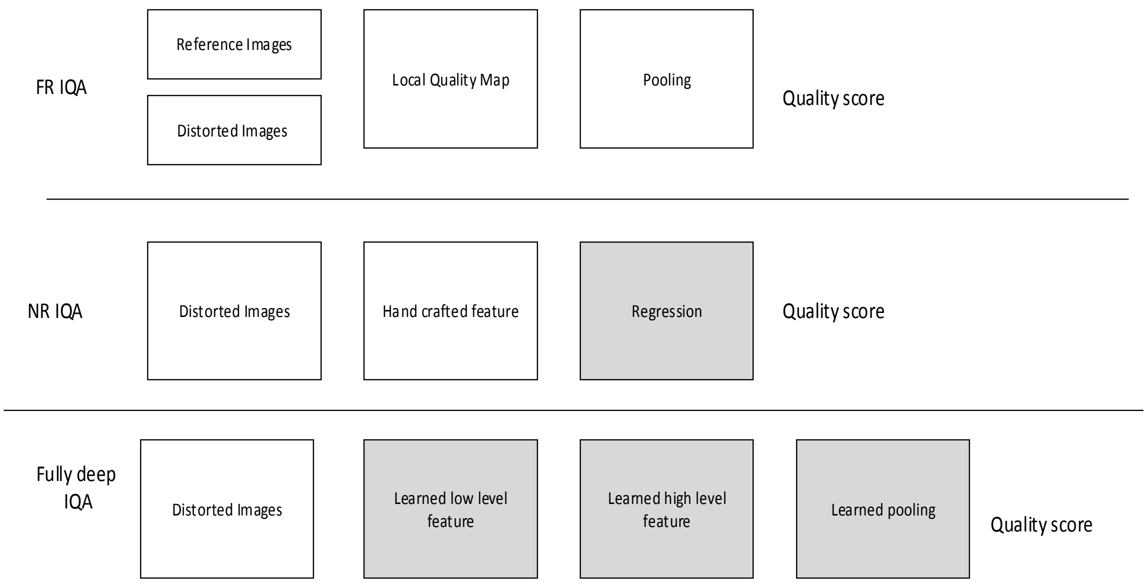

Fig. 3. Flow chart comparison of FR IQA, NR IQA, and fully deep NR-IQA .Grey boxes indicate learned processes.

C. Neural Network Based NR- IQA

Removing the branch that extracts features from the reference patch. It is a straight forward approach to use the deep network in a NR IQA context. As no features from the reference patch are available anymore, no feature pooling is necessary. The approaches are referred to as Deep Image Quality Measure for NR IQA and Weighted Average. This amounts to the same loss functions as for the FR IQA case. Features are extracted from the distorted patch by a CNN. The feature vector is regressed to a patch wise quality estimate. Patch wise estimates are aggregated to a global image quality estimate. The boxed branch of the network indicates an optional regression of the feature vector to a patch wise weight estimate that allows for pooling by weighted average patch aggregation [1].

V. CONCLUSION AND FUTURE WORK

In this paper we use a deep learning based on no reference and full reference image quality assessment method for convolutional neural network. We have studied the problem of the RR image QA by measuring the changes in suitably weighted entropies between the reference and distorted images in the wavelet domain. The algorithms differ in the nature of the distortion measurement and the quantity of the information required from the reference to compute quality for future work, it is important to explore the IQA algorithm in deep neural network in CNN. We plan to regularly update the versions of this database. In particular, updated versions will provide more reliable data due to taking into account the results of future experiments.

IQA algorithm combines feature learning and regression as a fully complete process which enable to modern training technique to energetic performance [20]. Moreover, new versions will include new types of distortion that take place in different applications of image processing and those distortions that might correspond to new peculiarities of HVS found in future experiments. The overall performance of the single-number algorithms may be further improved by better aligning the scores obtained for different distortion categories. Even though a relative generic neural network is able to achieve high prediction performance. Incorporating IQA specific adaptations to the architecture may lead to further improvements.

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