Image Quality Assessment using ANFIS Approach

El-Sayed M. El-Alfy and Mohammed R. Riaz
College of Computer Scineces and Engineering, King Fahd University of Petroleum and Minerals, Dharan 31261, Saudi Arabia

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Abstract: Due to the increasing use of digital images in electronic systems, it becomes important to evaluate the degradation in image quality during acquisition, processing, storage and transmission. In this paper, we investigate the ability of the adaptive neuro-fuzzy inference system (ANFIS) for quality assessment of digital images with respect to original (reference) images. Several metrics for objective quality assessment are calculated and used as inputs to an adaptive fuzzy inference system which in turn estimates a differential mean opinion score (DMOS) for different types of distortions. The predicted values are compared with the actual DMOS values using correlation and error measures. With 7-input ANFIS network, the results show that predicted DMOS values are highly correlated to the actual values using a publicly available and subjectively rated image database. For example, for distorted images due to JPEG 2000 compression, the attained results for correlation coefficient, Spearman's ranked correlation, and RMSE are 0.9944, 0.9902, and 3.32, respectively. These results show that combining the advantages of neural networks with fuzzy systems can be a promising approach for predicting the subjective quality of digital images.

1 INTRODUCTION

Digital images are gaining great importance in the domain of electronic technology in recent years. However, images can be corrupted due to various reasons during acquisition, processing, storage and transmission. With the increasing use of digital imaging systems such as digital cameras, high definition cameras, monitors and printers, Image Quality Assessment (IQA) has attracted great attention in image processing applications (Kudelka Jr., 2012). Moreover, a variety of image processing techniques can benefit from image quality assessment for adaptive parameter tuning and prediction of required resources.

Image quality assessment methods can be classified into two main categories: subjective and objective. The subjective assessment is conducted through the human visual perception. Subjective quality assessment is the optimal solution when human beings are the ultimate recipients of the image processing applications (Yi et al., 2008). To reduce subjectivity, a group of human evaluators are asked to visually judge the quality of a target image as it relates to its original (reference) image. Then, a Mean Opinion Score (MOS) is assigned to the target image. This score can be scaled to range from 0 (very low quality) to 1 (very high quality). It can also be expressed as differential MOS (DMOS) which represents the difference between the scores assigned to the reference and target images, respectively. If we assume the reference image has perfect quality, i.e. its MOS will be 1, then the range for DMOS assigned to the target image will be from 0 (very high quality) to 1 (very low quality). Notice that it is the opposite of MOS.

The automation of subjective quality assessment is difficult as it depends on modelling the human visual perception. In contrast, objective quality assessment uses numeric measures to quantify the degree of quality degradation. Hence, it can be automated to replace the way a human assesses the quality of an image. The majority of objective quality assessment methods are based on pixel difference metrics due to their low computational complexity (Bouzerdoum et al., 2004). However, these methods can suffer from some limitations in dealing with the wide spectrum of image distortion types. Hence, a number of other quality metrics have been proposed in the literature for various situations by different researchers (He et al., 2013).

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Whether subjective or objective, image quality assessment techniques can be classified as no-reference, full-reference or reduced-reference. This classification depends on the availability of information from the original image besides the target or query image. In a no-reference technique, the assessor has only access to the query image; hence it is also termed as blind assessment, e.g. (De and Sil, 2009; Li et al., 2011). But when the original image is also available, it is termed as full-reference; e.g. (Larson and Chandler, 2010). In some applications, only partial information about the original image can be available besides the query image and hence it is termed reduced-reference (Rehman and Wang, 2012).

This paper therefore explores the ability of adaptive neuro-fuzzy inference system (ANFIS) approach in predicting the subjective quality of images. This is implemented through estimating a combined score using a set of image quality metrics. The predicted value is compared to the actual differential mean opinion score (DMOS). We consider five types of distortion at different levels including JPEG compression, JPEG 2000 compression, additive pink Gaussian noise (APGN), additive white Gaussian noise (AWGN) and Gaussian blurring. The performance is evaluated and compared in terms of Pearson's correlation coefficient, Spearman's rank order correlation coefficient, mean absolute error (MAE), and root mean square error (RMSE).

The rest of the paper is structured as follows. Section 2 gives a brief background of the main ANFIS characteristics and how it can be used for function approximation and prediction. The related work is reviewed in Section 3. Section 4 provides more details on image quality assessment and defines the quality metrics that are used in this work. Section 5 describes the dataset and discusses the experimental work. Finally, Section 6 concludes the paper and highlights future work.

2 BACKGROUND

In the case of fuzzy logic based systems, the mapping of prior human knowledge or experience into the inference process using linguistic variables is an advantage but a cumbersome task. No standard procedure is found to provide an efficient way of this transformation. Usually, a trial and error approach determines the type, size and settings of the input and output membership functions (MFs). Effective tuning methods for the input and output membership functions and the reduction of the rule base to the least necessary rules have always been on the list of issues to be explored.

Adaptive neuro-fuzzy inference system or ANFIS is emerged to mitigate the above mentioned issues by providing a learning capability to the fuzzy system through its integration with a neural network (Jang, 1993). Thus, ANFIS combines the advantages of both the fuzzy inference system and the neural network. ANFIS has been widely used to solve several problems in different domains (Balamurugan and Rajesh, 2007; Khuntia and Panda, 2011; Meharrar et al., 2011; Meena et al., 2012).

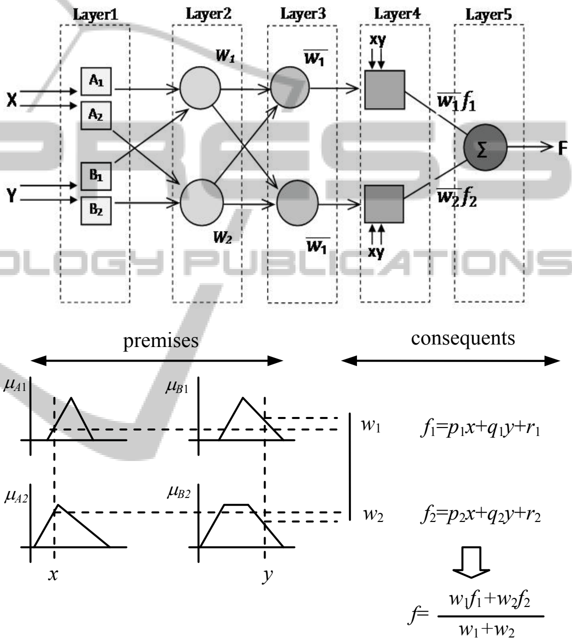


Figure 1: A typical example of an ANFIS architecture and reasoning.

The ANFIS system works in two distinct phases. The first phase is a neural-network phase, where a system classifies data and finds patterns. The other phase develops a fuzzy expert system through adaptive tuning of membership functions (Khuntia and Panda, 2011). Figure 1 shows a typical example of a Sugeno-type ANFIS system, with two rules, two inputs X and Y, and one output F. Each input variable is assumed to have two terms (e.g. small and large). This system consists of five layers; where the output from each node in every layer is represented by O_i^l. Here, l denotes the layer number while the symbol i denotes the neuron number within the layer. The purpose of the first layer is to fuzzify the crisp input values using a set of linguistic terms (e.g., small, medium, and large). Membership functions of these linguistic terms determine the output of this layer as given by:

$$O^1_{A_i} = \mu_{A_i}(x), O^1_{B_i} = \mu_{B_i}(y) \quad (1)$$

where $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ represent the membership functions that establish the degree to which the given input values x and y satisfy the quantifiers A_i and B_i. A variety of membership functions exists such as bell-shaped, trapezoidal, triangular, Gaussian, and sigmoidal.

The firing strength for each rule quantifies the extent that any input data belongs to that rule, and is computed in the second layer as the multiplication of all the incoming signals at each node as follows:

$$O^2_i = w_i = \mu_{A_i}(x) * \mu_{B_i}(x) \quad (2)$$

The nodes in the third layer perform normalization operation by calculating the ratio of the i-th rule's firing strength to the sum of all rule's firing strengths as follows:

$$O^3_i = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad (3)$$

In Sugeno-type ANFIS system, the consequent part of each rule is expressed as a linear combination of the inputs. The fourth layer has square-shaped nodes with node functions given as:

$$O^4_i = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (4)$$

Finally, the last layer node conducts summation of all incoming signals to generate the output as weighted sum:

$$O^5_1 = \overline{w}_1 f_1 + \overline{w}_2 f_2 = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i} \quad (5)$$

The objective of a learning algorithm is to update the consequent and premise parameters in order to achieve the least error between the predicted and the desired target output. A hybrid training algorithm is normally applied to tune the parameters of an ANFIS network. Such a learning technique is composed of least square estimates and a gradient descend (back-propagation) algorithm. The first stage updates the consequent parameters through least-square estimates by passing of function signals forward until layer 4. In the second stage, the error rates are propagated backward which help in updating the premise parameters by a gradient descent algorithm.

3 RELATED WORK

In (Bouzerdoum et al., 2004), the authors proposed a neural network approach for the assessment of image quality. The neural network measured the quality of an image by predicting the mean opinion score (MOS) with the help of six key features extracted from both the reference and target images. These features are the two means, two standard deviations, covariance and mean-square error. The experimental work was carried out using 352 images compressed by JPEG/JPEG2000. The resulting correlation is about 0.9744 between the predicted and actual MOS values. Similar work has been conducted in (Kaya et al., 2011) where a neural network approach is used to predict the subjective image quality score DMOS using statisitical features extracted from both the reference and target images. In 2011, Li et al. developed a no-reference image quality assessment using regression neural networks to approximate the functional relationship between a range of distortion types and the human subjective judgment.

In (Yi et al., 2008), the authors developed an image quality assessment method based on structural distortion and image definition. They carried out their experiments on 'Lena' and 'Barbara' original and distorted images. In their work, it was shown that the proposed method is more consistent with human perception. In (Kung et al., 2010), the authors used characteristics of structural similarity index and artificial neural network for image quality assessment. The experimental results showed that their proposed approach can achieve adaptability for image quality of different types. In (Lin and Kuo, 2011), the authors conducted a survey on perceptual visual quality metrics, in which they compared the commonly used 6 image metrics using seven public image databases. In (Wee, 2010), a new full-reference quality assessment metric is proposed to automate the quality assessment of an image in the discrete orthogonal moment domain. The metric was constructed by using the spatial information of an image using low-order moments.

When concerned with the use of ANFIS approach in recent literature, in (Balamurugan and Rajesh, 2007) the authors worked on classifying greenery and non-greenery image classification using ANFIS technique. They used a hybrid set of parameters which involved texture and color coherence vector (CCV). More recently in (Meena et al., 2012), ANFIS was used for classification and detection purposes for the brain Magnetic Resonance (MR) images and tumor detection. The decision making was performed in two stages. The first stage involved using feature extraction using principal component analysis (PCA) and in the second stage, ANFIS was trained. The authors mentioned that ANFIS, as a fuzzy logic based paradigm, grasps the learning abilities of neural network to improve the performance of the intelligent system using a priori knowledge. The authors demonstrated that ANFIS can be a promising approach for image classification in the field of medical sciences.

In (De and Sil, 2009), ANFIS is used to assess quality of distorted/decompressed images without reference to the original image using three statistical features as inputs expressed as linguistic variables, namely area, extent and eccentricity.

4 IMAGE QUALITY ASSESSMENT

In this paper, we have developed a full-reference quality assessment. The outline of the proposed predictive model is shown in Figure 2. As a full-reference method, the quality of a query image is compared with a reference image of perfect quality. Image quality is determined through various image quality metrics computed based on features extracted from the reference and target images. These features are based on existing studies (Lin and Kuo, 2011; Chetouani et al., 2010).

Here, we considered seven significant full-reference quality metrics as follows:

- Peak signal to noise ratio (PSNR)
- Universal quality index (UQI)
- Mean Structural similarity index (MSSIM)
- Weighted Signal to Noise Ratio (WSNR)
- Visual Information Fidelity (VIF)
- Noise Quality Measure (NQM)
- Information Fidelity Criterion(IFC)

These quality assessment measures are discussed briefly in the following subsections.

4.1 Peak Signal-to-Noise Ratio (PSNR)

The traditional and most widely used objective image quality assessment metric for many years is the peak signal to noise ratio (PSNR). PSNR is a pixel-based method, which means that the distorted image and reference image are compared pixel by pixel. The PSNR metric is a good measure for its simplicity and power to assess white noise distortion. However, a disadvantage of using it is that it is inconsistent to human's subjective perception (Wang and Bovik, 2009). Moreover, it may not capture the wide spectrum of distortion

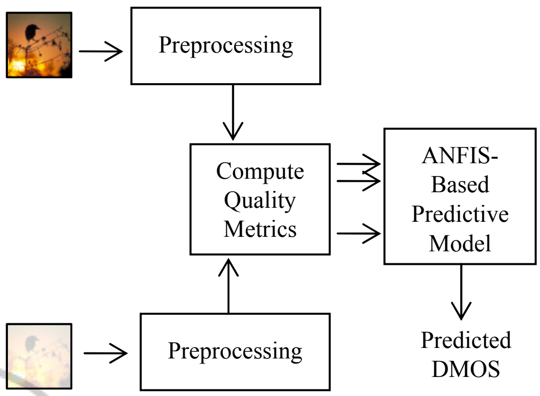


Figure 2: Outline of the proposed ANFIS-based quality assessment system.

types.

The peak signal to noise ratio between a reference image and target image can be computed utilizing the mean square error (MSE). For a reference image A and target image B of size $N \times M$, the mean square error is computed using:

$$MSE = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(a_{ij} - b_{ij}\right)^2 \qquad (6)$$

where a_{ij} and b_{ij} are the gray levels of the pixels at location (i, j) in the original and test images, respectively. If we assumed 8-bit encoding for each pixel, i.e. a maximum gray level of 255, then the PSNR can be determined as follows:

$$PSNR = 10 * log\left(\frac{255^2}{MSE}\right) \qquad (7)$$

4.2 Universal Quality Index (UQI)

Wang et al. (2004) proposed a universal quality index (UQI) between target and reference images by utilizing three different factors. The three factors are luminance, contrast, and structural comparisons. The luminance comparison $l(a, b)$ between a reference image A and a target image B is determined in terms of mean values μ_a and μ_b by the relation:

$$l(a, b) = \frac{2\mu_a\mu_b}{\mu_a^2 + \mu_b^2} \qquad (8)$$

The contrast comparison $c(a, b)$ is performed utilizing the standard deviations for images A and B as:

$$c(a, b) = \frac{2\sigma_a\sigma_b}{\sigma_a^2 + \sigma_b^2} \qquad (9)$$

Utilizing covariance between the images A and B, the structural comparison $s(a,b)$ is given by:

$$s(a,b) = \frac{2\sigma_{ab}}{\sigma_a \sigma_b} \tag{10}$$

Hence, the universal quality index is defined as:

$$UQI(a,b) = l(a,b)c(a,b)s(a,b) = \frac{4\mu_a \mu_b \sigma_{ab}}{(\mu_a^2 + \mu_b^2)(\sigma_a^2 + \sigma_b^2)} \tag{11}$$

The value of UQI lies between [-1, 1]. UQI is an improved metric when compared to the PSNR.

4.3 Mean Structural Similarity Index (MSSIM)

The structural similarity index (SSIM) measures the similarity between two images (Wang et al., 2004). This metric is an improved version of the UQI resulting in improvement in the correlation between the subjective and objective measures. The value of SSIM lies between [0, 1] and is calculated as:

$$SSIM(a,b) = \frac{(2\mu_a \mu_b + C_1)(2\sigma_{ab} + C_2)}{(\mu_a^2 + \mu_b^2 + C_1)(\sigma_a^2 + \sigma_b^2 + C_2)} \tag{12}$$

where $C_1 = (K_1 L)^2$, $C_2 = (K_2 L)^2$, L denotes the dynamic range of pixel values, and K_1 and K_2 are small positive constants. The SSIM index is calculated for the whole image as one block. However, when the features are highly spatially non-stationary, SSIM can be calculated within local windows and the overall image quality is measured by the mean SSIM index as given by:

$$MSSIM = \frac{1}{K} \sum_i \sum_j SSIM(i,j) \tag{13}$$

where K is the total number of local SSIM indices.

4.4 Weighted Signal-to-Noise Ratio (WSNR)

In (Damera-Venkata et al., 2000), a different approach to signal-to-noise ratio was used. It is known as weighted signal-to-noise ratio (WSNR). This measure is defined as the ratio of average weighted signal power to the average weighted noise power. Here, the contrast sensitivity functions (CSF) are used as weights.

4.5 Visual Information Fidelity (VIF)

VIF metric was proposed by (Sheikh and Bovik, 2006). In this metric the image quality assessment depends upon the amount of information shared between the source (reference) image and the distorted image. A fundamental limit is imposed on how much information can flow from the source image through the channel (i.e., the image distortion process) to the receiver (i.e., human being). VIF is distinctive over traditional image quality assessment methods.

4.6 Noise Quality Measure (NQM)

NQM metric was proposed by (Damera-Venkata et al., 2000) as a better measure for visual quality than PSNR. It considers variation in contrast sensitivity with distance, image dimensions and spatial frequency. It also considers the variation in local luminance, mean and contrast interaction between spatial frequencies, and masking effects. NQM is given by:

$$\text{NQM (dB)}=10 \log_{10}\left(\frac{\sum_i \sum_j a_{ij}^2}{\sum_i \sum_j (a_{ij}^2 - b_{ij}^2)^2}\right) \tag{14}$$

where a_{ij} and b_{ij} denote the (i,j) pixels in the reference and distorted images.

4.7 Information Fidelity Criterion (IFC)

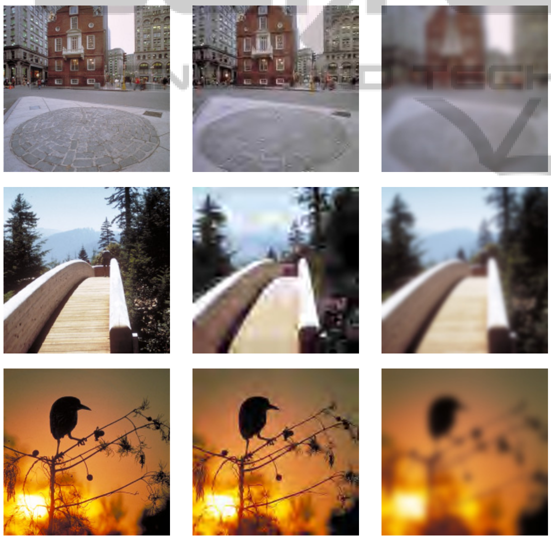
IFC image quality assessment was proposed by (Sheikh et al., 2005). This metric is based on natural scene statistics. The IFC is the mutual information between the source and distorted images. Firstly, the mutual information is derived for one sub-band and then generalized for multiple sub-bands. The IFC quantifies the perceptual quality of the image.

5 EXPERIMENTS AND RESULTS

The images used in our study are collected from the Oklahoma state university image database (also known as CSIQ image database) (Larson and Chandler, 2010). This image database is chosen for our experiments because it has a large number of images distorted with a variety of types. In addition, it was previously used in several image quality assessments in the literature, e.g. (Larson and Chandler, 2010) and (Zhang et al., 2011).

The adopted dataset has 30 original images and 750 distorted versions of the original images. We chose 5 types of distortions each is taken at five levels (This means there are 5×30=150 images for each distortion type). These distortions include JPEG compression, JPEG 2000 compression, additive pink Gaussian noise (APGN), additive white Gaussian noise (AWGN) and Gaussian blurring. Each image in the database is of 512×512 pixels and each color has 256 levels (from 0 to 255). Examples of the images in this database are shown in Figure 3.

Each distorted image in the database has a subjective rating in the form of DMOS (Differential Mean Opinion Score) ranging from 0 (no distortion or lightly distorted) to 1 (highly distorted). Ratings are conducted by 35 male and female observers with ages from 21 to 35 years. The actual DMOS score for each image pair is also taken from the Oklahoma State University CSIQ image database website. Figure 4 shows distorted images with top ten and bottom ten DMOS ratings including distortion name and index, image name, distortion level, standard deviation of DMOS, and DMOS. It is clear that rating is high when the level of distortion is high and vice versa.



(a) Original b) JPEG 2000 c) Blur

Figure 3: Examples of the images in CSIQ database for two types of distortions JPEG 2000 and Gaussian Blur.

We paired each distorted image with the corresponding original image as a reference. This gave us 750 pairs. Out of the 750 image pairs, we used 600 pairs for training the model, 50 pairs for validating the model and 100 pairs for testing the model. Using MATLAB, we computed the seven image quality measures under consideration (see Section 4) using the code developed by their inventors.

We then built different ANFIS models using subsets of these measures and evaluated their performances. The desired output of the ANFIS

dst_idx	dst_type	image	dst_lev	dmos_std	dmos
1	noise	log_seaside	1	0.000	0.000
2	jpeg	boston	1	0.000	0.000
2	jpeg	log_seaside	1	0.000	0.000
3	jpeg 2000	log_seaside	1	0.000	0.000
3	jpeg 2000	boston	1	0.000	0.000
3	jpeg 2000	turtle	1	0.003	0.002
3	jpeg 2000	couple	1	0.000	0.002
2	jpeg	couple	1	0.000	0.002
1	noise	roping	1	0.004	0.003
3	jpeg 2000	shroom	1	0.005	0.004
3	jpeg 2000	aerial_city	5	0.000	0.956
5	blur	sunsetcolor	4	0.023	0.963
5	blur	swarm	5	0.031	0.963
5	blur	lady_liberty	5	0.000	0.966
3	jpeg 2000	swarm	5	0.032	0.967
3	jpeg 2000	fisher	5	0.000	0.972
3	jpeg 2000	family	5	0.000	0.977
3	jpeg 2000	turtle	5	0.001	0.984
5	blur	sunsetcolor	5	0.012	0.999
3	jpeg 2000	sunsetcolor	5	0.021	1.000

Figure 4: Distorted images with top ten and bottom ten DMOS ratings.

network was the crisp DMOS values. The first ANFIS model has only three inputs (PSNR, UQI and MSSIM) whereas the second ANFIS model has five inputs (PSNR, UQI, MSSIM, WSNR and VIF). The last ANFIS model has seven inputs (PSNR, UQI, MSSIM, WSNR, VIF, NQM, and IFC). Table 1 shows the ANFIS parameters and their values used for training with 7 input variables. Figure 5 shows a snapshot of the corresponding ANFIS model for the 7 input variables. The other two models use similar parameter types but the values for input and output MFs differs accordingly.

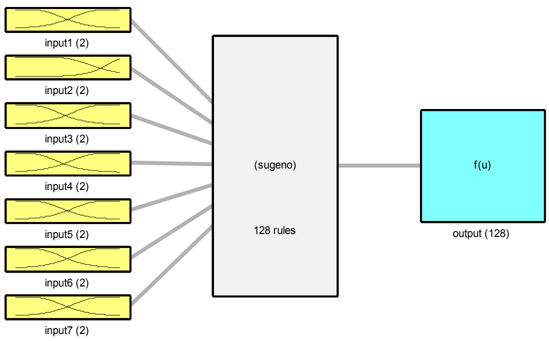


Figure 5: ANFIS model with 7 inputs.

For the purpose of evaluating the performance of each model, we used four measures. The Pearson's linear correlation coefficient ρ is given by:

$$\rho = \frac{Cov(DMOS^a, DMOS^p)}{Var(DMOS^a)Var(DMOS^p)} \qquad (15)$$

where $DMOS^a$ and $DMOS^p$ are vectors containing the actual and predicted values for DMOS. To assess the monotonicity relationship between predicted value and actual value for a particular model, we

Table 1: ANFIS parameters and their values that are used for training with 7 input variables.

ANFIS Parameter	Value
Number of training data records	600
Number of validation data records	50
Number of testing data records	100
AND method	Product
OR method	Probabilistic OR (probor)
Implication method	Product
Defuzzification method	Weighted average (wtaver)
Aggregation method	Sum
Output MF function	Linear
Input MFs type	Generalized bell MF (gbellmf)
Number of inputs	7
Number of outputs	1
Number of MFs per variable	2
Number of rules	128

used Spearman's rank order coefficient ρ_s. This measure is computed suing the same equation for Pearson's coefficient but replacing the raw scores by their ranks. In order to find the error of the model, we used Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) which as calculated as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|DMOS_i^a - DMOS_i^p| \qquad (16)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(DMOS_i^a - DMOS_i^p)^2} \qquad (17)$$

where $DMOS_i^a$ and $DMOS_i^p$ are the actual and predicted values for DMOS for the *i*-th image.

We started with the three features metrics PSNR, UQI and MSSIM, selected arbitrarily as inputs to the ANFIS network. The results of our experiment are given in Table 2. In order to study the performance as more features become available, we added two more feature metrics, i.e. WSNR and VIF, and repeated the experiment with a 5-input ANFIS network. The corresponding results are shown in Table 3. We again added two more feature metrics, i.e. NQM and IFC, and repeated the experiment with a 7-input ANFIS network and the yielded results are shown in Table 4. The rationale behind repeating the experiments was to judge the performance of the ANFIS network by increasing the feature metrics incrementally and document the results.

Considering the results in Tables 1, 2 and 3, we can see that the predicted DMOS values are highly correlated with the actual DMOS values for all distortion types except APGN. The correlation improves as more inputs become available. Similar conclusions can be made regarding MAE and RMSE.

For the sake of comparison, Figure 6 shows the average values for the correlation of two types of distortion JPEG/JPEG 2000 for our method and two other methods from the literature: neural network (Bouzerdoum et al., 2004) and MSSIM (Wang et al., 2004). We should mention that the authors for the other works used a different image database and provided the results for only these two types of distortions.

Table 2: Results for a 3-input ANFIS model (using PSNR, UQI and MSSIM).

Distortion	ρ	ρ_s	MAE	RMSE
Blur	0.9641	0.9665	5.4136	7.8199
JPEG 2000	0.9887	0.9837	3.9443	4.9776
JPEG	0.9477	0.9519	7.7900	10.3173
APGN	0.2413	0.6019	25.7500	60.2763
AWGN	0.9510	0.9562	11.4998	15.3729

Table 3: Results for a 5-input ANFIS model (using PSNR, UQI, MSSIM, WSNR and VIF).

Distortion	ρ	ρ_s	MAE	RMSE
Blur	0.9862	0.9811	3.3941	4.8836
JPEG 2000	0.9938	0.9881	2.6951	3.5981
JPEG	0.9762	0.9693	6.1521	7.8826
APGN	0.6181	0.7143	94.3118	98.5724
AWGN	0.9646	0.9636	16.7365	22.4688

Table 4: Results for a 7-input ANFIS model (using PSNR, UQI, MSSIM, WSNR, VIF, NQM, and IFC).

Distortion	ρ	ρ_s	MAE	RMSE
Blur	0.9937	0.9902	2.2626	3.2177
JPEG 2000	0.9944	0.9902	2.4395	3.3292
JPEG	0.9814	0.9758	5.7428	7.1629
APGN	0.7035	0.7338	96.1683	99.8975
AWGN	0.9548	0.9590	16.8990	22.7204

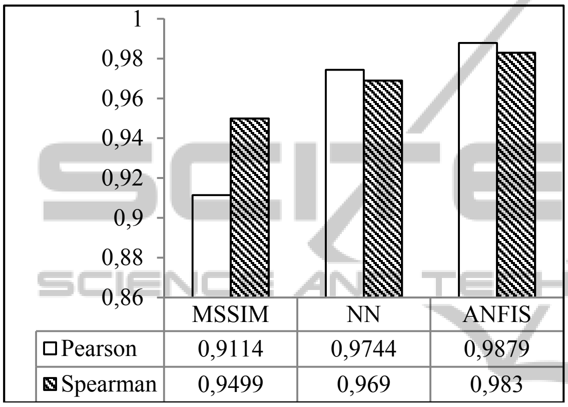


Figure 6: Comparing the average correlation results for JPEG/JPEG 2000 distortion for three methods: ANFIS with 7 inputs (proposed), neural network (NN) (Bouzerdoum et al., 2004) and MSSIM (Wang et al., 2004).

6 CONCLUSIONS

In this paper, we explored the application of an adaptive neuro-fuzzy inference system (ANFIS) for full-reference assessing the quality of images with references. The experimental results showed that ANFIS network can be trained using image quality assessment metrics to predict the differential mean opinion score (DMOS) with high correlation coefficients and low errors. The ANFIS results compare favourably with two other methods in the literature. As a future work, the proposed method can be evaluated using *k*-fold cross validation and other databases. More quality assessment metrics can be considered and in this case the selection of the most relevant features for building the predictive models will be of interest.

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REFERENCES

Balamurugan, P., Rajesh, R., 2007. Greenery image and non-greenery image classification using adaptive neuro-fuzzy inference system. In *International Conference on Computational Intelligence and Multimedia Applications*.

Bouzerdoum, A., Havstad, A., Beghdadi. A., 2004. Image quality assessment using a neural network approach. In *Fourth IEEE International Symposium on Signal Processing and Information Technology*.

Chetouani, A., Beghdadi, A., Deriche, M., 2010. Image distortion analysis and classification scheme using a neural approach. In *2nd European Workshop on Visual Information Processing (EUVIP)*.

Damera-Venkata, N., Kite, T., Geisler, W., Evans, B., Bovik, A., 2000. Image quality assessment based on a degradation model. *IEEE Transactions on Image Processing*, 9(4): 636-650.

De, I., Sil, J., 2009. No-reference quality prediction of distorted/decompressed images using ANFIS. In *International Conference on Computer Technology and Development*.

He, L., Gao, F., Hou W., Hao, L., 2013. Objective image quality assessment: a survey. *International Journal of Computer Mathematics*.

Kaya, S., Milanova, M., Talburt, J., Tsou, B., Altynova, M. 2011. Subjective image quality prediction based on neural network. In *Proceedings of the 16th International Conference on Information Quality*.

Kudelka Jr., M., 2012. Image quality assessment. *WDS'12 Proceedings of Contributed Papers*, Part I, 94–99.

Kung, C.-H., Yang, W.-S., Huang, C.-Y., Kung, C.-M., 2010. Investigation of the image quality assessment using neural networks and structure similarity. In *Proceedings of the 3rd International Symposium Computer Science and Computational Technology*.

Jang, J. S. R., 1993. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, Cybernetics*, 23(5/6):665–685.

Khuntia, S. R., Panda, S. 2011. ANFIS approach for SSSC controller design for the improvement of transient stability performance. *Mathematical and Computer Modelling,* 57(1–2): 289–300.

Larson, E. C., Chandler, D. M. 2010. Most apparent distortion: full-reference image quality assessment and the role of strategy. *Journal of Electronic Imaging*, 19 (1): 011006: 1–011006:21.

Li, C., Bovik, A. C., Wu, X., 2011. Blind image quality assessment using a general regression neural network. *IEEE Trans. Neural Network*, 22(5): 793-799.

Lin, W., and Kuo, C-C., 2011. Perceptual visual quality metrics: A survey. *Journal of Visual Communication and Image Representation*, 22(4): 297–312.

Meena, R. S., Revathi, P., Begum, H. M. R., Singh, A. B., 2012. Performance analysis of neural network and ANFIS in brain MR image classification. In: S. Patnaik & Y.-M. Yang (Eds.): *Soft Computing Techniques in Vision Sci*., SCI 395, pp. 101–113.

Meharrar, A., Tioursi, M., Hatti, M., Stambouli, A., 2011. A variable speed wind generator maximum power tracking based on adaptive neuro-fuzzy inference system. *Expert Systems with Applications*, 38(6): 7659–7664.

Rehman, A., Wang, Z., 2012. Reduced-reference image quality assessment by structural similarity estimation. *IEEE Transactions on Image Processing*, 21(8): 3378–3389.

Sheikh, H.R., Bovik, A., De Veciana, G., 2005. An information fidelity criterion for image quality assessment using natural scene statistics. *IEEE Transactions on Image Processing*, 14(12): 2117–2128.

Sheikh, H. R., Bovik, A., 2006. Image information and visual quality. *IEEE Transactions on Image Processing*, 15(2): 430–444.

Wang, Z., Bovik, A. C., Sheikh, H. R., Simoncelli, E. P., 2004. Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4): 600–612.

Wang, Z., Bovik, A. C., 2009. Mean squared error: Love it or leave it? A new look at signal fidelity measures. *IEEE Signal Processing Magazine,* 26(1):98–117.

Wee, C.-Y., Paramesran, R., Mukundan, R., Jiang, X., 2010. Image quality assessment by discrete orthogonal moments. *Pattern Recognition* 43(12): 4055–4068.

Yi, Y., Yu, X., Wang, L., Yang, Z., 2008. Image quality assessment based on structural distortion and image definition. *International Conference on Computer Science and Software Engineering.*

Zhang, F., Ma, L., Li, S., Ngan, K. N., 2011. Practical image quality metric applied to image coding. *IEEE Transactions on Multimedia*, 13(4): 615–624.