A NOVEL FREE REFERENCE IMAGE QUALITY METRIC USING NEURAL NETWORK APPROACH

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ABSTRACT

A No Reference (NR) image quality index based on fusion of three NR metrics by neural networks is proposed. The idea is to combine different NR metrics in order to estimate various distortions. We believe that there is no NR metric able to objectively estimate all the known distortions. Therefore, the idea of combining some distortion measures in order to evaluate image quality is of great benefit. Here, the fusion is done using a neural network approach. The performance of the proposed method is evaluated subjectively using some known image databases.

Index Terms— Artificial, Image Quality, Fusion, Neural Networks, Subjective test.

1. INTRODUCTION

The development of image acquisition and projection technologies generates an increasing demand in terms of Image Quality Assessment (IQA) and control. Furthermore, the increase of image resolution requires efficient compression methods. The standards such as JPEG2000 offers a good performance as compared to JPEG but some structural artifacts such as ringing effect still remain unsolved, especially at low bit rate, limiting thus the efficiency of the compression efficiency. Many posttreatment methods have been developed to cope with compression artifacts. However, there is no satisfying solution for controlling such distortions. One of the reasons is the absence of a well accepted image quality measure dedicated to all these compression artifacts. Many studies have been done for developing a universal image quality measure [1]. To evaluate the performance of a given objective IQA metric, the only accepted strategy is to use subjective image database in order to analysis the correlation of the measure with the MOS. Despite the great interest into IQA and the great number of published papers, at present time there is no universal or accepted IQA metric able to account for all the known distortions. Very often, the correlation of the objective measure with the MOS depends on the type of the distortions and the image content. For example, it has been reported in some studies that SSIM is not adapted for measuring blur effect. We believe that the best way to evaluate image quality is first to identify for each distortion the most appropriate, in terms of correlation with MOS, IQA measure and then try to combine all the metrics to construct a global and multi-distortion measure. Here, we adopt this strategy for developing a No Reference (NR) image quality metric. We focus our work on the most common and annoying artifacts which are caused by the compression process that are blocking effect, blurring and ringing effect.

Blocking effect appears in block compression method as horizontal and vertical boundaries in image. It is due to the fact that the blocks are transformed and quantized independently. Some NR metrics have been developed to measure or to remove this artifact. In [2], a blind method for estimating the blocking effect in the frequency domain is proposed. In [3],[4], the blocking artifacts are measured in the DCT domain. In [5], an iterative algorithm is applied for reducing the blocking effect artefact in the wavelet domain. In [6], the blocking effect is removed by taking into account some HVS properties.

Blurring effect affects contours and details in image. It is due to the nature of the compression process. Indeed, details and contours in image correspond to the high frequencies in image and generally, the compression process affects firstly the high frequencies. This artifact is also widely studied. In [7] a no reference blur estimation method based on edge detection is proposed. A reduced reference method is also proposed in [8] where the edge estimation method is applied to the original image. In [9] a blur estimation method based on a combination of the high frequencies in wavelets domain is proposed. In [10], a new recent blur estimation based on some HVS models is also proposed. Another interesting HVS-based no reference blurriness metric using the concept of just noticeable blur has been proposed in [11].
Ringing effect is also one of the most annoying artefacts and appears in image as noise around edges and it is more visible when edges are near homogeneous regions. This artefact is caused by the quantization process. This phenomenon is also called Gibbs phenomenon [12]. In [8], a free reference metric based on an estimation of oscillation around edges in the spatial domain is proposed. In [13], the ringing estimation is performed in the wavelet domain.

In this work we propose a NR image quality metric using a fusion model based on neural network to better take advantage of some efficient NR metrics. This method aims at estimating the most annoying and known distortions namely, ringing, blocking and blurring effect. The basic idea is to use the quantitative measures of these degradations as input to an Artificial Neural Network (ANN). The output of this neural network is a single value corresponding to the image quality level.

Section 2 describes in details the NR metrics used as input to the neural network. Section 3 presents the neural network and the used data in the learning process. The performance evaluation and the results are given in section 4. The last section is devoted to conclusion and perspectives.

2. PROPOSED METHOD

In this study, we propose to use an ANN to measure the quality of the image without reference. The flowchart of the proposed method is illustrated in fig.1. The first step consists in extracting some features from the image. These features are here three NR metrics described below. These NR metrics are used to measure respectively the blocking, blurring and ringing effect. Then, the obtained features are used as input to the ANN.

2.1. Inputs values

In this section, we describe briefly the NR metrics used as input to the ANN.

2.1.1. Blocking measure

Here, we use the NR proposed by [2]. This method is based on blocking effect visibility analysis on the block’s frontiers. The first step consists to compute the image difference between adjacent rows (the same operation is applied to the horizontal frontiers). Then, we sum all these measures at the boundaries only. Finally, after applying a zero detection to the image difference obtained before, the global index quality is achieved by weighting these values.

2.1.2. Blurring measure

For blurring estimation, we use a recent blurring estimation method proposed in [14]. The proposed method consists to add blur to a test image. Then the impact of this added blur is measured, using a radial analysis performed in the spatial frequency domain as done in [15].

2.1.3. Ringing measure

For ringing effect estimation we use the method described in [13]. This method is based on wavelet transform and Natural Scene Statistics (NSS). From the wavelet transform coefficient a statistical model is derived and used in the computation of the quality index after a training process.

2.2. Artificial neural networks

Once the features extracted, we combine these features by an ANN to obtain an Index quality. The NN used here, is a Multi Layer Perceptron (MLP) presented in figure 2. The subjective and objective scores are first scaled to the range [-1, +1] where subjective scores equal -1 denotes the best quality and +1 denotes the worst quality. This is due to the activation function range. The number of input neurons is equal to the number of the features, here 3. In the output layer, there is only one neuron. For the hidden layer, to not increase the complexity, we fix the number of hidden layers to one. The sigmoid function is used as activation function.

Figure 1. Flowchart of the proposed method.

Figure 2. Artificial neural networks model.
in the hidden and output layers. Note that these sigmoid functions are used in the Visual Quality Experts Group (VQEG) [16] to describe the relation between objective scores and subjective scores.

3. LEARNING AND TESTING

In order to train our ANN and test the efficiency of the obtained model, we used the LIVE database [17] as image database. This database provides the Difference Mean Opinion Scores (DMOS) and it is described by the authors as follows: ‘Observers were asked to provide their perception of quality on a continuous linear scale that was divided into five equal regions marked with adjectives “Bad”, “Poor”, “Fair”, “Good” and “Excellent”. About 20-29 human observers rated each image. Each distortion type was evaluated by different subjects in different experiments using the same equipment and viewing conditions”. Note that a zero DMOS value corresponds to a high image quality, whereas high DMOS value reflects a poor image quality. The database used contains different types of degradations. Here, the performance of our method is tested using only the Gaussian blur images. Some original images are presented in figure 3.

Figure 3. Some original images of the LIVE database.

Once the database chosen, we first divide it in both:

- Training set: used only in the learning process and containing around 100 images per degradation.
- Test set: used only to test the efficiency of the proposed method. This set contains around 50 images per degradation.

The learning phase is done using the back propagation method. The best results are obtained with 19 neurons in the hidden layer. Finally, the structure of the ANN-MLP is as follows:

- Input: 3 (NR metrics)
- Hidden Layer: 1 with 19 neurons
- Output: 1 (Target DMOS scaled to the range [-1, +1])

4. EXPERIMENTAL RESULTS

After the learning process, we test the efficiency of the proposed method using the test set. The obtained correlations for each NR are show in table 1 below.

<table>
<thead>
<tr>
<th>NR metrics</th>
<th>Pearson correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blocking</td>
<td>0.8160</td>
</tr>
<tr>
<td>Blurring</td>
<td>0.8673</td>
</tr>
<tr>
<td>Ringing</td>
<td>0.9108</td>
</tr>
</tbody>
</table>

Table 1. Obtained correlation for each NR metric.

Table 2 and 3 show the correlation obtained by the proposed method for each distortion and all distortions, respectively.

<table>
<thead>
<tr>
<th>Degradation</th>
<th>Pearson correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blocking effect measure</td>
<td>0.9570</td>
</tr>
<tr>
<td>Blurring effect measure</td>
<td>0.8462</td>
</tr>
<tr>
<td>Ringing effect measure</td>
<td>0.9289</td>
</tr>
</tbody>
</table>

Table 2. Obtained correlation per degradation with the proposed method.

We note that the correlation with the MOS increases for all degradations excepted for blurring for which it slightly decreases.

The Pearson and Spearman correlation obtained for the three degradations is respectively equal to 0.89 and 0.86.

<table>
<thead>
<tr>
<th>Correlation type</th>
<th>Obtained value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson</td>
<td>0.89964</td>
</tr>
<tr>
<td>Spearman</td>
<td>0.86214</td>
</tr>
</tbody>
</table>

Table 3. Obtained correlation for all degradation with the proposed method.
To better visualize the obtained results, we show in figure 4 the scaled DMOS and ANN-output for each test image. It could be observed that the shape of the two curves is nearly the same.

5. CONCLUSION AND PERSPECTIVES

A new free reference image quality index is proposed. This method is based on some structural distortion NR measures. The combination of these NR image quality metrics through a neural network provides good results in terms of correlation with subjective evaluation as expressed in the image quality database.

The following issue is how to combine other NR image quality metrics in order to offer a global blind image quality measure.

![Figure 4. DMOS and Output for each test image.](image)

6. REFERENCES


