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New feature selection algorithms for no-reference image quality assessment

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Abstract

No reference image quality assessment (NR-IQA) is a challenging task since reference images are usually unavailable in real world scenarios. The performance of NR-IQA techniques is vastly dependent on the features utilized to predict the image quality. Many NR-IQA techniques have been proposed that extract features in different domains like spatial, discrete cosine transform and wavelet transform. These NR-IQA techniques have the possibility to contain redundant features, which result in degradation of quality score prediction. Recently impact of general purpose feature selection algorithms on NR-IQA techniques has shown promising results. But these feature selection algorithms have the tendency to select irrelevant features and discard relevant features. This paper presents fifteen new feature selection algorithms specifically designed for NR-IQA, which are based on Spearman rank ordered correlation constant (SROCC), linear correlation constant (LCC), Kendall correlation constant (KCC) and root mean squared error (RMSE). The proposed feature selection algorithms are applied on the extracted features of existing NR-IQA techniques. Support vector regression (SVR) is then applied to selected features to predict the image quality score. The fifteen newly proposed feature selection algorithms are evaluated using eight different NR-IQA techniques over three commonly used image quality assessment databases. Experimental results show that the proposed feature selection algorithms not only reduce the number of features but also improve the performance of NR-IQA techniques. Moreover, features selection algorithms based on SROCC and its combination with LCC, KCC and RMSE perform better in comparison to other proposed algorithms.

Keywords No-reference image quality assessment · Feature extraction · Feature selection · Perceived quality · Computational intelligence

1 Introduction

In the past decade rapid spread of image acquisition and communication technologies have paved the way for a broad spectrum of applications in the field of compression, health care, social networks etc. Images are subject to a variety of distortions in the acquisition, compression, transmission or reproduction phase [1]. Quality evaluation of images is essential for guaranteeing quality of experience to an end user in many applications. Image quality assessment (IQA) is broadly divided into subjective and objective techniques. Image quality assessment performed by human beings is known as subjective IQA and has the advantage of being highly accurate and reliable, but renders it inapplicable to majority of the applications due to tedious and expensive nature of the task, high consumption of time and non-reproducible nature of results. On the other hand, objective IQA techniques evaluate the perceptual quality of the image in terms of quality score that correlates with subjective IQA using computational models [1]. Various objective IQA techniques have been proposed that can be categorized

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into full reference (FR), reduced reference (RR) and no reference (NR) IQA techniques [2].

FR-IQA [3–8] techniques require reference image to perform IQA whereas, RR-IQA [9–12] techniques evaluate the quality of an image using partial information about the original undistorted image. Mean square error and peak signal to noise ratio are among the most commonly used FR-IQA techniques because they are computationally efficient and perform IQA pixel wise. However, FR-IQA do not show high correlation with subjective IQA [1]. Structural similarity index measure (SSIM) [13] is considered to be a turning point in the development of FR-IQA techniques, which is based on universal quality index. SSIM works under the assumption that human visual system is highly sensitive to the structural information in the image. SSIM is extended to multi-scale and is named as MS-SSIM [14]. Information-content weighting is introduced in MS-SSIM to develop IW-SSIM. SSIM map is constructed using local weights assigned based on the information content in the local patches of the reference and distorted images. In [15], visual information fidelity (VIf) index is introduced, which is an extended version of the information fidelity criterion (IFC) index [16]. Both IFC and VIf compute image quality based on information fidelity and aim to measure the similarity between the reference and distorted image. Utility of FR-IQA and RR-IQA techniques in real world applications is limited due to the requirement of reference image to perform IQA [1]. NR-IQA techniques are also known as blind image quality assessment (BIQA) techniques and they solve this problem because they do not require the reference image to assess the quality of image [1, 17–22].

The main objective of NR-IQA techniques is to extract quality aware features from distorted images and then utilize machine learning tools to map these features to a quality score. Natural undistorted images are statistically regular and highly structured, which is disrupted in the presence of distortion [23]. Features that measure deviation in characteristics between distorted and undistorted images are called natural scene statistics (NSS) and are the most popular features adopted by NR-IQA techniques. Various NR-IQA techniques based on NSS features have been proposed, which extract features in the discrete cosine transform (DCT), spatial, wavelet and curvelet domain. In [24], DCT based NSS features are extracted at two scales to assess the quality score of image using Bayesian inference model. Features are extracted over six orientations and across two scales using wavelet transform in [23], to predict image quality score. Locally normalized luminance features and their products are extracted in spatial domain to perform IQA in [25]. In [17], maximum value of log of histogram and energy of scale and orientation are extracted in curvelet transform to evaluate the quality of images. In [26], Gaussian magnitude and Laplacian of Gaussian are used with support vector regession (SVR) for IQA. In [27], 8×8 patches of the image are used to compute spatial and spectral entropies. In [1], perceptual structural features and luminance based features are utilized with a SVR model for evaluating the quality of an image. Non-negative matrix factorization is used in [28] to measure distortion in the image along with extreme learning machine for assessing the quality of images. In [29], multi-threshold local tetra pattern is used to extract changes in spatial distribution and Weber Laplacian of Gaussian is used to model changes in intensity contrast for the purpose of NR-IQA.

All the aforementioned techniques extract features in different domains but does not focus on obtaining optimum features. The performance of NR-IQA techniques declines and shows lower correlation with mean observer score (MOS) in the presence of irrelevant and redundant features. Feature selection algorithms reduces the feature vector length by discarding redundant and irrelevant features. Therefore, feature selection is vital in improving the performance of NR-IQA techniques by selecting relevant features, which improve their prediction capability and result in higher correlation with MOS. Feature selection have been used in various domains such as forensic feature analysis [30], implementation of an efficient algorithm for k-barrier coverage based on integer linear programming [31], and detection of fingerprint liveliness [32] to improve the overall performance of the system. Recently, impact of feature selection algorithms on NR-IQA has been explored in [33], which shows improvements in the prediction of quality score of existing BIQA techniques. The feature selection algorithms used are random search, linear forward selection, genetic search, incremental wrapper feature subset selection with the Naive bayes classifier and particle swarm optimization. As all the feature selection algorithms used in [33] are generic and are not specifically proposed for NR-IQA, which may result in selection of irrelevant features and rejection of relevant features. Therefore, feature selection algorithms specifically designed for NR-IQA are required, which selects most relevant features to improve the prediction of quality score.

In this paper, we propose fifteen new feature selection algorithms based on correlation and error parameters namely Spearman ranked order correlation constant (SROCC), linear correlation constant (LCC, Kendall correlation constant (KCC) and root mean squared error (RMSE). The NR-IQA framework used in this paper extracts features using existing NR-IQA techniques, selects features based on the newly proposed feature selection algorithms and predicts the quality score based on the selected features using SVR. The proposed algorithms are tested on eight state-of-the-art NR-IQA techniques that extract features in different domains. Furthermore database and NR-IQA technique independence is also established in order to evaluate the effect of proposed feature selection algorithms on NR-IQA. The contributions of this paper are as follows

1. New correlation and error based feature selection algorithms are proposed for NR-IQA.
2. Effect of proposed feature selection algorithms on NR-IQA techniques is studied.
3. Proposed feature selection algorithms improve the image quality score prediction capacity of NR-IQA techniques by showing low error and high correlation with mean observer scores.

The rest of the paper is organized as follows. Section 2 explains related work on NR-IQA techniques. Section 3 discusses newly proposed feature selection algorithms for NR-IQA. Section 4 presents the experimental results on three commonly used subjective IQA databases over eight NR-IQA techniques and fifteen proposed feature selection algorithms followed by conclusion in Section 5.

2 Related work

2.1 Traditional NR-IQA framework

Most of the NR-IQA techniques proposed in literature follows a two-step approach as shown in Fig. 1. In the first step features are extracted and in the second step, prediction of image quality score is performed. Details of some of the NR-IQA techniques that follow a two-step approach and extract features in different domains are explained below.

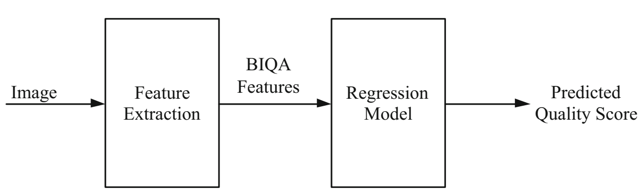

Fig. 1 Traditional two-step approach for NR-IQA

2.1.1 Blind image integrity notator using DCT statistics (BLIINDS-II)

In [24], DCT based statistical features are extracted by dividing the image into patches of 17×17. Three directional regions are considered in each patch and Gaussian fitting is performed. Four types of features are extracted i.e., generalized Gaussian model shape parameters, coefficients of frequency variation, energy subband ratio measure and orientation model based features. A total of 24 features are extracted that are given as an input to the Bayesian inference model for the prediction of quality score.

2.1.2 Blind/Referenceless image spatial quality evaluator (BRISQUE)

In [25], feature extraction is performed in the spatial domain for the purpose of NR-IQA. The features are extracted over two scales using shape, variance, mean value, left variance, right variance parameters for horizontal, vertical and diagonal pairwise products of locally normalized luminance coefficients. A total of 36 features are extracted with 18 features on each scale. The quality score is predicted using the extacted features as input for SVR.

2.1.3 Curvelet quality assessment (CurveletQA)

Curvelet transform is used in [17] to extract three groups of features. Asymmetric Gaussian distribution is used on the finest scale to compute four NSS features. One feature is extracted using mean value of kurtosis and one is extracted using standard deviation of the non-cardinal orientation energies. Six features are extracted by taking the difference between logarithmic magnitude mean values of scalar energy distribution at adjacent scales. SVM regression is used to estimate the quality score of image using extracted features.

2.1.4 Spatial-Spectral entropy based quality (SSEQ)

A technique that extracts features in spatial and spectral domain for NR-IQA is introduced in [27]. SSEQ extracts features at three scales. During down sampling, bi-cubic interpolation is used so that aliasing can be avoided. The image is divided into patches of 8×8 pixels. Spatial and spectral entropies are computed on each patch and the features are sorted in ascending order. Top 60% of the central elements are selected for NR-IQA, which forms a feature vector of length 12. Quality score is computed using SVR that utilizes these features as input.

2.1.5 Gradient magnitude and laplacian of gaussian based IQA (GM-LOG)

In [26], image structural information is described using luminance discontinuity that is computed by applying GM and LOG operator in the spatial domain. Joint adaptive normalization is used to normalize Gaussian magnitude and Laplacian of Gaussian marginal distributions for assessing the quality of images. The technique uses 40 features to determine the type of distortion affecting the image. SVR is used to estimate the quality score of image once the type of distortion is identified. Dependency index in GM-LOG is used to measure and improve the relationship between GM and LOG statistics.

2.1.6 Integrated local natural image quality evaluator (IL-NIQE)

An opinion unaware IQA technique termed as IL-NIQE is proposed in [34]. Natural image statistics derived from multiple cues that include normalized luminance statistics, locally mean subtracted and contrast normalized coefficients, gradient statistics, statistics based on log-Gabor filter responses and color statistics are used for IQA. A multivariate Gaussian model is learned using these cues for a set of pristine images. Each image is resized to 504×504 using bi-cubic interpolation. The distorted image is divided into several patches of size 84×84 and the feature vector of each patch is mapped to a multivariate gaussian model. A distance measure resembling bhattacharyya is used to measure the quality of each image patch by comparing it to the multivariate Gaussian model of the pristine images. Average pooling is used to obtain the overall quality score of the image.

2.1.7 Oriented gradients image quality assessment (OG-IQA)

OG-IQA uses gradient orientation information relative to the surroundings for IQA [18]. The gradient orientation is taken with reference to the background of local orientations. Gaussian partial derivative aligned filters are used in horizontal and vertical directions to compute directional gradient components. Change in the statistical distributions of gradient and relative gradient quantities is used to identify the distortion type and assess the quality of images. Three group of features are extracted i.e., gradient magnitude, relative gradient orientation and relative gradient magnitude to form a feature vector of length 6. These features are give as input to the adaptive boosting back propagation neural network to predict image quality.

2.1.8 Distortion type classification and label transfer (TCLT)

In [19], three set of features are extracted i.e., quality-aware features for extracted in the DCT, wavelet domain and multichannel feature fusion for trichromatic property extracted from Y, Cb and Cr channels. The technique works under the assumption that similar images have similar perceptual quality. First the type of distortion affecting the image is determined and then an image retrieval approach is used to predict the quality score using a K-nearest neighbor (KNN) based non parametric model termed as label transfer. The images KNN's are searched from a set of distortion specific annotated images and a weighted average of MOS values is taken to compute the quality score.

2.2 Feature selection based NR-IQA

All the above mentioned traditional NR-IQA techniques extract features in different domains and use all features for the prediction of quality score. The effect of feature selection algorithm is not explored in these NR-IQA techniques. Traditional NR-IQA techniques may contain redundant and irrelevant features in the feature set that degrade the ability of NR-IQA techniques to predict the image quality score. Figure 2 shows a three step feature selection based approach for NR-IQA. The framework utilizes feature selection algorithms for NR-IQA. Firstly, a feature vector of length N is extracted using existing NR-IQA techniques. Feature selection is performed that selects M number of features i.e., F_S, where $M \leq N$ using feature selection algorithms. The selected features are used for the prediction of image quality score using regression.

Impact of feature selection on NR-IQA techniques using existing feature selection algorithms has been explored in [33]. Five existing feature selection algorithms namely

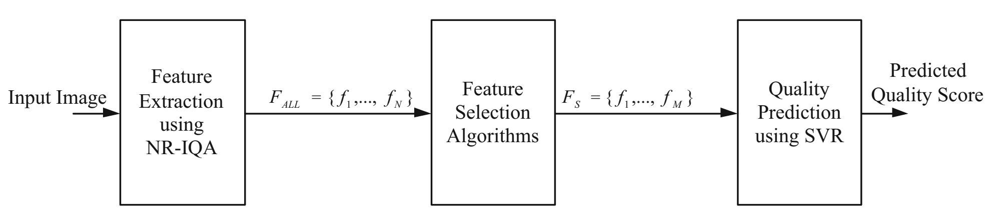

Fig. 2 Feature selection based NR-IQA

random search, linear forward selection, genetic search, incremental wrapper feature subset selection with Naive Bayes classifier and particle swarm optimization are utilized and their effect on the performance of existing NR-IQA techniques is studied. It is concluded that genetic search showed the best performance for NR-IQA.

3 Proposed feature selection algorithms

This work proposes fifteen new feature selection algorithms specifically designed for NR-IQA based on the mean values of Spearman rank ordered correlation constant i.e., $SROCC_{mean}$, linear correlation constant i.e., LCC_{mean}, Kendall correlation constant i.e., KCC_{mean} and root mean squared error i.e., $RMSE_{mean}$, computed over all the features are proposed. If d_i is the difference between paired ranks then, SROCC is given as

$$SROCC = 1 - \frac{6\Sigma d_i^2}{n(n^2-1)}, \tag{1}$$

where n is the total number of instances. LCC is computed as

$$LCC = \frac{\sum\limits_{i=1}^{n}(a_i - \bar{a})(l_i - \bar{l}))}{\sqrt{\sum\limits_{i=1}^{n}(a_i - \bar{a})^2}\sqrt{\sum\limits_{i=1}^{n}(l_i - \bar{l})^2}}, \tag{2}$$

where a_i and l_i are the first and second dataset respectively, $\bar{a}$ and $\bar{l}$ are mean values of a_i and l_i respectively. KCC is calculated as

$$KCC = \frac{n_c - n_d}{n(n-1)/2}, \tag{3}$$

where n_c is the number of concurrent pairs and n_d is the number of opposing pairs. RMSE is computed by

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(x_{dmos} - x_{score})^2}, \tag{4}$$

where x_{dmos} is MOS and x_{score} is the image quality score. Generally, SROCC, LCC and KCC are used to measure the coherence between the predicted quality score and the mean observer score. A value close to 1 suggests a superior performance. RMSE measures the error between the predicted value and MOS. A value close to zero for RMSE shows superior performance. Therefore, we select those features having SROCC, LCC and KCC score close to 1 and RMSE close to 0.

Algorithm 1 S, selects only those features that have individual SROCC score greater than or equal to $SROCC_{mean}$.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have $SROCC_i$ greater than or equal to $SROCC_{mean}$
end
return F_S

Algorithm 2 L, selects those features have individual LCC score greater than or equal to LCC_{mean}

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, LCC_i.
Output: F_S : Set of M selected features.
Compute mean LCC value over all the features, denoted by LCC_{mean}
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have LCC_i greater than or equal to LCC_{mean}
end
return F_S

Algorithm 3 K, selects features that have individual KCC score greater than or equal to KCC_{mean}.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, KCC_i.
Output: F_S : Set of M selected features.
Compute mean KCC value over all the features, denoted by KCC_{mean}
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have KCC_i greater than or equal to KCC_{mean}
end
return F_S

Algorithm 4 R, selects those features, which have individual RMSE value less than or equal to $RMSE_{mean}$.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $RMSE_i$,
Output: Set of M selected features, $F_S = \{F_1, F_2, ..., F_k\}$
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq n$ **do**
  Add feature F_i to feature set F_S that have $RMSE_i$ less than or equal to $RMSE_{mean}$
end
return F_S

Algorithm 5 SL, selects features that have individual SROCC or LCC score greater than or equal to $SROCC_{mean}$ or LCC_{mean} score respectively.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$, LCC_i.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
Compute mean LCC value over all the features, denoted by LCC_{mean}
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  $SROCC_i$ greater than or equal to $SROCC_{mean}$
  OR
  LCC_i greater than or equal to LCC_{mean}
end
Remove redundant features F_i from F_S
return F_S

Algorithm 6 SK, selects features that have individual SROCC or KCC score greater than or equal to $SROCC_{mean}$ or KCC_{mean} score respectively.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$, KCC_i.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
Compute mean KCC value over all the features, denoted by KCC_{mean}
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  $SROCC_i$ greater than or equal to $SROCC_{mean}$
  OR
  KCC_i greater than or equal to KCC_{mean}
end
Remove redundant features F_i from F_S
return F_S

Algorithm 7 LK, selects features that have individual LCC or KCC score greater than or equal to LCC_{mean} or LCC_{mean} score respectively.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, LCC_i, KCC_i.
Output: F_S : Set of M selected features.
Compute mean LCC value over all the features, denoted by LCC_{mean}
Compute mean KCC value over all the features, denoted by KCC_{mean}
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  LCC_i greater than or equal to LCC_{mean}
  OR
  KCC_i greater than or equal to KCC_{mean}
end
Remove redundant features F_i from F_S
return F_S

Algorithm 8 SR, selects features that have individual SROCC score greater than or equal to $SROCC_{mean}$ or individual RMSE score less than or equal to $RMSE_{mean}$ score.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$, $RMSE_i$.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  $SROCC_i$ greater than or equal to $SROCC_{mean}$
  OR
  $RMSE_i$ less than or equal to $RMSE_{mean}$
end
Remove redundant features F_i from F_S
return F_S

Algorithm 9 LR, selects features that have individual LCC score greater than or equal to LCC_{mean} or individual RMSE score less than or equal to $RMSE_{mean}$ score.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, LCC_i, $RMSE_i$.
Output: F_S : Set of M selected features.
Compute mean LCC value over all the features, denoted by LCC_{mean}
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  LCC_i greater than or equal to LCC_{mean}
  OR
  $RMSE_i$ less than or equal to $RMSE_{mean}$
end
Remove redundant features F_i from F_S
return F_S

Algorithm 10 KR, selects features that have individual KCC score greater than or equal to KCC_{mean} or individual RMSE less than or equal to $RMSE_{mean}$ score.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, KCC_i, $RMSE_i$.
Output: F_S : Set of M selected features.
Compute mean KCC value over all the features, denoted by KCC_{mean}
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  KCC_i greater than or equal to KCC_{mean}
  OR
  $RMSE_i$ less than or equal to $RMSE_{mean}$
end
Remove redundant features F_i from F_S
return F_S

Algorithm 11 SLR, selects features that have individual SROCC or LCC score greater than or equal to $SROCC_{mean}$ or LCC_{mean} score respectively or individual RMSE score less than or equal to $RMSE_{mean}$.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$, LCC_i, $RMSE_i$.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
Compute mean LCC value over all the features, denoted by LCC_{mean}
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  $SROCC_i$ greater than or equal to $SROCC_{mean}$
  OR
  LCC_i greater than or equal to LCC_{mean}
  OR
  $RMSE_i$ less than or equal to $RMSE_{mean}$
end
Remove redundant features F_i from F_S
return F_S

Algorithm 12 SKR, selects features that have individual SROCC or KCC score greater than or equal to $SROCC_{mean}$ or KCC_{mean} score respectively or individual RMSE score less than or equal to $RMSE_{mean}$.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$, KCC_i, $RMSE_i$.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
Compute mean KCC value over all the features, denoted by KCC_{mean}
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  $SROCC_i$ greater than or equal to $SROCC_{mean}$
  OR
  KCC_i greater than or equal to KCC_{mean}
  OR
  $RMSE_i$ less than or equal to $RMSE_{mean}$
end
Remove redundant features F_i from F_S
return F_S

Algorithm 13 LKR, selects features that have individual LCC or KCC score greater than or equal to $SROCC_{mean}$ or KCC_{mean} score respectively or individual RMSE less than or equal to $RMSE_{mean}$.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, LCC_i, KCC_i, $RMSE_i$.
Output: F_S : Set of M selected features.
Compute mean LCC value over all the features, denoted by LCC_{mean}
Compute mean KCC value over all the features, denoted by KCC_{mean}
Compute mean RMSE value over all the features, denoted by $RMSE_{mean}$
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  LCC_i greater than or equal to LCC_{mean}
  OR
  KCC_i greater than or equal to KCC_{mean}
  OR
  $RMSE_i$ less than or equal to $RMSE_{mean}$
end
Remove redundant features F_i from F_S
return F_S

Algorithm 14 SLK, outlines features selection by selecting those features that have individual SROCC or LCC or KCC score greater than or equal to $SROCC_{mean}$ or LCC_{mean} or KCC_{mean} score respectively.

Input : $F_{All} = \{F_1, F_2, ..., F_N\}$, $SROCC_i$, LCC_i, KCC_i.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features, denoted by $SROCC_{mean}$
Compute mean LCC value over all the features, denoted by LCC_{mean}
Compute mean KCC value over all the features, denoted by KCC_{mean}
while $i \leq N$ **do**
  Add feature F_i to feature set F_S that have
  $SROCC_i$ greater than or equal to $SROCC_{mean}$
  OR
  LCC_i greater than or equal to LCC_{mean}
  OR
  KCC_i greater than or equal to KCC_{mean}
end
Remove redundant features F_i from F_S
return F_S

Algorithm 15 $SLKR$, outlines features selection by selecting those features that have individual SROCC or LCC or KCC score greater than or equal to $SROCC_{mean}$ or LCC_{mean} or KCC_{mean} score respectively and RMSE less than or equal to $RMSE_{mean}$.

```
Input  : F_All = {F_1, F_2, ..., F_N}, SROCC_i, LCC_i,
         KCC_i, RMSE_i.
Output: F_S : Set of M selected features.
Compute mean SROCC value over all the features,
  denoted by SROCC_mean
Compute mean LCC value over all the features,
  denoted by LCC_mean
Compute mean KCC value over all the features,
  denoted by KCC_mean
Compute mean RMSE value over all the features,
  denoted by RMSE_mean
while i ≤ N do
    Add feature F_i to feature set F_S that have
    SROCC_i greater than or equal to SROCC_mean
    OR
    LCC_i greater than or equal to LCC_mean
    OR
    KCC_i greater than or equal to KCC_mean
    OR
    RMSE_i less than or equal to RMSE_mean
end
Remove redundant features F_i from F_S
return F_S
```

To perform feature selection $SROCC_i$, LCC_i, KCC_i and $RMSE_i$ for each individual feature F_i and NR-IQA technique is computed. The quality score for each individual feature is computed using SVR. The SVR model is trained by using 80% images and 20% images are used for testing. Mean scores of $SROCC_{mean}$, LCC_{mean}, KCC_{mean} and $RMSE_{mean}$ over 1000 runs are considered for selecting features F_S, where $F_S \leq F_{All}$. Details of the proposed feature selection algorithms are given in Algorithm 1 to Algorithm 15.

After features are selected using newly proposed feature selection algorithms, the quality score of the image is predicted using support vector regression. SVR is implemented using LibSVM package [35]. SVR is given in [36] as

$$\xi(y) = \vartheta\beta(y) + c_1, \tag{5}$$

where y is the input features extracted using NR-IQA, β is the feature space, c_1 is a constant and ϑ represents the i^{th} instance weight. SVR aims to approximate a support vector machine function so that the error between $\xi(y)$ and the target value is minimized. All computations in SVM are performed using kernel function $k(m)$. The advantage of using kernel function is that the inner product can be taken without constructing the vector space by using kernel function. The radial function of order P is represented in [36] as

$$k(x) = \Sigma_{i=1}^{K}\alpha_i \frac{1}{(2\pi)^{\frac{P}{2}}\sigma_i^P} exp(-\frac{||x-c_i||}{2\sigma_i^2}) + b_2, \tag{6}$$

where c_i is the i^{th} Gaussian basis function center, σ_i is the standard deviation, α_i is the weight associated with the i^{th} Gaussian basis function and b_2 is a constant that represents the bias value.

4 Experimental results

4.1 IQA databases and evaluation parameters

There are various available subjective image quality assessment databases. To evaluate the performance of proposed feature selection algorithms three commonly used IQA databases are used i.e., LIVE [38], TID2008 [39] and CSIQ [40]. The LIVE database has 29 reference images. Five types of distortions are considered, namely, fast fading (FF), Gaussian blur (GB), JPEG2000 (JP2K), JPEG and white noise (WN). There are total 779 images with varying degree of distortions in the LIVE database. A total of 25 reference images are present in TID2008 database. 17 type of distortions are considered in the TID2008 database. Four different levels of individual distortions are used to degrade each reference image. CSIQ database consists of 30 reference images. Images affected by five types of distortion i.e., JPEG, JP2K, contrast, WN and GB are considered in CSIQ database. The quality assessment of images in CSIQ database is performed by 35 observers.

To establish database independence, feature selection is performed by taking into account all the extracted image features in LIVE database for each NR-IQA technique. The selected features from LIVE database are used for the prediction of quality score in CSIQ and TID2008 databases for a particular NR-IQA technique. In this work, four common type of distortions from TID2008 and CSIQ database are used i.e., GB, JP2K, JPEG, WN. To train SVR, the dataset is divided into non-overlapping training and testing sets consisting of 80% and 20% data respectively. To negate the effect of any bias 1000 iterations are used to randomly select non-overlapping training and testing sets. Grid test is applied on each NR-IQA technique to select SVR parameters. SVR is implemented using LibSVM package [35]. SROCC, LCC, KCC and RMSE are used for the performance comparison of NR-IQA techniques.

4.2 Performance comparison

NSS based NR-IQA techniques perform under the assumption that certain properties are possessed by natural images, which are represented by NSS features. These NSS properties change in the presence of distortion. Divergence of these NSS properties from natural image are used for estimation of image quality score. As feature selection algorithm selects a subset of features, therefore, effect of selected features on existing NR-IQA techniques should be addressed. A normalized histogram of features selected for each NR-IQA technique is shown in Fig. 3. It can be observed that the properties of distorted and undistorted images are differ-

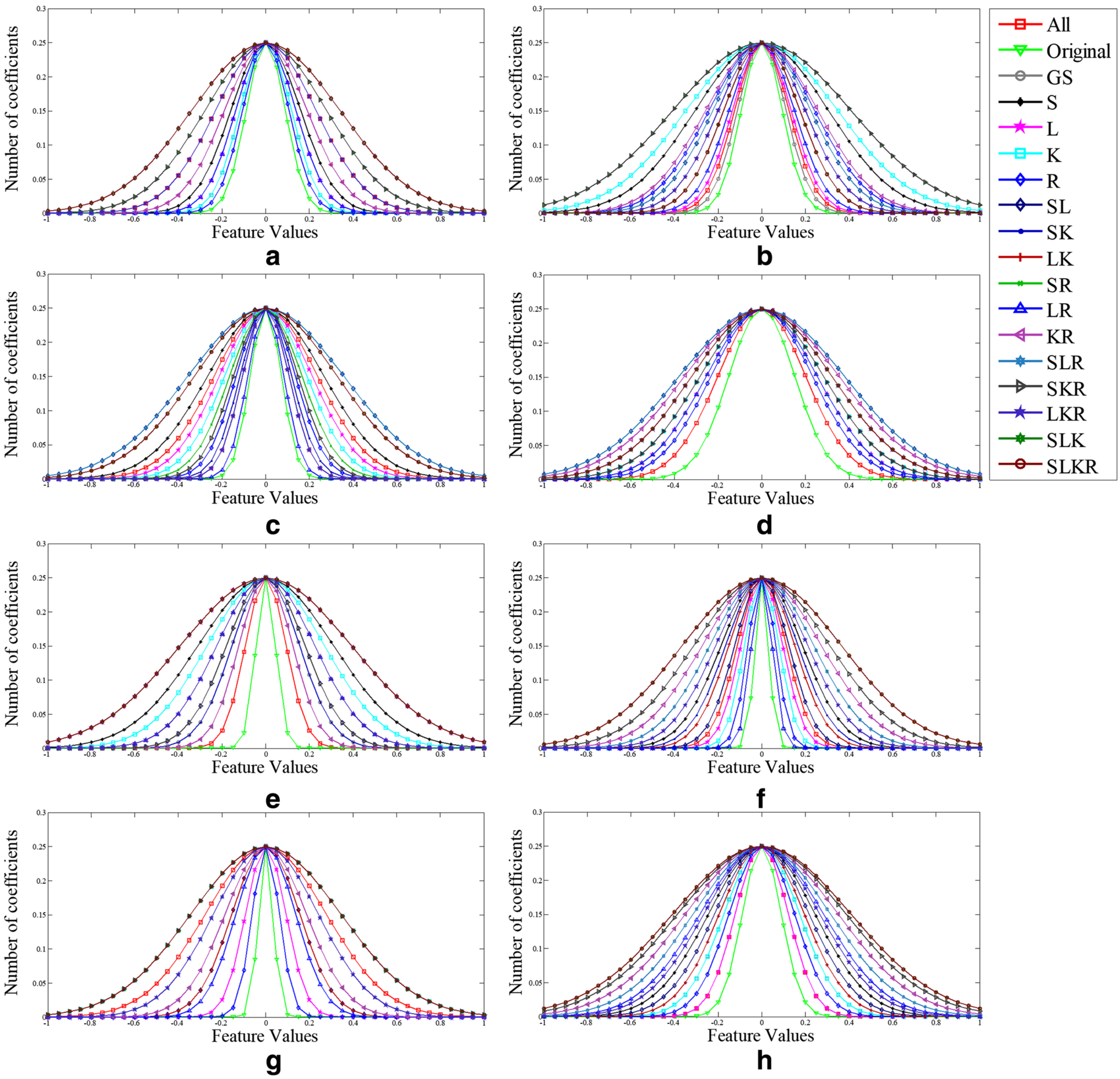

Fig. 3 Effect of proposed feature selection algorithms on normalized feature histogram for different NR-IQA techniques **a** BLIINDS-II [37], **b** BRISQUE [25], **c** CurveletQA [17], **d** SSEQ [27], **e** GM-LOG [26], **f** IL-NIQE [34], **g** OG-IQA [18], **h** TCLT [19]

Table 1 Performance comparison in terms of SROCC median value for individual distortion on different databases using prposed feature selection algorithms

NR-IQA	Database	Distortion	Feature selection algorithm																
Technique		Type	All	GS [33]	S	L	K	R	SL	SK	LK	SR	LR	KR	SLR	SKR	LKR	SLK	$SLKR$
BLIINDS-II [37]	LIVE	FF	0.8893	**0.9133**	**0.9043**	**0.8913**	**0.9043**	**0.8972**	**0.9018**	**0.9043**	**0.9018**	**0.9043**	**0.8913**	**0.9043**	**0.9018**	**0.9043**	**0.9018**	**0.9018**	**0.9018**
		GB	0.9231	**0.9246**	0.9108	0.9078	0.9108	0.9034	0.9152	0.9108	0.9152	0.9152	0.9078	0.9152	0.9152	0.9152	0.9152	0.9152	0.9152
		JP2K	0.9285	0.9104	**0.9345**	**0.9379**	**0.9345**	**0.9372**	**0.9345**	**0.9345**	**0.9345**	**0.9345**	**0.9379**	**0.9379**	**0.9345**	**0.9345**	**0.9345**	**0.9345**	**0.9345**
		JPEG	0.9422	0.8127	**0.9548**	**0.9528**	**0.9528**	**0.9527**	**0.9548**	**0.9548**	**0.9528**	**0.9548**	**0.9528**	**0.9528**	**0.9548**	**0.9548**	**0.9528**	**0.9548**	**0.9548**
		WN	0.9691	0.9266	0.9666	0.9686	**0.9711**	0.9605	0.9681	0.9666	0.9681	0.9627	0.9632	0.9627	0.9627	0.9627	0.9627	0.9681	0.9627
	CSIQ	GB	0.8816	**0.8854**	0.8812	**0.8865**	0.8812	**0.8848**	**0.8861**	0.8812	**0.8861**	**0.8861**	**0.8865**	**0.8861**	**0.8861**	**0.8861**	**0.8861**	**0.8861**	**0.8861**
		JP2K	**0.9155**	0.8979	0.9141	0.9137	0.9141	0.9137	0.9141	0.9141	0.9141	0.9141	0.9137	0.9137	0.9141	0.9141	**0.9157**	0.9141	0.9141
		JPEG	0.8739	0.8492	**0.8794**	0.8701	0.8701	0.8701	**0.8794**	**0.8794**	0.8701	**0.8794**	0.8701	0.8701	**0.8794**	**0.8794**	0.8701	**0.8794**	**0.8794**
		WN	**0.9453**	0.9275	0.9359	0.9404	0.9319	0.9230	0.9413	0.9359	0.9413	0.9373	0.9359	0.9373	0.9373	0.9373	0.9373	0.9413	0.9373
	TID2008	GB	0.8662	0.8451	**0.9012**	**0.8975**	**0.9013**	**0.8883**	**0.9016**	**0.9013**	**0.9016**	**0.8977**	**0.8975**	**0.8977**	**0.9016**	**0.8977**	**0.9016**	**0.9016**	**0.9016**
		JP2K	0.8947	**0.9218**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**	**0.9323**
		JPEG	**0.8331**	0.7549	0.8150	0.7865	0.7865	0.7850	0.8150	0.8150	0.7865	0.8150	0.7865	0.7865	0.8150	0.8150	0.7865	0.8150	0.8150
		WN	**0.7744**	0.6999	0.6867	0.7263	0.7082	0.7098	0.7217	0.6867	0.7217	0.7273	0.7323	0.7273	0.7273	0.7273	0.7273	0.7217	0.7273
BRISQUE [41]	LIVE	FF	0.8768	0.8133	**0.8874**	**0.8874**	**0.8874**	**0.8891**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**	**0.8874**
		GB	0.9511	0.8916	**0.9711**	**0.9559**	**0.9711**	**0.9830**	**0.9588**	**0.9711**	**0.9588**	**0.9711**	**0.9559**	**0.9711**	**0.9588**	**0.9711**	**0.9588**	**0.9588**	**0.9588**
		JP2K	0.9139	0.8011	**0.9699**	0.9137	**0.9699**	**0.9638**	0.9136	**0.9699**	**0.9150**	**0.9699**	**0.9150**	**0.9150**	**0.9150**	**0.9699**	**0.9150**	**0.9150**	**0.9150**
		JPEG	0.9647	0.8986	**0.9877**	**0.9834**	**0.9832**	**0.9905**	**0.9868**	**0.9877**	**0.9834**	**0.9877**	**0.9834**	**0.9832**	**0.9868**	**0.9877**	**0.9834**	**0.9868**	**0.9868**
		WN	0.9787	0.9635	**0.9897**	**0.9892**	**0.9920**	**0.9851**	**0.9892**	**0.9897**	**0.9892**	**0.9897**	**0.9892**	**0.9841**	**0.9892**	**0.9897**	**0.9892**	**0.9892**	**0.9892**
	CSIQ	GB	0.7833	**0.8536**	**0.8963**	**0.9030**	**0.8932**	**0.9030**	**0.8928**	**0.9030**	**0.8928**	**0.9030**	**0.8932**	**0.9030**	**0.8928**	**0.9030**	**0.8928**	**0.8928**	**0.8928**
		JP2K	0.8418	0.8309	**0.8790**	**0.8863**	**0.8716**	**0.8863**	**0.8716**	**0.8863**	**0.8716**	**0.8863**	**0.8716**	**0.8716**	**0.8716**	**0.8863**	**0.8716**	**0.8716**	**0.8716**
		JPEG	0.7749	**0.8616**	**0.8104**	**0.7928**	**0.7880**	**0.7940**	**0.7864**	**0.7928**	**0.7880**	**0.7928**	**0.7880**	**0.7940**	**0.7864**	**0.7928**	**0.7880**	**0.7864**	**0.7864**
		WN	0.9301	**0.9568**	**0.9604**	**0.9568**	**0.9577**	**0.9631**	**0.9577**	**0.9568**	**0.9577**	**0.9568**	**0.9577**	**0.9631**	**0.9577**	**0.9568**	**0.9577**	**0.9577**	**0.9577**
	TID2008	GB	0.8810	0.7398	**0.8895**	0.8096	**0.8895**	0.8673	0.8644	**0.8895**	0.8644	**0.8895**	0.8096	**0.8895**	0.8644	**0.8895**	0.8644	0.8644	0.8644
		JP2K	0.8321	0.7832	0.8310	**0.8534**	0.8310	0.8143	**0.8534**	0.8310	**0.8534**	0.8310	**0.8534**	**0.8534**	**0.8534**	0.8310	**0.8534**	**0.8534**	**0.8534**
		JPEG	0.9241	0.8090	**0.9511**	**0.9368**	**0.9301**	0.9043	**0.9496**	**0.9511**	**0.9368**	**0.9511**	**0.9368**	**0.9301**	**0.9496**	**0.9511**	**0.9368**	**0.9496**	**0.9496**
		WN	0.8290	0.7158	**0.8452**	**0.8437**	**0.8656**	**0.8708**	**0.8437**	**0.8452**	**0.8437**	**0.8452**	**0.8437**	**0.8720**	**0.8437**	**0.8452**	**0.8437**	**0.8437**	**0.8437**
CurveletQA [17]	LIVE	FF	0.9006	0.8261	**0.9038**	0.8952	0.9001	0.8705	**0.9075**	**0.9038**	**0.9021**	**0.9038**	0.8952	0.9001	**0.9075**	**0.9038**	**0.9021**	**0.9075**	**0.9075**
		GB	0.9651	0.9365	**0.9742**	**0.9749**	**0.9749**	**0.9740**	**0.9749**	**0.9749**	**0.9740**	**0.9740**	**0.9749**	**0.9742**	**0.9749**	**0.9742**	**0.9740**	**0.9740**	**0.9740**
		JP2K	0.9377	0.8890	**0.9424**	**0.9424**	**0.9424**	0.9367	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**	**0.9424**
		JPEG	**0.9117**	0.8770	0.9101	0.9101	0.9082	0.8752	0.9101	0.8354	0.7722	0.8354	0.7722	0.7722	0.8354	0.8354	0.7722	0.9101	0.9101
		WN	**0.9876**	0.9828	**0.9876**	**0.9876**	**0.9876**	0.9856	0.9872	**0.9876**	**0.9876**	**0.9876**	**0.9876**	**0.9876**	**0.9876**	**0.9876**	**0.9876**	**0.9876**	**0.9876**
	CSIQ	GB	0.8827	**0.9010**	0.8680	**0.8840**	0.8736	**0.8849**	0.8825	0.8736	**0.8845**	**0.8845**	**0.8840**	**0.8847**	**0.8840**	**0.8847**	**0.8845**	**0.8845**	**0.8845**
		JP2K	0.5500	**0.5848**	0.5482	0.5482	0.5482	**0.6069**	0.5482	0.5482	0.5482	0.5482	0.5482	0.5482	0.5482	0.5482	0.5482	0.5482	0.5482

Table 1 (continued)

NR-IQA	Database	Distortion	Feature selection algorithm																
Technique		Type	All	GS [33]	S	L	K	R	SL	SK	LK	SR	LR	KR	SLR	SKR	LKR	SLK	$SLKR$
		JPEG	0.8648	0.8392	**0.8777**	0.7911	0.7911	0.7911	**0.8777**	**0.8777**	0.7911	**0.8777**	0.7911	0.7911	**0.8777**	**0.8777**	0.7911	**0.8777**	**0.8777**
		WN	0.8589	**0.9573**	**0.9023**	**0.9023**	**0.9083**	**0.8823**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**	**0.9023**
	TID2008	GB	0.9233	0.8823	0.9158	**0.9304**	0.9158	0.9323	**0.9304**	0.9158	**0.9293**	0.9323	**0.9304**	**0.9304**	**0.9304**	**0.9304**	**0.9293**	**0.9293**	**0.9293**
		JP2K	0.9056	0.8887	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**	**0.9113**
		JPEG	0.9075	0.8870	**0.9403**	0.8283	0.8283	0.8283	**0.9403**	**0.9403**	0.8283	**0.9403**	0.8283	0.8283	**0.9403**	**0.9403**	0.8283	**0.9403**	**0.9403**
		WN	0.9059	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9101**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**	**0.9128**
SSEQ [27]	LIVE	FF	0.9035	0.8778	**0.9410**	**0.9419**	**0.9410**	**0.9410**	**0.9419**	**0.9410**	**0.9419**	**0.9410**	**0.9419**	**0.9410**	**0.9419**	**0.9410**	**0.9419**	**0.9419**	**0.9419**
		GB	**0.9607**	0.9281	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526
		JP2K	0.9422	0.9365	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**	**0.9660**
		JPEG	0.9510	0.8745	0.9508	0.9423	**0.9538**	0.9299	**0.9538**	**0.9538**	**0.9538**	**0.9538**	0.9423	**0.9538**	**0.9538**	**0.9538**	**0.9538**	**0.9538**	**0.9538**
		WN	0.9784	0.9352	**0.9810**	**0.9810**	**0.9879**	**0.9884**	**0.9810**	**0.9810**	**0.9810**	**0.9810**	**0.9810**	**0.9884**	**0.9810**	**0.9810**	**0.9810**	**0.9810**	**0.9810**
	CSIQ	GB	**0.8547**	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412	0.8412
		JP2K	0.8356	0.8283	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**	**0.8527**
		JPEG	0.8282	**0.8616**	**0.8496**	**0.8494**	**0.8496**	**0.8494**	**0.8496**	**0.8496**	**0.8496**	**0.8496**	**0.8494**	**0.8496**	**0.8496**	**0.8496**	**0.8496**	**0.8496**	**0.8496**
		WN	0.9123	**0.9257**	**0.9288**	**0.9288**	**0.9364**	**0.9390**	**0.9288**	**0.9288**	**0.9288**	**0.9288**	**0.9288**	**0.9390**	**0.9288**	**0.9288**	**0.9288**	**0.9288**	**0.9288**
	TID2008	GB	**0.8421**	0.7925	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120	0.8120
		JP2K	0.8722	**0.8857**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**	**0.8767**
		JPEG	0.8075	0.7459	**0.8602**	**0.8616**	**0.8602**	**0.8302**	**0.8602**	**0.8602**	**0.8602**	**0.8602**	**0.8616**	**0.8602**	**0.8602**	**0.8602**	**0.8602**	**0.8602**	**0.8602**
		WN	**0.8256**	0.8238	0.7864	0.7864	0.7751	0.8030	0.7864	0.7864	0.7864	0.7864	0.7864	0.8030	0.7864	0.7864	0.7864	0.7864	0.7864
GM-LOG [26]	LIVE	FF	0.9010	0.8990	**0.9334**	**0.9314**	**0.9334**	**0.9334**	**0.9314**	**0.9334**	**0.9314**	**0.9334**	**0.9314**	**0.9334**	**0.9314**	**0.9334**	**0.9314**	**0.9314**	**0.9314**
		GB	0.9395	0.8941	**0.9705**	**0.9750**	**0.9705**	**0.9599**	**0.9750**	**0.9705**	**0.9750**	**0.9602**	**0.9750**	**0.9602**	**0.9750**	**0.9602**	**0.9750**	**0.9750**	**0.9750**
		JP2K	0.9283	0.8964	**0.9468**	**0.9427**	**0.9468**	**0.9468**	**0.9427**	**0.9468**	**0.9427**	**0.9468**	**0.9427**	**0.9427**	**0.9427**	**0.9468**	**0.9427**	**0.9427**	**0.9427**
		JPEG	0.9659	0.9039	**0.9686**	**0.9686**	**0.9686**	**0.9700**	0.9657	**0.9686**	**0.9686**	**0.9686**	**0.9686**	**0.9686**	**0.9686**	**0.9686**	**0.9686**	**0.9686**	**0.9686**
		WN	0.9853	0.9813	0.9851	**0.9878**	**0.9883**	**0.9873**	**0.9878**	**0.9868**	**0.9878**	**0.9868**	**0.9878**	**0.9873**	**0.9878**	**0.9868**	**0.9878**	**0.9878**	**0.9878**
	CSIQ	GB	0.9070	0.8690	**0.9342**	**0.9368**	**0.9342**	**0.9270**	**0.9368**	**0.9342**	**0.9368**	**0.9270**	**0.9368**	**0.9270**	**0.9368**	**0.9270**	**0.9368**	**0.9368**	**0.9368**
		JP2K	0.9173	0.9146	**0.9413**	**0.9442**	**0.9413**	**0.9418**	**0.9442**	**0.9413**	**0.9442**	**0.9413**	**0.9442**	**0.9442**	**0.9442**	**0.9413**	**0.9442**	**0.9442**	**0.9442**
		JPEG	0.9328	0.8852	**0.9368**	**0.9368**	**0.9368**	**0.9341**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**	**0.9368**
		WN	0.9406	**0.9497**	0.9357	0.9379	0.9384	0.9366	0.9375	0.9357	0.9375	0.9357	0.9380	0.9366	0.9375	0.9357	0.9375	0.9375	0.9375
	TID2008	GB	0.8812	0.8376	**0.9128**	**0.9233**	**0.9128**	**0.9128**	**0.9248**	**0.9128**	**0.9248**	**0.9128**	**0.9233**	**0.9128**	**0.9248**	**0.9128**	**0.9248**	**0.9248**	**0.9248**
		JP2K	0.9263	0.8947	**0.9353**	**0.9368**	**0.9353**	**0.9353**	**0.9368**	**0.9353**	**0.9368**	**0.9353**	**0.9368**	**0.9368**	**0.9368**	**0.9353**	**0.9368**	**0.9368**	**0.9368**
		JPEG	0.9338	0.9023	**0.9488**	**0.9488**	**0.9488**	**0.9477**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**	**0.9488**
		WN	0.9068	0.8947	0.9066	**0.9127**	0.9006	0.8976	**0.9127**	0.9066	**0.9127**	0.9066	**0.9128**	0.9067	**0.9127**	0.9066	**0.9127**	**0.9127**	**0.9127**
IL-NIQE [34]	LIVE	FF	0.8881	**0.8910**	**0.8905**	0.8832	**0.8892**	0.8875	0.8812	**0.8905**	**0.8905**	**0.8891**	0.8812	**0.8891**	**0.8891**	**0.8885**	0.8812	**0.8896**	**0.8896**

Table 1 (continued)

NR-IQA Technique	Database	Distortion Type	Feature selection algorithm All	GS [33]	S	L	K	R	SL	SK	LK	SR	LR	KR	SLR	SKR	LKR	SLK	$SLKR$
		GB	0.9153	0.9121	**0.9178**	**0.9160**	0.9145	**0.9176**	**0.9181**	**0.9178**	**0.9178**	**0.9210**	**0.9181**	**0.9210**	**0.9210**	0.9120	**0.9181**	**0.9251**	**0.9251**
		JP2K	0.8939	0.8913	**0.9010**	**0.8945**	**0.8943**	0.8932	0.8911	**0.9010**	**0.9010**	0.8890	0.8021	0.889	0.889	0.8901	0.8911	**0.9019**	**0.9019**
		JPEG	0.9418	**0.9458**	**0.9472**	**0.9452**	**0.9432**	0.9402	**0.9487**	**0.9472**	**0.9472**	**0.9489**	**0.9487**	**0.9489**	**0.9489**	**0.9513**	**0.9487**	0.9389	0.9389
		WN	0.9807	**0.9832**	**0.9812**	0.9792	**0.9812**	**0.9832**	**0.9812**	**0.9812**	**0.9812**	**0.9829**	**0.9812**	**0.9829**	**0.9829**	**0.9843**	**0.9812**	**0.9852**	**0.9852**
	CSIQ	GB	0.8578	0.8528	**0.8594**	0.8535	0.8522	**0.8621**	**0.8591**	0.8542	0.8542	0.8434	**0.8591**	**0.8634**	0.8434	**0.8590**	**0.8591**	0.8521	0.8521
		JP2K	0.9063	**0.9072**	0.9012	0.9005	**0.9091**	**0.9072**	**0.9123**	0.9012	0.9012	0.8963	**0.9123**	0.8963	0.8963	0.9055	**0.9123**	**0.9148**	**0.9148**
		JPEG	0.8991	0.8954	**0.9032**	**0.9021**	0.8933	0.8972	0.8932	**0.9032**	**0.9032**	**0.9045**	0.8932	**0.9045**	**0.9045**	**0.9008**	0.8932	**0.9014**	**0.9014**
		WN	0.8502	**0.8543**	0.8476	**0.8532**	**0.8513**	**0.8514**	0.8481	**0.8576**	0.8476	**0.8631**	0.8481	**0.8631**	**0.8631**	**0.8572**	0.8481	**0.8591**	**0.8591**
	TID2008	GB	0.8242	**0.8272**	**0.8272**	**0.8269**	0.8210	**0.8254**	**0.8311**	0.8212	0.8212	**0.8269**	**0.8311**	**0.8269**	**0.8269**	**0.8271**	**0.8311**	**0.8294**	**0.8294**
		JP2K	0.8678	0.8666	0.8654	0.8621	**0.8691**	0.8623	**0.8692**	0.8654	0.8654	0.8621	**0.8692**	0.8621	0.8621	**0.8711**	**0.8692**	**0.8721**	**0.8721**
		JPEG	0.8379	0.8350	**0.8431**	0.8335	0.8351	0.821	0.8321	**0.8431**	**0.8431**	**0.8385**	0.8321	**0.8385**	**0.8385**	**0.8391**	0.8321	**0.8412**	**0.8412**
		WN	0.8790	0.8753	**0.8812**	**0.8821**	0.8767	0.8613	**0.8834**	0.8752	0.8752	**0.8846**	**0.8834**	**0.8846**	**0.8846**	**0.8857**	**0.8834**	**0.8813**	**0.8813**
OG-IQA [18]	LIVE	FF	0.8669	0.7783	0.8263	0.8622	0.8622	0.8622	**0.8704**	0.8622	0.8622	0.8622	**0.8704**	0.8622	**0.8704**	**0.8704**	**0.8704**	**0.8704**	**0.8704**
		GB	0.9518	0.8687	0.9291	**0.9619**	0.9496	**0.9619**	**0.9545**	**0.9619**	**0.9619**	**0.9619**	**0.9545**	**0.9619**	0.9385	**0.9545**	**0.9545**	**0.9545**	**0.9545**
		JP2K	0.9522	0.8984	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**	**0.9702**
		JPEG	0.9672	0.7872	**0.9744**	0.9516	0.9265	0.9265	0.9265	0.9516	0.9265	0.9516	0.9516	0.9265	0.9265	0.9516	0.9516	0.9265	0.9265
		WN	0.9813	0.9665	0.9650	**0.9961**	**0.9961**	**0.9961**	0.9636	**0.9961**	**0.9961**	**0.9961**	0.9636	**0.9961**	0.9636	0.9636	0.9636	0.9636	0.9636
	CSIQ	GB	0.8590	**0.8705**	0.8532	**0.8705**	**0.8667**	**0.8705**	**0.8607**	**0.8705**	**0.8705**	**0.8705**	**0.8607**	**0.8705**	0.8541	**0.8607**	**0.8607**	**0.8607**	**0.8607**
		JP2K	0.8580	0.7717	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**	**0.8717**
		JPEG	0.7993	0.7976	**0.8570**	**0.8278**	**0.8147**	**0.8147**	**0.8147**	**0.8278**	**0.8147**	**0.8278**	**0.8278**	**0.8147**	**0.8147**	**0.8278**	**0.8278**	**0.8147**	**0.8147**
		WN	0.8727	0.8185	0.7593	0.8656	0.8656	0.8656	**0.8736**	0.8656	0.8656	0.8656	**0.8736**	0.8656	**0.8736**	**0.8736**	**0.8736**	**0.8736**	**0.8736**
	TID2008	GB	0.8902	0.7759	0.7656	0.8707	0.7639	0.8707	**0.8932**	0.8707	0.8707	0.8707	**0.8932**	0.8707	0.8881	**0.8932**	**0.8932**	**0.8932**	**0.8932**
		JP2K	0.9068	0.8857	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**	**0.9169**
		JPEG	**0.9188**	0.7474	0.8015	0.8754	0.9008	0.9008	0.9008	0.8754	0.9008	0.8754	0.8754	0.9008	0.9008	0.8754	0.8754	0.9008	0.9008
		WN	0.8857	0.7504	0.7806	**0.8901**	**0.8901**	**0.8901**	0.8815	**0.8901**	**0.8901**	**0.8901**	0.8815	**0.8901**	0.8815	0.8815	0.8815	0.8815	0.8815
TCLT [19]	LIVE	FF	0.9210	0.9177	**0.9282**	0.9176	**0.9249**	0.9158	0.9188	**0.9282**	**0.9282**	**0.9312**	**0.9288**	**0.9312**	**0.9312**	**0.9285**	0.9188	**0.9350**	**0.9350**
		GB	0.9530	**0.9568**	**0.9579**	**0.9531**	0.9498	**0.9533**	**0.9594**	**0.9579**	**0.9579**	**0.9595**	**0.9594**	**0.9595**	**0.9595**	0.9512	**0.9594**	**0.9620**	**0.9620**
		JP2K	0.9170	**0.9541**	**0.9198**	**0.9212**	**0.9222**	**0.9211**	0.9162	**0.9198**	**0.9198**	0.9149	0.9162	0.9149	0.9149	0.9101	0.9162	**0.9245**	**0.9245**
		JPEG	0.9250	**0.9690**	**0.9297**	**0.9287**	**0.9263**	0.9222	**0.9311**	**0.9297**	**0.9297**	**0.9334**	**0.9311**	**0.9334**	**0.9334**	**0.9383**	**0.9311**	0.9210	0.9210
		WN	0.9810	**0.9863**	**0.9876**	0.9792	**0.9829**	**0.9832**	**0.9842**	**0.9876**	**0.9876**	**0.9829**	**0.9842**	**0.9829**	**0.9829**	**0.9843**	**0.9842**	**0.9852**	**0.9852**
	CSIQ	GB	0.8980	0.8076	**0.9042**	0.8935	0.8922	**0.9021**	**0.8991**	0.8942	0.8942	0.8934	**0.8991**	**0.9034**	0.8934	**0.8990**	**0.8991**	0.8921	0.8921
		JP2K	0.9000	0.8041	**0.9156**	0.8905	**0.9191**	**0.9172**	**0.9223**	**0.9112**	**0.9112**	**0.9063**	**0.9223**	0.8963	0.8963	0.8955	**0.9223**	**0.9248**	**0.9248**
		JPEG	0.9150	**0.9214**	**0.9232**	**0.9221**	0.9033	0.9072	0.9032	**0.9232**	**0.9232**	**0.9245**	0.9032	**0.9245**	**0.9245**	**0.9208**	0.9032	**0.9214**	**0.9214**

Table 1 (continued)

NR-IQA	Database	Distortion	Feature selection algorithm																
Technique		Type	All	GS [33]	S	L	K	R	SL	SK	LK	SR	LR	KR	SLR	SKR	LKR	SLK	$SLKR$
		WN	0.9100	**0.9299**	0.9076	**0.9232**	**0.9213**	**0.9214**	**0.9181**	0.9076	0.9076	**0.9331**	**0.9181**	**0.9331**	**0.9331**	**0.9272**	0.9081	**0.9391**	**0.9391**
	TID2008	GB	0.8640	**0.9090**	0.8612	**0.8669**	0.8610	**0.8654**	**0.8711**	0.8612	0.8612	**0.8669**	**0.8711**	**0.8669**	**0.8669**	**0.8671**	**0.8711**	**0.8694**	**0.8694**
		JP2K	0.9300	0.8730	**0.9354**	0.9221	**0.9391**	0.9223	**0.9392**	0.9254	0.9254	0.9221	**0.9392**	0.9221	0.9221	**0.9411**	0.9292	**0.9421**	**0.9421**
		JPEG	0.8780	**0.8789**	**0.8831**	0.8735	0.8751	0.8721	0.8721	**0.8831**	**0.8831**	**0.8885**	0.8721	**0.8885**	**0.8885**	**0.8891**	0.8721	**0.8812**	**0.8812**
		WN	0.8390	0.8308	**0.8421**	**0.8421**	0.8267	0.8213	**0.8434**	0.8252	0.8252	**0.8446**	**0.8434**	**0.8446**	**0.8446**	**0.8457**	**0.8434**	**0.8413**	**0.8413**
Hit count			11	30	71	67	65	62	73	71	71	75	73	75	75	79	73	82	82

ent and this difference is increased when feature selection algorithms are used. Feature selection algorithms select features for NR-IQA that are most affected when distortion is present in the image. Figure 3 validates that the deviation in NSS properties between natural and distorted images are effectively represented when proposed feature selection algorithms are used.

The SROCC score for each distortion type over three commonly used IQA databases, fifteen proposed feature selection algorithms and eight NR-IQA techniques i.e., BLINDS II [37], BRISQUE [25], curveletQA [17], SSEQ [27], GM-LOG [26], IL-NIQE [34], OG-IQA [18], TCLT [19] is presented in Table 1. The performance of NR-IQA techniques is improved for majority of distortions when proposed feature selection algorithms are used. Hit count in Table 1 indicates the number of times each algorithm shows better or equal performance in comparison with using all the features. The bold face values in Table 1 also represent the performance of feature selection algorithms that outperform NR-IQA techniques using all the features. The highest hit count of 82 is achieved for $SLKR$ and SLK feature selection algorithms. The lowest hit count of 62 is achieved for R feature selection algorithm, which is still much higher than the hit count of 11 when using all the features and hit count of 30 for existing genetic search feature selection algorithm. It is evident from Table 1 that single correlation based feature selection algorithms are better than error based feature selection algorithm. Feature selection algorithms based on two correlations parameters are better than single correlation parameter based algorithms. The feature selection algorithms based on two correlations parameters with error are better than the algorithms based only on two correlations parameters. It is also observed that algorithms based on three correlations parameters show better results than the algorithms based only on two correlations parameters. Furthermore, two algorithms i.e., algorithm based on three correlations parameters (SLK) and algorithm based on three correlation parameters and error parameter (SLKR) show the best results.

Table 2 shows an overall performance comparison of the proposed feature selection algorithms for NR-IQA techniques. Bold face values in Table 2 represents better performance of feature selection algorithms when compared with all features and existing feature selection algorithm. For the overall performance it can be observed that algorithms based on three correlations parameters and error parameter i.e., $SLKR$ perform at par with algorithms based on three correlations parameters i.e., SLK. Algorithms based on two correlations parameters and error parameter perform better than algorithms based only on two correlations parameters i.e., SKR performs better than SK, LKR performs better than LK and SLR

Table 2 Proposed feature selection algorithms performance comparison averaged over all distortion types for each NR-IQA technque

NR-IQA technique	Feature selection algorithm	SROCC	LCC	KCC	RMSE
BLIINDS II [37]	All features	0.8948	0.9146	0.7413	2.7249
	GS [33]	0.8923	0.9103	0.7357	2.7891
	S	0.8935	0.9134	0.7379	2.7379
	L	0.8930	0.9104	0.7368	2.7653
	K	0.8923	0.9103	0.7357	2.7891
	R	0.8891	0.9101	0.7352	2.7946
	SL	**0.8973**	**0.9176**	**0.7419**	**2.7154**
	SK	**0.8971**	**0.9150**	**0.7414**	**2.7232**
	LK	0.8943	0.9142	0.7390	2.7250
	SR	**0.8971**	**0.9150**	**0.7414**	**2.7232**
	LR	0.8930	0.9104	0.7368	2.7653
	KR	0.8943	0.9142	0.7390	2.7250
	SLR	**0.8973**	**0.9176**	**0.7419**	**2.7154**
	SKR	**0.8971**	**0.9150**	**0.7414**	**2.7232**
	LKR	0.8948	0.9146	0.7413	2.7249
	SLK	**0.8973**	**0.9176**	**0.7419**	**2.7154**
	SLKR	**0.8973**	**0.9176**	**0.7419**	**2.7154**
BRISQUE [41]	All features	0.8899	0.8962	0.7299	5.1886
	GS [33]	0.8880	0.8950	0.7263	5.1982
	S	**0.9169**	**0.9255**	**0.7497**	**4.2513**
	L	**0.9022**	**0.9084**	**0.7336**	**5.0845**
	K	**0.9170**	**0.9258**	**0.7499**	**4.0403**
	R	**0.9127**	**0.9206**	**0.7481**	**4.4155**
	SL	**0.9120**	**0.9177**	**0.7453**	**4.8495**
	SK	**0.9205**	**0.9285**	**0.7500**	**3.7960**
	LK	**0.9107**	**0.9134**	**0.7394**	**4.9204**
	SR	**0.9205**	**0.9285**	**0.7500**	**3.7960**
	LR	**0.9059**	**0.9122**	**0.7358**	**5.0812**
	KR	**0.9164**	**0.9245**	**0.7490**	**4.4118**
	SLR	**0.9120**	**0.9177**	**0.7453**	**4.8495**
	SKR	**0.9205**	**0.9285**	**0.7500**	**3.7960**
	LKR	**0.9107**	**0.9134**	**0.7394**	**4.9204**
	SLK	**0.9084**	**0.9126**	**0.7379**	**5.0758**
	SLKR	**0.9084**	**0.9126**	**0.7379**	**5.0758**
CurveletQA [17]	All features	0.9095	0.9044	0.7610	3.8603
	GS [33]	0.8802	0.8787	0.7258	4.3299
	S	**0.9163**	**0.9196**	**0.7644**	**3.8504**
	L	0.9034	0.9042	0.7527	3.8940
	K	0.9021	0.9034	0.7512	3.8967
	R	0.8993	0.8794	0.7462	4.1212
	SL	**0.9187**	**0.9210**	**0.7822**	**3.8388**
	SK	0.8992	0.8793	0.7260	4.1295
	LK	0.8802	0.8787	0.7258	4.3299
	SR	0.9012	0.9026	0.7472	4.1144
	LR	0.8798	0.8779	0.7256	4.3420
	KR	0.8802	0.8787	0.7258	4.3299
	SLR	**0.9187**	**0.9210**	**0.7822**	**3.8388**
	SKR	0.9010	0.9001	0.7463	4.1202
	LKR	0.8802	0.8787	0.7258	4.3299
	SLK	**0.9185**	**0.9207**	**0.7666**	**3.8418**
	SLKR	**0.9185**	**0.9207**	**0.7666**	**3.8418**

Table 2 (continued)

NR-IQA technique	Feature selection algorithm	SROCC	LCC	KCC	RMSE
SSEQ [27]	All features	0.8844	0.9070	0.7039	3.3012
	GS [33]	**0.8886**	**0.9084**	**0.7119**	**3.2899**
	S	**0.8909**	**0.9087**	**0.7257**	**3.2449**
	L	**0.8900**	**0.9086**	**0.7241**	**3.2496**
	K	**0.8909**	**0.9087**	**0.7257**	**3.2449**
	R	**0.8886**	**0.9084**	**0.7119**	**3.2899**
	SL	**0.8964**	**0.9162**	**0.7310**	**2.8269**
	SK	**0.8909**	**0.9087**	**0.7257**	**3.2449**
	LK	**0.8910**	**0.9089**	**0.7273**	**3.2095**
	SR	**0.8900**	**0.9086**	**0.7241**	**3.2496**
	LR	**0.8900**	**0.9086**	**0.7241**	**3.2496**
	KR	**0.8935**	**0.9107**	**0.7297**	**3.1994**
	SLR	**0.8964**	**0.9162**	**0.7310**	**2.8269**
	SKR	**0.8909**	**0.9087**	**0.7257**	**3.2449**
	LKR	**0.8910**	**0.9089**	**0.7273**	**3.2095**
	SLK	**0.8910**	**0.9089**	**0.7273**	**3.2095**
	$SLKR$	**0.8910**	**0.9089**	**0.7273**	**3.2095**
GM-LOG [26]	All features	0.9390	0.9488	0.7562	3.3565
	GS [33]	**0.9508**	**0.9633**	**0.7662**	**2.6485**
	S	**0.9538**	**0.9662**	**0.7892**	**2.6219**
	L	**0.9558**	**0.9664**	**0.7914**	**2.6070**
	K	**0.9536**	**0.9647**	**0.7875**	**2.6231**
	R	**0.9518**	**0.9634**	**0.7856**	**2.6376**
	SL	**0.9558**	**0.9664**	**0.7914**	**2.6070**
	SK	**0.9508**	**0.9633**	**0.7662**	**2.6485**
	LK	**0.9528**	**0.9646**	**0.7870**	**2.6232**
	SR	**0.9496**	**0.9628**	**0.7635**	**3.3369**
	LR	**0.9528**	**0.9646**	**0.7870**	**2.6232**
	KR	**0.9496**	**0.9628**	**0.7635**	**3.3369**
	SLR	**0.9558**	**0.9664**	**0.7914**	**2.6070**
	SKR	**0.9518**	**0.9634**	**0.7856**	**2.6376**
	LKR	**0.9528**	**0.9646**	**0.7870**	**2.6232**
	SLK	**0.9558**	**0.9664**	**0.7914**	**2.6070**
	$SLKR$	**0.9558**	**0.9664**	**0.7914**	**2.6070**
IL-NIQE [34]	All features	0.8894	0.8943	0.7167	4.4310
	GS [33]	0.8860	0.8900	0.7137	4.6329
	S	**0.8916**	**0.8961**	**0.7198**	**4.2621**
	L	0.8887	0.8936	0.7158	4.4237
	K	0.8886	0.8934	0.7158	4.4232
	R	0.8865	0.8917	0.7152	4.5227
	SL	**0.8900**	**0.8946**	**0.7172**	**4.4263**
	SK	**0.8909**	**0.8956**	**0.7186**	**4.3426**
	LK	**0.8903**	**0.8953**	**0.7182**	**4.4210**
	SR	**0.8947**	**0.8992**	**0.7248**	**4.0123**
	LR	0.8860	0.8900	0.7137	4.6329
	KR	**0.8958**	**0.9002**	**0.7362**	**3.8422**
	SLR	**0.8947**	**0.8992**	**0.7248**	**4.0123**
	SKR	**0.8961**	**0.9016**	**0.7388**	**3.7523**
	LKR	**0.8944**	**0.8980**	**0.7212**	**4.1537**
	SLK	**0.8976**	**0.9032**	**0.7432**	**3.6921**
	$SLKR$	**0.8976**	**0.9032**	**0.7432**	**3.6921**
OG-IQA [18]	All features	0.9080	0.9198	0.7376	3.7080
	GS [33]	**0.9084**	**0.9204**	**0.7388**	**3.7040**

Table 2 (continued)

NR-IQA technique	Feature selection algorithm	SROCC	LCC	KCC	RMSE
	S	**0.9084**	**0.9204**	**0.7388**	**3.7040**
	L	0.8971	0.9113	0.7310	4.4015
	K	**0.9084**	**0.9204**	**0.7388**	**3.7040**
	R	0.8728	0.8866	0.7309	4.4157
	SL	0.9058	0.9174	0.7327	3.7648
	SK	0.9068	0.9182	0.7338	3.7413
	LK	0.9058	0.9174	0.7327	3.7648
	SR	0.9068	0.9182	0.7338	3.7413
	LR	0.9003	0.9130	0.7322	3.8785
	KR	0.9068	0.9182	0.7338	3.7413
	SLR	0.9073	0.9188	0.7351	3.7271
	SKR	**0.9084**	**0.9204**	**0.7388**	**3.7040**
	LKR	0.9073	0.9188	0.7351	3.7271
	SLK	**0.9084**	**0.9204**	**0.7388**	**3.7040**
	$SLKR$	**0.9084**	**0.9204**	**0.7388**	**3.7040**
TCLT [19]	All features	0.9105	0.9155	0.7397	4.8233
	GS [33]	**0.9113**	**0.9163**	**0.7401**	**3.4120**
	S	**0.9152**	**0.9200**	**0.7533**	**3.3698**
	L	0.9105	0.9155	0.7397	4.8233
	K	**0.9113**	**0.9163**	**0.7401**	**3.4120**
	R	0.9093	0.9143	0.7342	4.9432
	SL	**0.9140**	**0.9188**	**0.7498**	**3.3743**
	SK	**0.9121**	**0.9166**	**0.7452**	**3.3792**
	LK	**0.9121**	**0.9166**	**0.7452**	**3.3792**
	SR	**0.9199**	**0.9249**	**0.7606**	**3.3323**
	LR	**0.9192**	**0.9240**	**0.7588**	**3.3587**
	KR	**0.9199**	**0.9249**	**0.7606**	**3.3323**
	SLR	**0.9193**	**0.9243**	**0.7592**	**3.3532**
	SKR	**0.9201**	**0.9251**	**0.7610**	**3.3296**
	LKR	**0.9169**	**0.9216**	**0.7563**	**3.3652**
	SLK	**0.9224**	**0.9274**	**0.7624**	**3.3252**
	$SLKR$	**0.9224**	**0.9274**	**0.7624**	**3.3252**

performs better than SL. Algorithms based on single correlation parameter and error parameter perform better than algorithms based on single correlation parameter i.e., SR and S perform at par with each other, L and LR perform at par with each other, K and KR perform at par with each other i.e., S, SR, K, KR and GS improve the performance of four NR-IQA techniques and also degrade the performance of four NR-IQA techniques,

Table 3 Comparison of features selection algorithms on NR-IQA in terms of improvement of performance

NR-IQA technique	GS [33]	S	L	K	R	SL	SK	LK	SR	LR	KR	SLR	SKR	LKR	SLK	SLKR
BLIINDS-II [24]	×	×	×	×	×	✓	✓	×	✓	×	×	✓	✓	×	✓	✓
BRISQUE [25]	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
CurveletQA [17]	×	✓	×	×	×	✓	×	×	×	×	×	✓	×	×	✓	✓
SSEQ [27]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GM-LOG [26]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
IL-NIQE [34]	×	✓	×	×	×	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓
OG-IQA [18]	✓	✓	×	✓	×	×	×	×	×	×	×	×	✓	×	✓	✓
TCLT [19]	✓	✓	×	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Count	4	7	3	5	3	7	6	5	6	4	5	7	7	5	8	8

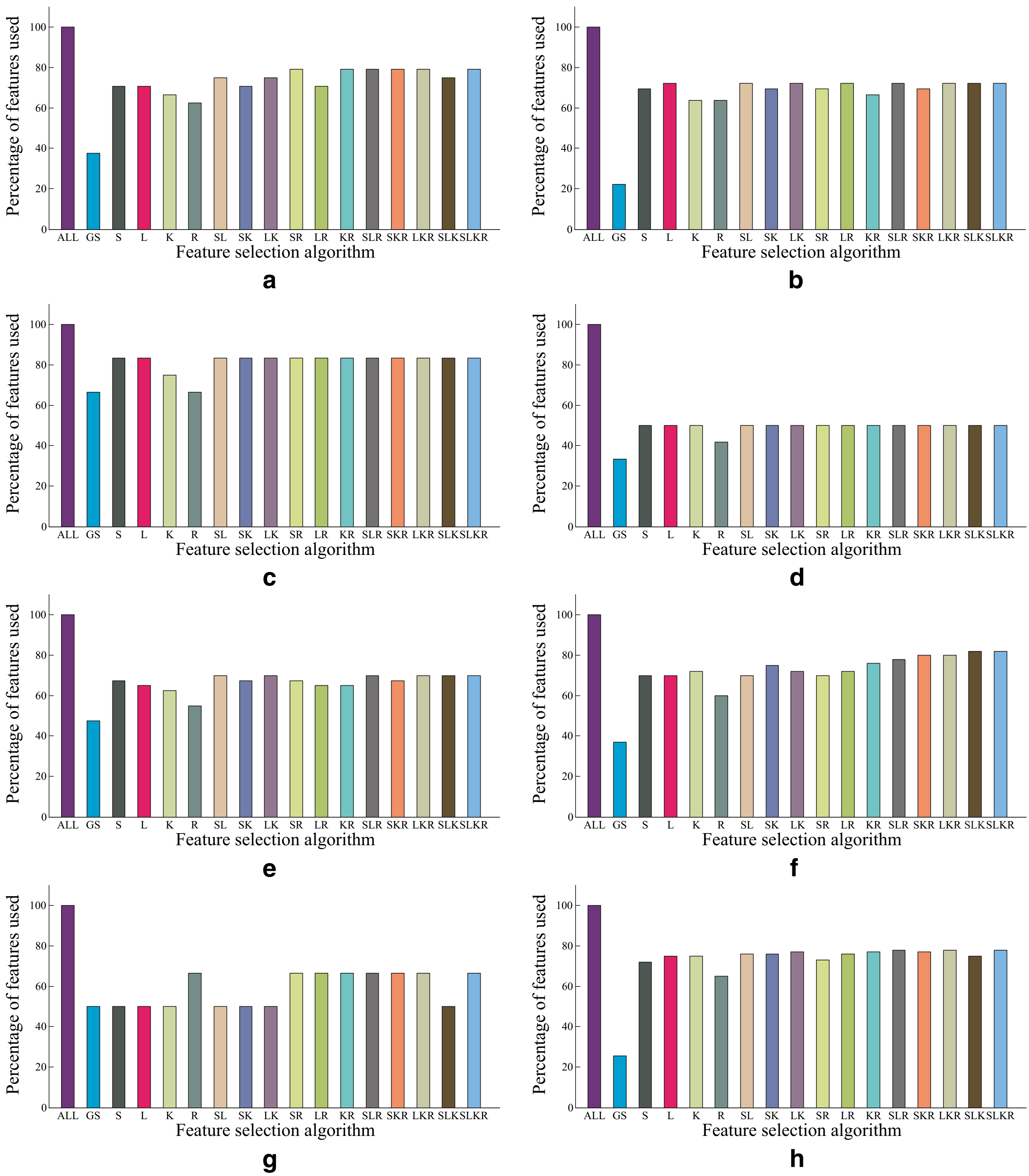

Fig. 4 Percentage of features selected by the proposed feature selection algorithms for different NR-IQA techniques **a** BLIINDS-II [37], **b** BRISQUE [41], **c** CurveletQA [17], **d** SSEQ [27], **e** GM-LOG [26], **f** IL-NIQE [34], **g** OG-IQA [18], **h** TCLT [19]

whereas L and LR improve the performance of three NR-IQA techniques and also degrade the performance of three NR-IQA techniques. Feature selection algorithms such as GS, R and K has reduced the most number of features in majority of NR-IQA techniques and does not show good performance because these algorithms discard relevant features. Therefore, in case of these algorithms all features show better results. On the other hand, feature selection algorithms such as SLK and $SLKR$ show better performance for all NR-IQA when compared with all features because these algorithms select the most relevant features for NR-IQA.

Table 3 shows the comparison of feature selection algorithms in terms of overall performance improvement. A (✓) indicated that the performance of a particular NR-IQA improves and a (✗) represents that the performance of particular NR-IQA does not improve after feature selection. It can be seen that SLKR and SLK improve the performance in all eight NR-IQA techniques, S, SL, SLR and SKR help to enhance the performance of seven IQA techniques, SK and SR upgrade the performance of six IQA techniques, K, LK, KR and LKR improve the performance of five IQA techniques, LR and GS [33] enhance the performance of four IQA techniques, L and R upgrade the performance of only three IQA techniques. It can be concluded from Table 3 that all feature selection algorithms with S parameter and its various combinations L, K and R perform superior to all other feature selection algorithms. Since SLK and SLKR improve the performance of all eight NR-IQA techniques therefore, these two proposed feature selection algorithms are NR-IQA independent.

The number of features used by different feature selection algorithms as compared to using all the features for each distortion type are shown in Fig. 4. It is evident that the proposed feature selection algorithms reduce the number of features for all NR-IQA techniques. Although GS [33] reduces the most amount of features for all the feature selection algorithms but the hit count of GS is only 29 as observed from Table 1 i.e., lowest among all the feature selection algorithms. Among the proposed algorithms R reduces the largest number of features for BLIINDS-II [37], CurveletQA [17], SSEQ [27], GM-LOG [26], IL-NIQE [34] and TCLT [19]. R and K perform the largest reduction in features for BRISQUE [41] whereas, GS, [33] S, L, K, SL, SK, LK and SLK reduce the most features for OG-IQA [18]. To implement NR-IQA in real-world scenarios the system can be connected to large database using a cloud infrastructure and the challenge of resource allocation to the users may be addressed using techniques such as [42]. Copy attacks such as change in orientation of an image, flipping, rescaling, change in illumination, contrast change and gaussian noise can affect the quality of an image [43] and a copy attack can be detected using features selected for BIQA techniques.

5 Conclusion

No-reference image quality assessment has gained importance due to wide-ranging use of multimedia content in daily life. The performance of NR-IQA techniques depends on extracted features to assess image quality, which can be degraded in the presence of redundant and irrelevant features. This paper proposes fifteen new feature selection algorithms based on SROCC, LCC, KCC and RMSE for NR-IQA techniques. The performance is evaluated on three IQA databases and eight NR-IQA techniques that extract features in different domains. The experimental results reveal that the performance of NR-IQA techniques using feature selection algorithms shows high correlation with mean observer score. The best overall performance is achieved by two algorithms i.e., algorithm based on three correlations parameters (SLK) and the algorithm based on three correlations and error parameters (SLKR). The experimental results also show that the proposed feature selection algorithms are database independent, since the features selected on LIVE database improve the performance of NR-IQA techniques over TID2008 and CSIQ IQA databases. The proposed SLK and SLKR feature selection algorithms are also NR-IQA technique independent since these algorithms improve the performance of all eight NR-IQA techniques.

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