Performance of Levenberg-Marquardt Backpropagation for Full Reference Hybrid Image Quality Metrics

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***Abstract*—Image quality analysis is to study the quality of images and develop methods to efficiently and swiftly determine the quality of images. It is an important process especially in this digital age whereby transmission, compression and conversion are compulsory. Therefore, this paper proposed a hybrid method to determine the image quality by using Levenberg-Marquardt Back-Propagation Neural Network (LMBNN). Three known quality metrics were combined as the input element to the network. A proper set of network properties was chosen to represent this element and was trained using Levenberg-Marquardt algorithm (*trainlm*) in MATLAB. From the preliminary simulation, a promising output result was obtained indicated by good performance metrics results and good regression fitting.**

***Index Terms*—**Image Quality Metrics, Levenberg-Marquardt, Neural Network, hybrid

I. INTRODUCTION

Image quality analysis is the science of analyzing and comparing the characteristics and features of an image with reference to the original image of predetermined/preset standards. Image quality analysis measures should be employed to determine the usability of images after they have undergone any kind of manipulation, for example, compression, transmission or conversion. Therefore, studying the various approaches to image quality analysis will provide information on method of image quality assessment that can be efficiently employed under any circumstances.

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Method of image quality assessment can be classified into subjective and objective methods. The subjective method requires the use of human discretion to decide the level of the image's quality [1-2]. This method is subject to bias in the form of the tester's taste and preferences. However, the result of the subjective analysis is very often a trusted method as it is only natural for people to judge with their own eyes. The demerit of subjective assessment is that it is time and labour consuming. The objective method is unbiased and automated therefore it provides a result that is faithful to all assigned parameters [1-2]. The demerit of objective assessment is that it may not be reliable.

Most of digital image analysis processes trying to simulate the human visual cortex as the human eye remains a very superior judge of image quality. For example, if the computer saying the image is of a good quality but a human saying it is of a bad quality, the image will most likely be scrapped. Therefore, the computer's reliability and accuracy will be considered low if there is a poor correlation between its results and the human eye's judgment.

Depending on the existence of reference images, there are three categories of objective image quality metrics (IQMs); full-reference (FR), reduced reference (RR) and non reference (NR) [3-5]. These IQMs are developed based on color appearance, blur assessment, wavelet, pixels comparison, hue saturation and many others. Among the available image quality metrics, the widely known metrics are Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE) and Structural Similarity (SSIM) [6-7].

The objective of this paper is to investigate the potential of combining multiple metrics with artificial neural network (ANN) in order to achieve image quality score that similar to human visual measure. Another objective is to evaluate the performance of LMBP as a hybrid IQM. To achieve these objectives, a number of objective assessments was conducted and compared to a corresponding subjective assessment. Afterward, this measurement data were combined and used as the input vectors to Levenberg-Marquardt Back-propagation network.

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The paper aims to combine PSNR, MSE and SSIM metrics with the assumption each of the metrics could overcome each other weaknesses. Each of this metrics has its own weakness in term of detecting certain types of image degradation. Other limitations of the existing metrics are consistency, accuracy and computational cost. By combining these metrics values, and trained using LMBP ANN, it is hopefully will become a new image quality metrics which is more intelligent and accurate.

II. METHODOLOGY

Four assessments were modeled consist of three objectives and one subjective assessments. A subjective assessment was conducted using a sample set of 34 images and 80 participants. The sample set consists of a reference image and 33 digitally altered images using four categories of operations namely, morphological operations, noise-adding, format conversion and filtered images. The results of this subjective assessment were tabulated as Mean Opinion Score (MOS) values ranging from 1 to 5, with 5 being the highest quality. These values will be further used as the target for the network.

Three objective assessments were conducted with the aim of determining the Mean Squared Error (MSE), the Peak Signal-to-Noise Ratio (PSNR), and the Structural Similarity (SSIM) between the reference image and the sample images. The results of all four image quality assessments were then tabulated and analyzed to determine correlation characteristics using *Regression, R* correlation between each objective and subjective assessment.

The measured data of PSNR, MSE and SSIM were used as input of the network and MOS as target for the network. Experimental was setup using MATLAB Neural Network Toolbox. This network was trained with Levenberg-Marquardt backpropagation algorithm (*trainlm*). This network was chosen due to its good characteristic for solving fitting problems. The neural network must map well between a data set of numeric inputs and a set of numeric targets.

The network used is a two-layer feed-forward network as illustrated in Fig. 1. The two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (newfit), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. After a few experimental run, the number of neurons in the hidden layers was set to 20.

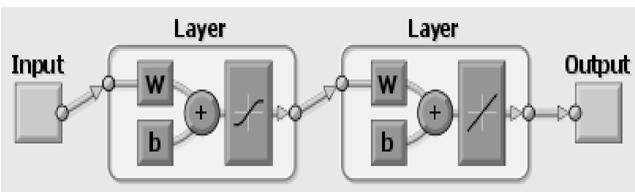

Fig.1 Two-layer feed-forward network

A. Levenberg-Marquardt BP

The application of Levenberg-Marquardt to neural network training is described in [8-9]. This algorithm has been shown to be the fastest method for training moderate-sized feed-forward neural networks (up to several hundred weights). It also has an efficient implementation in MATLAB software, since the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment [10].

The network *trainlm* can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate the Jacobian jX of performance with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt equation,

$$jj = jX * jX$$
$$je = jX * E$$
$$dX = -(jj+I*mu) \backslash je \tag{1}$$

where E is all errors and I is the identity matrix. The adaptive value mu is increased until the change results in a reduced performance value [10].

III. RESULTS AND DISCUSSIONS

For the purpose of analysis, the regression of existing IQMs with MOS will be discussed. Detailed correlation of these IQMs based on categories of degradation is also shown. Results of training and testing using hybrid metric using LMBP is also presented.

A. Existing IQMs (PSNR, MSE and SSIM)

Results of objective measurements for PSNR, SSIM and MSE are shown in Table I and Table II respectively. Table I shows the correlation of objective measure with subjective measure as overall while Table II shows the correlation between the three objective measurements and MOS for specific categories. From these results, the three metrics did show good correlation with MOS when measured based on categories. However, the correlation dropped when an overall score was considered.

TABLE I
CORRELATION COEFFICIENT

Metrics	SSIM	PSNR	MSE
Regression, R	0.5180	0.5007	0.5735

TABLE II
CORRELATION COEFFICIENT BASED ON CATEGORIES

Objective Assessment/ Category of Images	SSIM	PSNR	MSE
Morphologically Altered	0.7144	-0.1360	0.7326
Noise-Added	0.9121	-0.8290	0.3851
Format Converted	0.0000	0.9000	-0.9449
Filtered	0.6844	-0.0459	0.7901

Table II indicates that the SSIM algorithm achieved a satisfactory degree of correlation to the subjective assessment for every category except the format converted images. The MSE algorithm had satisfactory correlations

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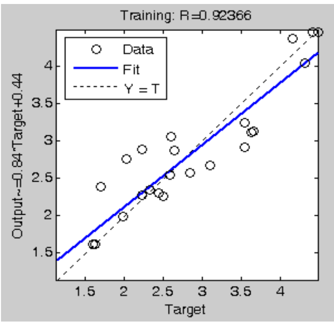
for 2 out of 4 of the categories and the PSNR performed the worst with negative correlations for 3 out of 4 categories. The results revealed that even though objective assessment could not achieved a satisfactory level of correlation to the subjective assessment in overall, each of the assessments did performed well in analyzing the image quality for certain categories.

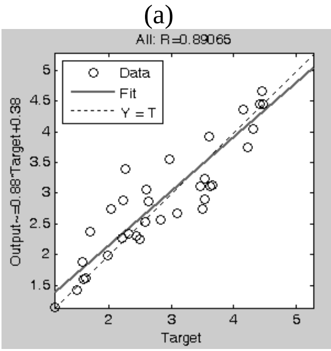
The following results show that by combining the three unique metrics, an intelligent hybrid metric was obtained. This is also supported by discussion of Table II that shown each metrics has its own merits over another depending on categories.

B. Network Predictive Ability and General Performance

Mean Squared Error (MSE) is performance metric adopted to determine the network performance, while *regressions, R* is used to measure the correlation between outputs and targets. The fitting curve between targets with inputs is shown in Fig. 2 and the MSE and Regression is tabulated in Table III. MSE is the average squared difference between outputs and targets. Lower values of MSE are better as zero indicate no error while *R* value of 1 indicated closed relationship while 0 is a random relationship.



(a)



(b)

Fig. 2 The fitting curve between output/target with input (a) training only (b)training and testing

TABLE III
THE MSE and REGRESSION OF THE NETWORK

Model	Training Set	Test Set	Whole Set
MSE	0.2435	0.3995	0.2634
Regression, R	0.9236	0.854	0.8907

From the results in Table III and Fig. 2, it is proven that Levenberg-Marquardt backpropagation algorithm has good ability to predict the MOS with high regression correlation for both training and testing. The training error is 0.244 and testing error is 0.399, indicative of about 70% accuracy. Comparing the new hybrid LMBP metric with the objective scores, Table IV shows the correlation of PSNR, SSIM, MSE and new hybrid LMBP metric with MOS in percentage (data is extracted from Table I and Table III).

TABLE IV
COMPARISON OF REGRESSION (%) FOR THE FOUR IQMs

Metrics	Regression, R
SSIM	51.8%
PSNR	50.1%
MSE	57.4%
LMBP	89.1%

It is shown that correlation with MOS is below 60% for the existing metrics but the new LMBP metric is more than 80% correlated with MOS. Performance of the new metric shown a promising result. Further investigation with larger sample and proper selection of network properties will definitely improve predictive ability and general performance of ANN.

IV. CONCLUSIONS

From the study, new method for constructing image quality metrics has been proposed. This paper is an attempt to investigate the potential of combining existing metrics with ANN to predict the quality of images. It was proven that Levenberg-Marquardt backpropagation algorithm has good ability to predict the MOS with high correlation for training and testing with training error and testing error of 0.244 and 0.399 respectively. The *regression, R* showed that it is highly correlated with mean opinion score (MOS) compared to individual metrics (PSNR, MSE or SSIM).

In future work, more distortion measures and feature domains will be used as the image samples. Also, the relationship between the metrics adopted for the combination will be further investigated to find the best combination among them. More experiments are needed to validate properties of the network such as it optimum number of neurons in hidden layers, validation etc. Performance comparison of LMBP with other networks should also be discussed.

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