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Generalized referenceless image quality assessment framework using texture energy measures and pattern strength features

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Abstract: Referenceless image quality assessment is a challenging and critical problem in today's multimedia applications. Texture patterns in images are normally at high frequencies compared to lower ones. Due to the effect of distortions during acquisition, compression, and transmission, texture deviation artifacts are generated that cause a granular effect in the image. Other artifacts, such as blocking, affect high frequencies in an image, causing distorted edges. Combining the analysis of texture deviation and other artifacts helps in determining the quality of an image. The proposed approach uses variation in the energy of pixels to quantify the quality of an image. These variations are calculated using texture energy measures and pattern strength-based statistical features. In the proposed approach, machine learning-based classifiers are used to predict the quality score for an image. The performance of the proposed method is tested for all images ranging from pristine to poor quality from LIVE and TID2008 databases. For different distortions, results are shown to have good correlation if they lie between the predicted score and the differential mean opinion score. Results obtained with this approach are compared with other widely used referenceless approaches. It is observed that the proposed approach shows better performance in the quantification of the quality of an image.

Key words: Referenceless image quality assessment, texture energy measures, pattern strength features, artificial neural network, mean opinion score, support vector machine

1. Introduction

With the rapid evolution of smart devices capable of handling multimedia contents on social networking media, an enormous amount of visual information is generated and exchanged. For efficient transmission and storage space management of the generated visual data, the compression of images and videos is highly essential. Widely used lossy compression schemes involve a transformation and quantization process. This transformation and quantization generates artifacts like blocking and ringing, which degrade the quality of images and videos to some extent [1]. In order to assure good quality of experience, the assessment of image quality is of the utmost importance. Quality assessment is mainly performed using objective and subjective means. Since the user is ultimately the final judge, subjective assessment is the preferred approach for quality assessment, but it has some drawbacks. In this approach, all images ranging from those that are pristine to distorted are tested, and the mean opinion score (MOS) or differential mean opinion score (DMOS) is computed. As these methods include manual interventions, they are slow and often expensive [2].

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Objective quality assessment includes categories such as full reference (FR), reduced reference (RR), and no reference (NR) [2,6]. In FR, a pristine or original image is used as a reference, and mathematically defined measures are used for quality assessment. These evaluations are computationally simple and inexpensive, but unfortunately these matrices do not correlate with human perception [3,4]. In order to have better correlation, human visual system-based measures like the mean structural similarity index (MSSIM) and edge-based structural similarity index have been developed [5–7].

In the RR method, a few possible degradation-based features are extracted before compression and stored or transmitted as additional information. These are later compared with the decompressed noisy image at the receiver end [8–10]. In various applications, the unavailability of the original image is a crucial issue in the area of quality assessment.

In the NR method, the quality of an image is assessed without reference. This assessment is very similar to a human visual system that assesses image quality without reference. The NR technique follows three basic methodologies: the first is a distortion-specific method that is based on quantifying various distortions or artifacts such as blocking and ringing. The features of the distortion-specific method are correlated with MOS or DMOS through some fitting algorithms or other regression techniques. The second technique uses a machine learning approach in which several features in the spatial and frequency domain depicting distortions are extracted from certain images and then given as input to the neural networks or other similar classifiers. The training of the classifier is done by taking MOS or DMOS as a target. Finally, the natural scene statistics (NSS) method presumes that natural or original images are a subset of the complete image set. The quality of an image is evaluated on the basis of the distance between the subspace of natural images and distorted images [11–13].

Most of the present methods are distortion-specific and work well for known distortions. As the texture patterns are high frequencies in the image, these are heavily hit by distortions. Texture deviation is another type of distortion that presents a granular effect in an image due to the loss of low and middle frequencies. This loss of texture because of distortions can be modeled using texture analysis. In this paper, we propose a generalized referenceless framework using texture energy measures and pattern strength features along with local texture-based features like entropy and standard deviation. The proposed framework assesses the quality of an image without an original image as a reference; as the extracted features exhibit nonlinear behavior patterns, a machine learning approach is proposed. This feature vector is presented as an input to the supervised machine learning-based classifier, and DMOS will be an expected output. In this paper, we present the comparative performance of an artificial neural network (ANN) and multiclass support vector machine (SVM) for different types of images. The feature vectors extracted from pristine to bad images are then presented as input to the classifier. The proposed approach is tested on the LIVE [14] and TID2008 [15] databases. Prediction accuracy for the neural network is around 85%; for the SVM, it is about 90%. The proposed method is also compared with other NR methods used. It shows better accuracy than the other NR methods.

The paper is organized as follows. Section 2 presents the previous work done in the field of NR image quality assessment. Feature extraction techniques are discussed in Section 3. The proposed technique for quality score estimation and experimentation is described in Section 4. Section 5 presents the experimental results and finally, in Section 6, the discussion and conclusion are presented.

2. Related work

Earlier NR methods focused on distortion specific approaches. In earlier algorithms, blockiness was estimated by extracting features like the average absolute difference and the zero-crossing rate. The parameterized mathematical model was used to compute the quality score and the results were tested for JPEG images [16]. Many algorithms were developed for blockiness and ringing estimation [17–19]. Sazzad et al. [20] worked on spatial features, whereas other authors proposed statistical information on the gradient profile along strong edges in [21]. Several authors worked with the noise and blur present in images [22,23].

Establishing a relationship between features, the subjective score, and the estimated quality score is a complex task. Due to the nonlinear nature of this relation, mathematical predictors sometimes lead to incorrect assessments [24,25]. The machine learning approach is used to solve this problem. Gastaldo et al. [26] addressed nonparametric statistical features for the NR metric. The quality score is predicted by the circular back propagation algorithm. Preprocessed images are used for feature extraction. Suresh et al. [27] proposed edge-based features along with the extreme machine learning algorithm for image quality assessment. In recent times, researchers have estimated the quality score on the basis of changes in discrete coefficient transform (DCT) coefficients due to distortion [11,28]. In [29], the authors demonstrated a model based on special features like local spatial and spectral entropies.

Social networking websites are becoming popular and are heavily used for sharing photographs. Natural images are also transmitted on these sites. Natural images follow different statistics that vary according to distortion. Many researchers have contributed to the study of this issue. Sheikh et al. [30] proposed a mathematical model of wavelet coefficients of images, while Chen et al. [31] worked with the gradient histogram model. Esteemed groups in the area of NR development have contributed many algorithms like the DIIVINE index, BLINDS-II, NIQE, BRISQUE, and C-DIIVINE [32–36]. Fang et al. [37] defined the NSS model for contrast-distorted images using moments and entropy features. Authors used the support vector regression model in the estimation of quality score. Liu et al. [38] proposed a curvelet transform for NR quality assessment. Extracted features are log-histograms of curvelet coefficient values and the energy distribution of both orientation and scale.

Since the last decade, researchers have worked with specific distortion types and images. Most of the parameters are tested with specific types of images like JPEG and JPEG 2000. These parameters work well for specific distortions and images. Various compression schemes introduce blocking and ringing artifacts. These artifacts are well represented by the blocking and edge distortion types of parameters. These distortions also affect the texture of the image. Along with these artifacts, other noises are introduced during transmission that affect the texture of images. As a result, there is a need to evaluate the textual parameters for quality assessment. In this paper, we propose textual parameters for image quality assessment.

Researchers have proposed textual parameters with first-order statistical parameters and the gray level cooccurrence matrix (GLCM) [26]. First-order statistics compute the characteristics of single pixels overlooking the spatial relationship with other pixels. The GLCM, which is a second-order statistical parameter, estimates the spatial relationship between adjacent pixel values. The GLCM is heavily dependent on directional information. It does not work well with isotropic images, whereas Laws filters use spatial filters or frequency domain filters for the frequency analysis of the texture. They are also able to define a spatial relationship between more pixel values. Laws filters recognize texture characteristics like uniformity, density, coarseness, and roughness.

The GLCM is heavily dependent on the magnitude of gray-level differences, but noise and change in luminance is not addressed well. The local binary pattern (LBP) handles the noise. It finds the relation between pixels P on a circle with radius R around the central pixel. LBP codes are rotation invariant. Laws filters and the LBP operator are applied on an image, and texture-based local statistical features are also extracted to obtain the textual features for quality assessment that are presented in this paper. These features are used as input to the multilayered back propagation artificial neural network-based prediction model to estimate the quality score. DMOS is then given as the target during training, and the multiclass SVM is also used to predict the class of the feature vector for the DMOS that it belongs to.

3. Feature extraction

In the proposed technique, two texture-based parameters, namely texture energy measures and pattern strength, are used to assess the quality of the images.

3.1. Texture energy measures

Laws [39] developed a texture energy measure that is utilized in different applications. These features are calculated by applying a small convolution mask to the image followed by a nonlinear windowing operation. A 2D convoluted kernel is applied for texture differentiation. This is created from 1D kernel L_5 = [1 4 6 4 1], E_5 = [–1 –2 0 2 1], S_5 = [–1 0 2 0 –1], R_5 = [1 –4 6 –4 1]. Feature extraction convolves the mask on an image and calculates energy information. The 2D kernel is defined as the convolution of the vertical 1D kernel and the horizontal 1D kernel; for example, L_5E_5 is computed as vertical L_5, which is convolved with horizontal E_5. In matrix notation, it is expressed as $L_5E_5 = L_5^T E_5$. The 2D kernel is then convolved with an image. The sample image of size $M \times N$ is convolved with a selected mask of size 5 × 5, which results in the set of gray images, each of which has the dimensions $N - window_{size} + 1 \times M - window_{size} + 1$, where the window size is the kernel size. It is mathematically expressed as $y_i = \Sigma_{i=1}^{N} x_i \times m_i$, where m represents mask weight and x represents the pixel value in the input image. A windowing operation is then performed on each of these images. Each pixel in the image is obtained by applying a different size of window around the pixel and calculating statistical descriptors like the mean of neighboring pixels and the standard deviation of neighboring pixels, which generate a set of images. Mathematically, it is defined for window size N = C × C as $z_j = f(y_1, y_z, ...y_n)$, where z_j can be the mean of neighborhood values, mean of absolute values, or standard deviation of neighborhood values. The next step involves the generated images being normalized using the min–max normalization method in the present study. The normalization process is used in order to present the image well. In the normalization process, an n-dimensional image $I : \left\{X \subseteq R^N\right\} \rightarrow \{Min, .., Max\}$, with intensity values in the range of (Min, Max), transforms into a new range (newMin, newMax), i.e. $I : \left\{X \subseteq R^N\right\} \rightarrow \{newMin, ..., newMax\}$. The output results in nine maps: L_5S_5, L_5R_5, E_5E_5, E_5S_5, E_5R_5, S_5S_5, S_5R_5, and R_5R_5. When L_5E_5 is applied to an image horizontally, it detects the edge. When it is applied vertically, it gives gray-level intensity. Other maps also work in a similar fashion.

3.2. Pattern strength

Ojala et al. [40] developed an LBP image operator based on the fact that texture is defined by two complementary measures, namely its pattern and its strength. The original version of the LBP operates on a 3 × 3 block of an image. The central pixel is subtracted from 8 neighbor pixels in the block. The sign of this difference is considered for thresholding. The LBP is computed as the summation of threshold differences weighted by a power of two. The texture descriptor is defined as the histogram of these $2^8 = 256$ values. This is mathematically presented as follows:

Consider an image $I(p,q)$ and let l_c denote the gray level of an arbitrary pixel (p, q), i.e. $l_c = I(p,q)$.

Let l_x denote the gray level of a sample point in evenly spaced circular neighbors of X sample points and let R represent the radius around the point (p,q).

$$l_x = I(p_x, q_x), x = 0, ..., X-1 \tag{1}$$

$$p_x = x + R\cos(2\Pi x/X) \tag{2}$$

$$q_x = y - R\sin(2\Pi x/X) \tag{3}$$

The texture of an image $I(p,q)$ is characterized as the joint distribution of gray values of $X+1$ pixels.

$$LT = m(l_c, l_0, l_1, ..., l_{x-1}) \tag{4}$$

Subtracting the center pixel from the neighborhood,

$$LT = m(l_c, l_0 - l_c, l_1 - l_c, ..., l_{x-1} - l_c), \tag{5}$$

the sign of the difference is considered for thresholding.

$$LT = m(si(l_0 - l_c), si(l_1 - l_c), ..., si(l_{x-1} - l_c)), \tag{6}$$

where $si(t)$ is the thresholding function.

$$si(t) = \begin{cases} 1, t \geq 0 \\ 0, t \leq 0 \end{cases} \tag{7}$$

The LBP operator is defined as:

$$LBP_{X,R}(p_c, q_c) = \sum\nolimits_{x=0}^{x-1} si(l_x - l_c)2^x \tag{8}$$

By applying the LBP operator on an image, this results in a vector size of 256 values. Wu et al. [41] proposed the LBP for structural degradation on a spatial distribution for full reference image assessment.

The feature vector is formed by calculating the statistical measures from the texture energy measures, the local binary pattern, and the texture-based statistical features. Texture energy measures give nine 9D map vectors. Two statistical measures, mean and standard deviation (SD), are computed for each vector, which produces 18 values. The size of the vector produced by pattern strength is 256. Statistical measures like SD, skewness, and kurtosis are computed for this vector. The size of the feature vector is now 21, and this fuses with local texture-based statistical features entropy and standard deviation. To compute local texture-based statistical features, the image is divided into overlapping 9 $\times$ 9 blocks and local descriptors for these blocks are calculated. Furthermore, the average of the local descriptors is calculated to define the global descriptor. In this study, the size of the feature vector is 23.

Figure 1 depicts the plots of the mean and SD of 9 maps for the original image and its five variants. The nature of the discrete white noise signal is a sequence of serially uncorrelated random variables with uniform distribution. Thus, statistical parameter values show higher impact for the entire set of masks. In fast fading,

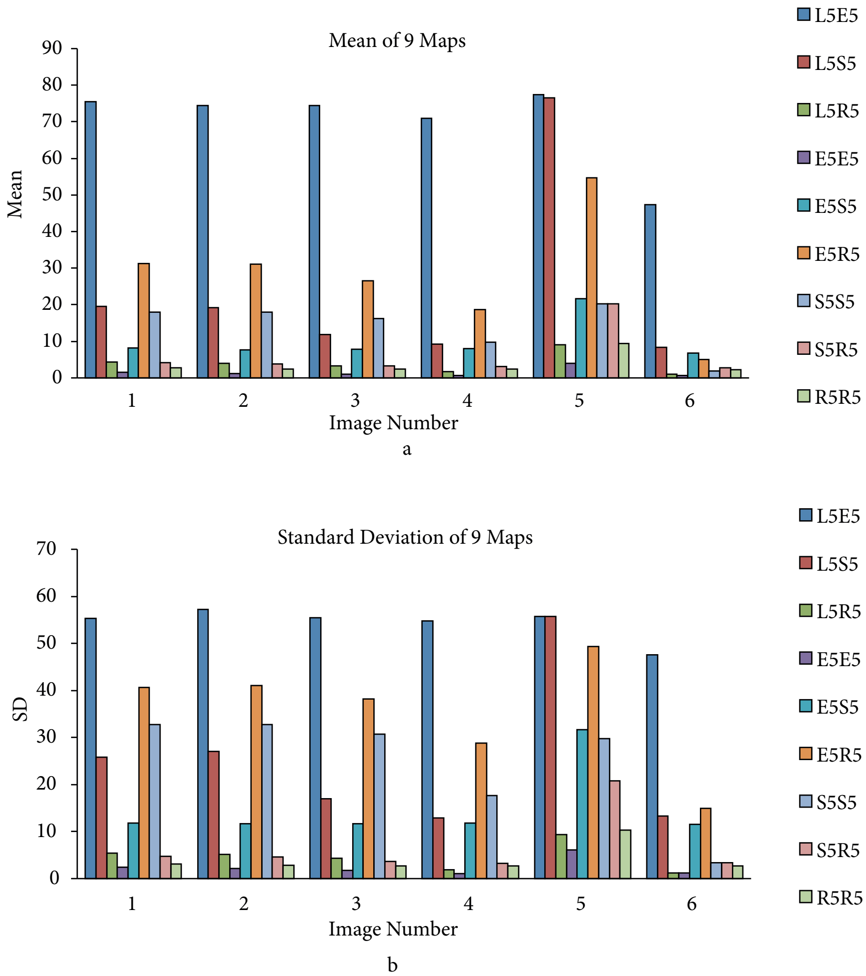

Figure 1. Plots for mean (a) and standard deviation (b) of 9 maps, respectively, for image number 1 (the original) and its variants: 2- JPEG; 3- JPEG2k; 4- Gaussian blur; 5- white noise; 6- fast fading.

each mask obtained fewer values due to the loss of frequencies and blurring effect. Texture is not prominently identified due to the blur, and it is observed that both parameters exhibit nonlinearity.

Figure 2 shows the plot for SD, skewness, and kurtosis of the LBP for the original image and its five variants. The LBP calculates the difference between the pixels and thus the issue of blocking artifacts is positively addressed. Therefore, data analysis shows higher values of statistical measures for JPEG, and these parameters show nonlinear behavior.

4. Methodology

Since the energy measure parameters and pattern strength show nonlinearity, it is difficult to model the nonlinear relationship between features and MOS by using different fitness and regression functions. An efficient way to characterize this nonlinear relationship is the use of the neural network-based model. Bagade et al. [24,25] presented blocking and frequency domain statistical features in their earlier work with 95% accuracy for JPEG images. The authors concluded that sometimes quality scores predicted by mathematical predictors do not correlate with MOS and may lead to incorrect prediction.

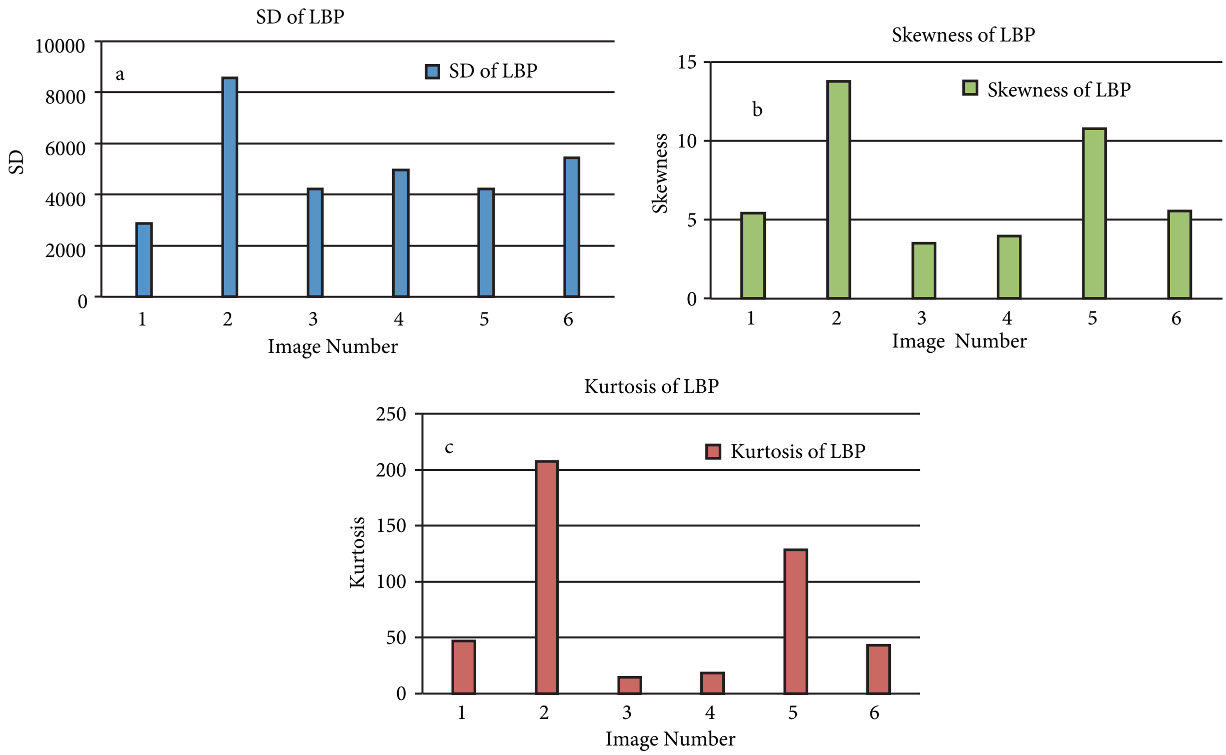

Figure 2. Plot for standard deviation, skewness, and kurtosis of local binary pattern for image number 1 (the original) and its variants: 2- JPEG; 3- JPEG2k; 4- Gaussian blur; 5- white noise; 6- fast fading.

The methodology for experimentation is depicted in Figure 3. The feature vector obtained as an output of the feature extraction process is given as an input to the classifier ANN or SVM. The classifier predicts a score or a class. The backpropagation neural network and the multiclass SVM are trained using the vector of the extracted features as an input. DMOS is used as a target for the backpropagation neural network. This trained classifier predicts the quality score for the test dataset. To train the SVM, the feature vectors of the training dataset images are categorized into four classes, namely best, good, average, and bad. This trained classifier classifies the test images in one of the four classes.

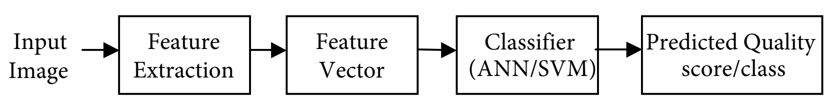

Figure 3. Block diagram for methodology.

In the present study, a three-layered feedforward network with the Levenberg–Marquardt training algorithm is used. The architecture of the ANN comprises 23 neurons in the input, 9 neurons in the hidden, and one neuron in the output layer. The log-sigmoid transfer function and linear transfer function were used in hidden neurons and output neurons, respectively. Nonlinear transfer functions of neurons in the hidden layers permit the network to gain knowledge about correlation between the input and the output [42]. The SVM needs a significantly smaller number of parameters than the ANN. The ANN is stuck with local minima, whereas the SVM is global and unique. The computational complexity of the SVM is independent of input space dimension. The SVM has simple geometric interpretation and provides the sparse solution.

The SVM model represents a feature vector obtained from an input image, as a point that is mapped in the feature space, so that input vectors of different categories are classified. New input vectors are mapped into the same space and predict the class for the vector. Along with linear classification, the SVM can also be used for nonlinear classification. Nonlinear behavior is achieved through the kernel function. It implicitly maps the input vector to a high dimension space. The selection of the kernel depends on the nature of the problem. In the proposed study, the radial basis kernel is used [43]. The SVM is implemented with 23 input nodes and a hidden layer with a radial basis kernel function with 4 output nodes.

5. Experimentations and results

To model the framework, the LIVE [14] database is used. The training set is composed of 20 original images and its five variants: JPEG, JPEG2000, Gaussian blur, white noise, and fast fading. The testing set contains 9 original images and their variants. In the training and testing phases, 29 original images, each of which has five distortions, and three images along with five distortions from the training dataset are used. Each image has five variants that eventually result in 960 images. The classifier is trained and tested on the 960 images. The feature vector is used to train the classifier. The trained classifier predicts the class for the test dataset. This model was also validated for the TID2008 [15] dataset. Eighteen original images along with different distortions like JPEG, JPEG 2000, Gaussian blur, and white noise are used as training data. Seven original images with their distortion variants are used as the testing dataset.

In the first experiment, the quality score computed by the neural network is compared with DMOS. The combination of extracted features is given as an input to the network for a particular image type. The linear coefficient between predicted scores by network and DMOS is obtained for the LIVE dataset, which is shown in Table 1. Table 2 depicts the performance of the ANN for the TID2008 dataset. Figure 4 depicts regression plots for the ANN for both of the datasets.

Table 1. Performance evaluation of classifiers using the LIVE dataset for the proposed features.

Image type/parameters	Correlation coefficient	
	ANN	SVM
JPEG	0.85	0.85
JPEG2k	0.88	0.85
Gaussian blur	0.93	0.95
White noise	0.91	0.95
Fast fading	0.86	0.80
Overall	0.85	0.90

Table 2. Performance evaluation of classifiers using the TID2008 dataset for the proposed features.

Image type/parameters	Correlation coefficient	
	ANN	SVM
JPEG	0.89	0.85
JPEG2k	0.89	0.85
Gaussian blur	0.90	0.95
White noise	0.90	0.95
Overall	0.90	0.92

In the second experiment, the mentioned features are used to train the SVM. The SVM requires classes as the target. Therefore, DMOS values are grouped into four groups. Class 1 is defined as a DMOS range from

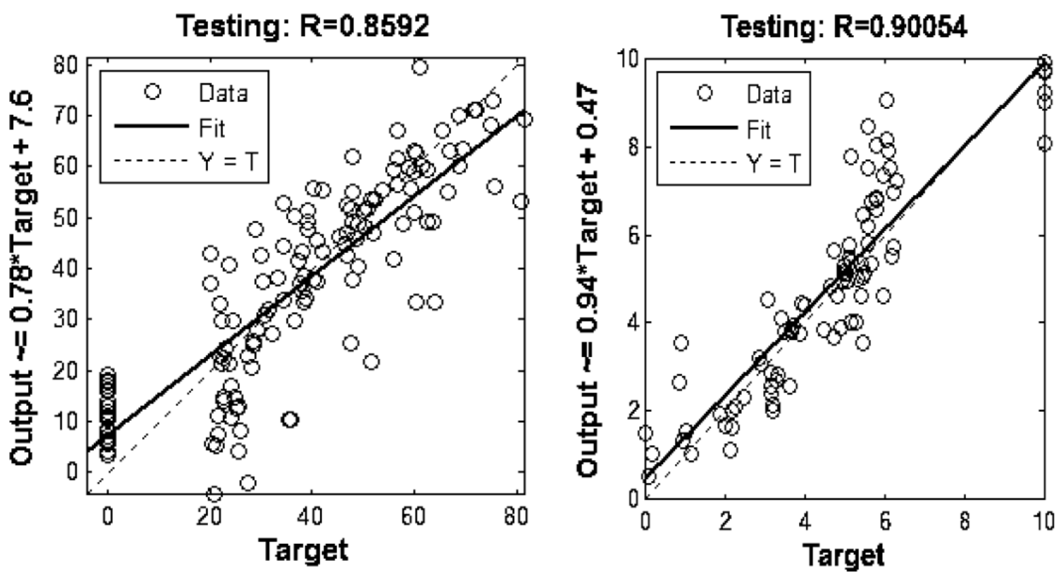

Figure 4. Regression plots for the ANN for the LIVE database and TID2008 databases, respectively.

0 to 25. DMOS values between 25 and 50, between 50 and 75, and above 75 are considered as Class 2, Class 3, and Class 4, respectively. From the training dataset, the corresponding feature vectors that are categorized into different classes are used to train the SVM. The trained classifier predicts the class for the test images. The obtained linear coefficients for testing the datasets are given in Tables 1 and 2. Figure 5 shows the regression plot for the SVM. It depicts the relationship between the expected class for the test image and the actual class predicted by the SVM. The SVM classifier shows better performance than the ANN. The proposed method, when compared with other NR methods, shows better performance, as shown in Table 3.

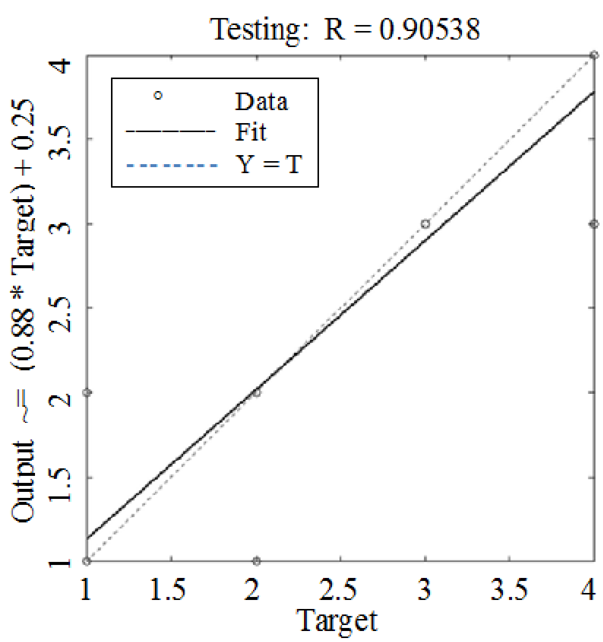

Figure 5. Regression plot for the SVM for LIVE database.

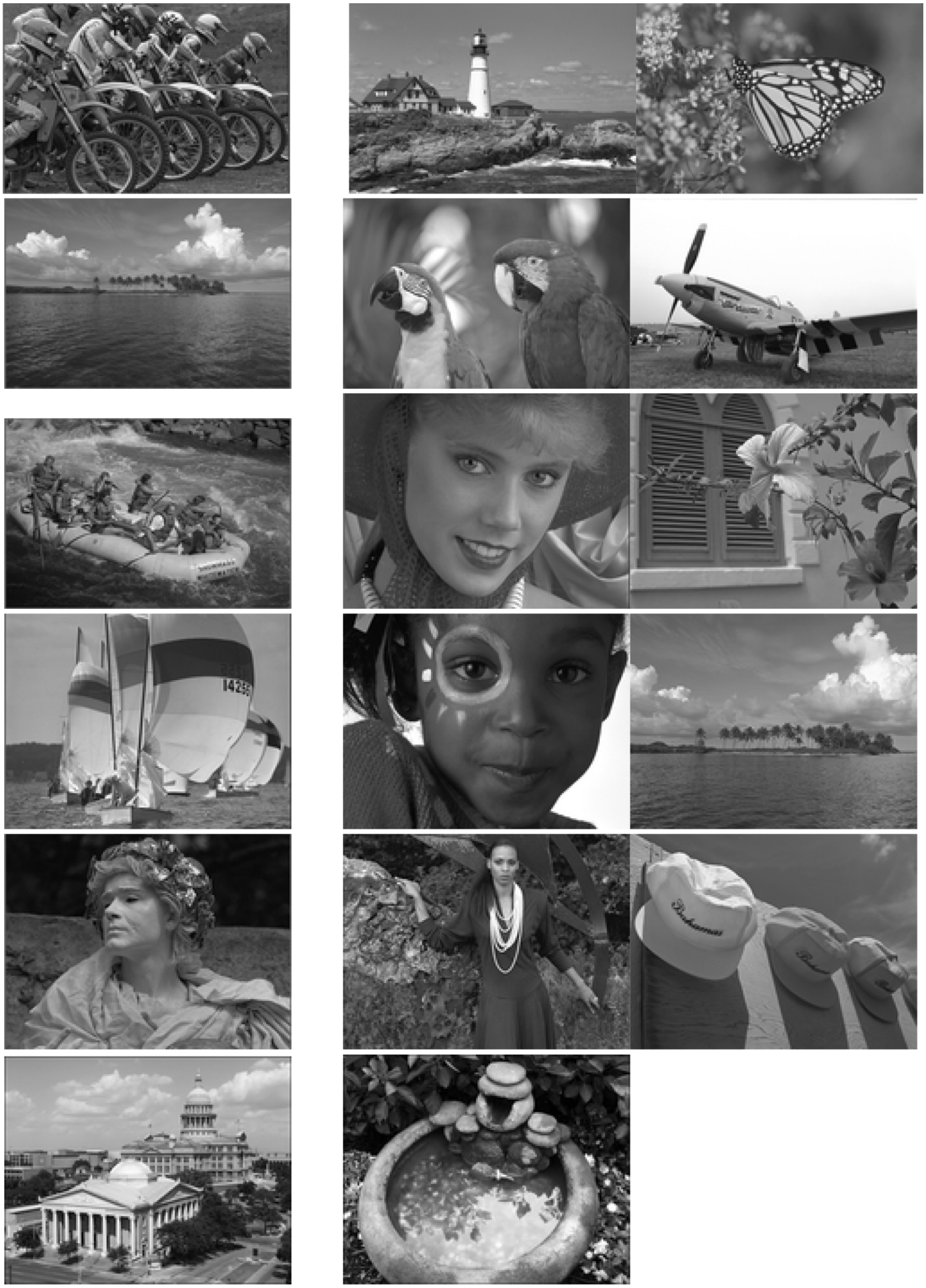

Figure 6. Sample images from the LIVE and TID2008 datasets.

Table 3. Comparison between the proposed approach and other referenceless approaches using the LIVE database.

Sr. no.	Approach	Linear coefficient	Spearman coefficient
1	Proposed method	0.90	0.90
2	DCT-based (NR-IQA) [11]	0.79	0.79
3	BIQ I [36]	0.82	0.81
4	RCGA-ELM [27]	0.70	0.69
5	CBP [26]	0.86	0.85

Table 4 shows the performance of the proposed method against widely used full reference assessment methods using the TID2008 database. Sample images used from both datasets are depicted in Figure 6. The proposed method exhibits good accuracy for both of the databases.

Table 4. Comparison of different FR approaches with the proposed approach using the TID2008 database.

Sr. no.	Approach	Spearman coefficient
1	Proposed method	0.92
2	UQI	0.60
3	SSIM	0.80
4	MSSIM	0.85

6. Conclusion

Texture is an important feature of an image but it can be seriously impacted by distortion. Texture energy measures compute the energy present in an image, and this was the basis of the current study. As quality is degraded, the texture energy that helps to assess quality also decreases. The pattern strength that works with differences between pixels addresses the issue of blockiness and noise. In fast fading distortion, there is a loss in frequencies, and these parameters are not able to handle the loss in frequencies. Unclassified images generated by the classifier are mostly fast fading images. Mathematical predictors often exhibit incorrect predictions for complex and nonlinear relations between features, expected output, and predicted score. Thus, a machine learning-based classifier is a good solution for the classification problem. Considering textual-based parameters, image quality assessment is done with different types of images and distortions. Original and distorted images are given as input to the neural network and the support vector machine trained with DMOS. The observed accuracy for the neural network is around 85%, and it is around 90% for the SVM. This approach works well because most of the distortions change the textual information of an image. Textual feature extraction is a good technique to evaluate the quality of an image. Extracted features work well with various distortions for best to worst quality images. This is achieved through the uniqueness of the machine learning approach to obtain the nonlinear relationship between extracted features and DMOS. The result from the ANN depends on initialization of weights, whereas the SVM is used to get stable results. However, there is definitely a need to define other parameters to address fast fading distortion. In the future, nontextural features should be extracted to address fast fading.

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