Image denoising based on BCOLTA: Dataset and study

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Abstract
Robot deburring is an effective method for improving the surface quality of the high-voltage copper contact. The first step of robot deburring is to acquire the burr images. We propose a new burr mathematical model and build a real burr image dataset for burr image denoising. In order to improve burr image denoising effects of the high-voltage copper contact, this study proposes an online burr image denoising algorithm, that is, block cosparsity overcomplete learning transform algorithm (BCOLTA). The penalty term and the condition number are affected by the burr parameter. The clustering and transform alternate minimisation algorithms are adopted to achieve lower computational cost and better denoising effect. In addition, BCOLTA also has a good adaptibility to inherent noise images, especially in Gaussian noise. Compared with other traditional and deep learning algorithms by no reference and full reference image quality assessment methods, BCOLTA has state-of-the-art denoising effects and computational complexity on dealing with burr images. This research will play an important role in the intelligent manufacturing field.

1 | INTRODUCTION
Burr is an excessive part of the workpiece in the process of mechanical processing (such as edge, flash, sharp corner, splash etc.) [1]. The appearance of the burr will have a bad influence on the precision, appearance quality, service life, assembly precision, service requirements, reprocessing positioning, and operation safety of the parts and greatly reduce the performance, reliability and stability of the whole mechanical system. High-voltage circuit breaker plays a control and protection role in the high-voltage circuit. The high-voltage copper contact is the key contact element of the high-voltage circuit breaker. Copper contacts and fingers of the high-voltage circuit breakers produce lots of burrs in the process of machining. Burr is easy to cause the phenomenon of point discharge, increase copper contact arc ablation, greatly shorten the service life of copper contact, produce poisonous metallic steam and powder, reduce dielectric insulation strength, impact breaker breaking capacity and cause immeasurable potential safety hazard. Therefore, it is necessary to remove the burrs. In this study, one of the representative copper contacts with small size and complex structure is used as a research object, without changing the physical and chemical properties of copper contact, how to improve the quality of the contact and reduce the cost in high-voltage copper contact deburring is important. Based on the machine vision, robot deburring is the most feasible scheme at present. The first step of robot deburring is to obtain images of high-voltage copper contact [2]. Image denoising is a key step in image preprocessing [3–5].

At present, there are many image denoising algorithms [6–14]. Kostadin gives a block-matching 3D algorithm (BM3D) algorithm [15] to implement image denoising. This algorithm is currently one of the best denoising methods, especially in preserving the image details and improving the image denoising performance. However, the shortcoming of BM3D is not capable of distinguishing the spatio-temporal similarity. The basic ideas of Michal et al. show a K-means clustering singular value decomposition (K-SVD) method [16] for image denoising. This method not only effectively suppresses the additive white Gaussian noise but also preserves the important information such as edges and textures of the images, especially for texture image processing. Because of the use of orthogonal matching pursuit (OMP) [17] and SVD [18] in K-SVD algorithm, when the image size is large, the matrix pseudo-inverse operation efficiency in the OMP algorithm is very low, and SVD is not only time-consuming but also occupies large memory, which often leads
to ‘out of memory’ problem. Vladimir [19] presents an image denoising algorithm based on a pointwise varying scale that is spatially adaptive to unknown smoothness and anisotropy of the function. Moreover, the time complexity of this method is good. However, this method is local and spatial. Daniel [20] and Var
dan [21] also propose a denoising algorithm based on expected patch log likelihood (EPLL). This algorithm achieves improvement in the performance both visually and qualitatively. Nevertheless, the computational complexity of this variance stabilising transformations (VST) for iterative poisson Gaussian denoising filters (iterVST poisson) algorithm [22] has better time complexity, but the denoising effect of this method is bad. Zhang et al. [23] propose a denoising convolutional neural networks (DnCNN) model for Gaussian denoising, super resolution (SR) and joint photographic experts group (JPEG) image blocking.

In the process of intelligent manufacturing, different factory producing different environment greatly impacts the quality of image acquisition. The existing denoising algorithms are mostly based on a public image dataset and specific noise, and this study creates the real high-voltage copper contact burr image dataset for denoising. In terms of image size and content, the different classification of burr image is created. The inherent and Gaussian noise images are used for denoising. A block cosparsity overcomplete learning transform algorithm (BCOLTA) is proposed. Burr parameter is used for influencing the penalty term and the condition number of the algorithm. The optimal values are obtained by alternating between the sparse clustering and the transform term. Compared with other traditional algorithms and DnCNN model by no reference (NR) and full reference (FR) image quality assessment (IQA) algorithms [24–27], BCOLTA has obvious advantages in image denoising effects and computational complexity.

2 | METHODS

In this study, high-voltage copper contact burr image dataset of a real factory environment is built. Compared with public dataset, our dataset has its own characteristics. The machining environment and detection objects are diverse. Different real images are acquired in different factory environments. Compared with ordinary images, such kind of images have obvious characteristics of their own. The model of the burr is built and the parameter of the burr has an important impact on the penalty term and the condition number.

2.1 | Burr mathematical model

The definition of a burr is a rough remainder of material outside the ideal geometrical shape of an external edge, residue of machining or a forming process in ISO 13715 [28]. The value of the burr is expressed as follows:

\[
g = \frac{4 \cdot b_r + 2 \cdot r_f + b_s + b_0}{8}
\]  

where \(b_r\) describes the root thickness of the burr, \(r_f\) represents the root radius of the burr, \(b_s\) describes the thickness of the burr, \(b_0\) is the height of the burr.

Combined with other burr models [28, 29], one new model of the burr is proposed [30, 31]:

\[
burr = b_0 \sqrt{1 - \left(\frac{r_f + b_s + r_d}{b_r}\right)^n}, \quad r_d \in [0, b_r] \tag{2}
\]

where \(b_0\) expresses the height of the burr, \(r_f\) describes the burr root radius, burr thickness is \(b_s\), \(b_r\) represents the root thickness of the burr, \(r_d\) is the relative deviation, the shape exponent of the burr is \(n\), the effective exit surface angle is \(\alpha\) and \(v_f\) represents feed direction of the workpiece (Figure 1).

2.2 | BCOLTA

The set of the transforms contains the image data \(i \in \mathbb{R}^n\). The sparsifying square transforms are \(\{T_k\}_{k=1}^K, T_k \in \mathbb{R}^{m \times n}, \forall k\), and there is a particular \(T_k, T_k i = s + \epsilon, \) and \(s \in \mathbb{R}^n\) is sparse, \(\epsilon\) is the error that is small. This sparse problem is defined as follows:

\[
\min_{1 \leq k \leq K} \min_{q^k} \left\| T_k i - q^k \right\|_2^2 \quad \text{s.t.} \left\| q^k \right\|_0 \leq mNk \tag{3}
\]

where \(q^k\) is a sparse representation of \(i\) in the transform \(T_k\), with the maximum allowable sparsity \(m\). First, we find the optimal \(q^k\) for each \(k\). Then we calculate the sparsification error for each \(k\). The best transform \(T_k^*\) provides the smallest sparse error about all \(T_k\). We assume the sparse code is \(\hat{q}^k\), and acquire a least squares estimate of the signal as \(\hat{i} = T_k^{-1} \hat{q}^k\).

We explain the set of transforms model as a BCOLTA and stack the collection of square transforms as \(T = \left[T_1^T \mid T_2^T \mid \cdots \mid T_K^T \right]^T\), where \(T \in \mathbb{R}^{mN \times n}\), with \(m > n, T = s + \epsilon\), \(\epsilon\) is a small deviation and \(s \in \mathbb{R}^n\) is the block cosparsity that is defined as \(\left\| s \right\|_0 \leq m\). The transform matrix \(W\) is tall. The indicator function \(I(\cdot) = 1\) when the statement
$S$ is true otherwise $I(S) = 0$. In BCOLTA model, the sparse model is formulated as follows:

$$\min_{I_j} \| T_j - s \|_2^2 \text{ s.t. } \| s \|_{0,m} \geq 1$$  \hspace{1cm} (4)

The optimal sparse problem in (Equation 3) is equal to the optimal blocks in (Equation 4) satisfying $\gamma^k = H_m(T_k)$ and $\| T_j \|_2 \leq m$. The function $H(\gamma)$ is defined when $k = k_0$, and we find the optimal $\gamma$ satisfies $\gamma^k = H_m(T_k)$, others satisfy $\gamma^k = T_k$.

Since the image data $I \in R^{\times N}$, BCOLTA learning problem is changed as follows.

$$\min_{\{D_k\}} \sum_{k=1}^{K} \left\{ \sum_{j \in D_k} \| T_k I_j - X \|_2^2 + \lambda_k W(T_k) \right\}$$  \hspace{1cm} (5)

where $\{D_k\}$ represents a clustering of the image data $\{T_j\}$. The regularisation term $W(T) = -\log|\text{det} T| + \| T \|_F^2$ controls the condition numbers. The weights $\lambda_k$ in (Equation 5) is chosen as $\lambda_k = \lambda_0 \| T_{D_k} \|_F^2$. $G$ contains all possible sets of $\{D_k\}$ and is defined as follows:

$$C = \left\{ \{D_k\} : \bigcup_{k=1}^{K} D_k = [1:N], D_k \cap D_l = \emptyset, \forall l \neq k \right\}$$  \hspace{1cm} (6)

When the condition number tends to 1, the spectral norm tends to $1/\sqrt{2}$.

In the process of solving (Equation 5), the sparse clustering and the transform terms are solved in turn.

2.2.1 Sparse clustering

First, $\{D_k\}$ is assumed as a constant and the question is how to determine $\{D_k\}$ and $\{S_j\}$:

$$\min_{\{D_k\},\{S_j\}} \sum_{k=1}^{K} \sum_{j \in D_k} \left\{ \| T_k I_j - S_j \|_2^2 + \beta_k \| I_j \|_2^2 \right\}$$  \hspace{1cm} (7)

where $\beta_k = \lambda_0 W(T_k)$ is the weight $\| T_k I_j - S_j \|_2^2 + \beta_k \| I_j \|_2^2$, and $S_j = H_m(T_k I_j)$ is the clustering measure corresponding to $T_k I_j$.

Thus, the model is equivalent to

$$\sum_{j=1}^{N} \min_{\alpha,k} \left\{ \| T_k I_j - H_m(T_k I_j) \|_2^2 + \beta_k \| I_j \|_2^2 \right\}$$  \hspace{1cm} (8)

For each $I_j$, $k$ provides the smallest clustering value. The optimal value is $S_j = H_m(T_k I_j)$.

2.2.2 Transform update step

Then, $\{D_k\}$ and $\{S_j\}$ are assumed as constants. The optimisation problem is changed into how to solve $\{T_k\}$. The model is expressed as follows:

$$\min_{T_k} \sum_{j \in D_k} \| T_k I_j - S_j \|_2^2 + \lambda_k W(T_k)$$  \hspace{1cm} (9)

Here, $\lambda_k = \lambda_0 \| T_{D_k} \|_F^2$ represents the weight, and the optimisation transform $T_k$ as follows:

$$T_k = 0.5V^\top \left( \sum_{j=1}^{2} \left( \sum_{j=2}^{2} + 2 \lambda_k I_j \right) \right) U^T L^{-1}$$  \hspace{1cm} (10)

According to the mathematical model of the burrs, various kinds of high-voltage copper contact burrs have different burr parameters. These parameters are the factors on infection of the peak signal to noise ratio (PSNR) of BCOLTA algorithm such as the weights $\beta_k$ and $\lambda_k$.

2.3 Burr image denoising

Because of the technical limitations of the machining, it is easy to form the burrs on the edge of the workpieces. Our research focuses on the intelligent deburring problem. Image denoising is an important application of image processing. The purpose of Burr image denoising is to acquire an estimate of the burr image vector $s \in R^G$. The measurement of $s$ is expressed as $i = s + b$, where $b$ is the noise. The block cosparse denoising method is explained as follows:

$$\min_{\{T_k\},\{S_j\}} \sum_{k=1}^{K} \sum_{j \in D_k} \left\{ \| T_k I_j - \alpha T_k I_j \|_2^2 + \lambda_j W(T_k) \right\}$$

$$+ \gamma \sum_{j=1}^{N} \| P_j - s \|_2^2$$  \hspace{1cm} (11)

s.t. $\| \alpha \|_0 \leq m, \forall k \in \{D_k\} \in C$

where $P_j \in R^{\times G}$ is block extraction factor, $P_j \in R^e$ denotes $j$th block of the Burr image $i$. The vector $s_j \in R^e$ denotes a denoised result of $P_j$. $\gamma$ is the inversely proportional coefficient of the noise level $\sigma$. The vector $\alpha_j \in R^e$ denotes the sparse representation of $s_j$ in a specific cluster transform $T_k$ with a prior unknown sparse level $m_j$. The weight $\lambda_j$ is set as $\lambda_0 \| P_j \|_2^2$. $W(T_k)$ is the regularisation term that is used to control condition number.

On account of $\gamma \propto 1/\sigma$ and $\sigma \rightarrow 0$, the optimal value $s_j \rightarrow P_j$. The denoised image $x$ is obtained by averaging the known $x_j$ at their respective locations in the burr image. Equation (11) is substituted by another version in which the penalty term $\gamma \sum_{j=1}^{N} \| P_j - s_j \|_2^2$ is replaced by the constraints $\| P_j - s_j \|_2^2 \leq \sigma B \sum_{j=1}^{N} \| P_j - s_j \|_2^2$ where $B$ is a constant. The inversely proportional
Numerical experiments

The model eliminates the issues of unknown sparse level \(m_j\); however, it brings many unknown parameters. For the sake of simplicity, the simple data accuracy penalty and the sparse constraints are used. Additionally, the method estimates the minimum sparse levels for satisfying the condition \(\|P_j s_j - s_j\|_2^2 \leq n B^2 \sigma^2 \gamma j\).

\(m_j\) is assumed as a constant such as one-fifth of the patch size. Each iteration of the algorithm contains three main sections (such as the internal clustering transformation learning, the sparse update and the clustering). The denoised patch \(s_j\) is updated in the last iteration. Moreover, when the iterations are completed, the denoised image is reconstructed.

Initially, the internal clustering transformation learning step.

Given \(\{s_j\}, \{m_j\}\) and \(D_k\), cluster transform \(T_k\) and the corresponding sparse codes \(\{\zeta_j\}\) are solved. \(K\) different single transform learning problems are separated. The \(k\)th problem is described as follows:

\[
\min_{\{u_k, \xi_j\} \in D_k} \left\{ \left\| T_k s_j - \xi_j \right\|_2^2 + \lambda' \| W (T_k) \right\}
\]

s.t. \(\|\xi\|_0 \leq m_j, \forall j \{D_k\} \in C\)

This problem is solved by alternating between the sparse clustering term and the transform term. Each step involves a closed-form solution.

Furthermore, the internal clustering sparsity update step.

Given a fixed transform update \(T_k\) and the sparse code \(\zeta_j, j \in D_k\), the sparse level \(m_j\) for all \(j\) can be updated. \(s_j\) is solved as follows:

\[
s_j = \left[ \sqrt{\gamma I} \right] T_k^{-1} \left[ \sqrt{\gamma P_j} \right] \zeta_j = C_1 P_j s_j + C_2 \zeta_j
\]

The matrices \(C_1 = \gamma (I + T_k^T T_k)^{-1}\) and \(C_2 = \gamma (I + T_k^T T_k)^{-1} T_k^T\) are computed once for each cluster. \(I\) is an \(n \times n\) matrix. In this step \(s_j\) satisfies the condition \(\|P_j s_j - s_j\|_2^2 \leq n B^2 \sigma^2\) except in the final iteration. The sparse code is also further updated for each \(j \in B_k\) as \(\zeta_j = H_{m_j}(T_k s_j)\), using the optimal value of \(m_j\).

Additionally, the clustering step.

In the last iteration of the method, the clustering step is not performed. \(\{m_j\}\{T_k\}^s_j\) are fixed. We calculate \(\tilde{\zeta}_j = H_{m_j}(T_k s_j)\\forall k\) and choose the cluster \(D_{k_j}\). We can conclude that

\[
\left\| T_k s_j - \tilde{\zeta}_j \right\|_2^2 + \beta_k \| \tilde{\zeta}_j \|_2^2 \leq \left\| T_k s_j - \zeta_j \right\|_2^2 + \beta_k \| \zeta_j \|_2^2 \forall l \neq k
\]

where \(\beta_k = \lambda_{d_j} W (T_k)\), the optimal value is \(\zeta_j = \tilde{\zeta}_j\).

Finally, calculating the expected image estimate step.

The image resolution limits the denoised image patches \(\{s_j\}\) is obtained from the iterative method. The final denoising image is obtained by averaging the denoised blocks, and a simple algorithm chart is shown in Figure 2.

Here, \(i\) is corrupted by the noises, \(m\) is the initial determinate value of the sparsity \(A_{m_j}\) is a constant, \(K\) is the cluster number, \(L\) is the iteration number, and \(\sigma^2\) is the variance estimation of the noise. The output result of \(S\) is an estimation of the denoised image.

Initialisation: Image patches \(s_j = P_j s_j, m_j = m, \) for \(j = 1, 2, ..., N, T_k = T_0, \forall k, D_k\) is the arbitrary cluster for each \(j \in \{1, 2, ..., N\}\).

For \(a = 1:\) L repeat

For \(k = 1, ..., K, T_k\) and \(\zeta_j\) are updated alternatingly, the cluster \(D_k\) is fixed, \(s_j = P_j s_j\). Update \(m_j\) for all \(j=1, 2, ..., N\), when \(m_j\) increases, \(\zeta_j = H_{m_j}(T_k s_j)\). Where \(j \in D_k\), until the error condition \(\|P_j s_j - s_j\|_2^2 \leq n B^2 \sigma^2\) is reached. For each \(j \in \{1, 2, ..., N\}\) and \(s_j - P_j s_j\), calculate \(\tilde{\zeta} = H_{m_j}(T_k s_j), \forall k\) and assign \(j\) to the cluster \(D_k\) if \(k\) is the smallest integer in \(\{1, 2, ..., K\}\) such that \(\|T_k s_j - \tilde{\zeta} \|_2^2 + \beta_k \| s_j \|_2^2 \leq \|T_j s_j - \tilde{\zeta} \|_2^2 + \beta_k \| s_j \|_2^2\)\iff \(k\) holds with \(\lambda_{d_j} W (T_k)\). The optimal code is \(\zeta_j = \tilde{\zeta}_j\).

Update \(s_j\) obtain the denoised patch \(\{s_j\}\) that satisfies the error condition of step 2, and the results are averaged.

In order to increase the computational efficiency of the method, the internal clustering transformation learning is performed by using part of the patches that are selected stochastically.

The model learns a set of transforms with the noisy patches, updates the sparse levels of \(m_j\), adaptively during the iterations and uses the final \(m_j\) of the algorithm with the fixed \(m_j\) by alternating between the internal clustering transformation learning \(m_j\) is updated by the least squares and the clustering. In fact, when the iteration number is increased, less improvement in denoising performance is produced.

3 | EXPERIMENTS

3.1 | Datasets

High-voltage copper contact image dataset is created in the study, which consists of 823 burr images. According to the content of the images, images are divided into two categories: Global and local images. On the basis of different size of images, images are divided into three kinds: 240 × 320, 256 × 256, 512 × 512. Different burr parameter is set in the experiment by different iterations and uses the final \(m_j\) of the algorithm with the fixed \(m_j\) by alternating between the internal clustering transformation learning \(m_j\) is updated by the least squares and the clustering. In fact, when the iteration number is increased, less improvement in denoising performance is produced.

3.2 | Numerical experiments

In the experiments, natural burr images with inherent noise and additive Gaussian noise are processed. The noise level (sigma) is 5, 10, 20, 25, 30, 50, respectively. Different sizes of the images are 240 × 320, 256 × 256, 512 × 512. The PSNR of local-burr
and global-burr images under different noise levels (sigma = 5, 10, 20, 25, 30, 50) and different sizes of images (240 × 320, 256 × 256, 512 × 512) are shown in Figures 3–5.

In Figure 3, the image size is 240 × 320, denoising effect of BCOLTA possesses more advantages than other algorithms. K-SVD algorithm gets the best results in some cases, however, the computational complexity of K-SVD is high, and cannot be used for online image denoising. IterVST poisson algorithm has the lowest computational complexity, but denoising result is the worst in experimental results. Denoising effects of EPLL algorithm are worst at the noise level 50. Figure 4 shows that BCOLTA achieves the best denoising result under different noise levels. EPLL and iterVST poisson algorithms are relatively ill-behaved. In Figure 5, experiments are based on 512 × 512 images. Experimental results show that when the image size is increased, PSNR of BCOLTA shows distinct advantages than smaller scale images. Experimental results demonstrate that BCOLTA exhibits some good performances than K-SVD and BM3D methods. The PSNR of the local burr image is higher than the global burr image. A significant amount of experimental data shows that BCOLTA obtains the best overall denoising effect. IterVST poisson algorithm has low computational complexity, but the denoising effect is the worst when the noise level is less than 50, and EPLL algorithm has the worst noise removal effect when noise level sigma is 50. Figures 6 and 7 show comparison of denoising effects of different algorithms on local and global burr image under the condition of noise level sigma 50 and the size of images is 512 × 512. Figure 8 shows the comparison of different denoising results on natural burr images with inherent noise. BCOLTA shows state-of-the-art (SOTA) results. The details of the number in the image is clearly conserved. BM3D and local polynomial approximation-intersection
of confidence intervals (LPA-I CI) algorithms have better performance. In addition, denoising result of DnCNN is relatively ill behaved.

Table 1 summarises the average increment of BCOLTA model. The experimental result shows that when the image size is increased, the PSNR of BCOLTA algorithm also increases. Moreover, when the noise level is high, BCOLTA has better performance. The black bold data are the optimal data of total results. Table 2 shows the comparison of execution time when noise level sigma is different and the image size is 240 × 320. Through a large number of numerical experiments, LPA-I CI, iterVST poisson and BCOLTA algorithms have better time complexity, which can be used for robot online deburring operation. As shown in Table 2, iterVST poisson algorithm has the lowest time complexity, but the algorithm has the worst denoising effect, which does not meet the requirements of industrial
manufacturing. Table 3 shows FR and NR IQA algorithms used for image denoising of different algorithms. BCOLTA is SOTA in different traditional algorithms and DnCNN model.

For any burr image, the maximum value of the total average increment PSNR of global burr image is 7.25 dB, and local burr image is 9.29 dB. The average increment maximum value of local burr image over global burr image is 2.2 dB. Experiment results indicate that the PSNR of local burr image is higher than global burr image. When the noise level sigma is 30 and 50, the increment of PSNR of BCOLTA obtains the maximum value of 8.82 dB (global burr) and 16.12 dB (local burr). Numerical experiments manifest that when the noise level...
FIGURE 8 Comparison of denoising effects of different algorithms on natural burr images with inherent noise

TABLE 1 The average PSNR increment of block cosparsity overcomplete learning transform algorithm (BCOLTA)

| Image         | Size          | 5   | 10  | 20  | 25  | 30  | 50  |
|---------------|---------------|-----|-----|-----|-----|-----|-----|
| Local burr    | 240 × 320     | 7.49| 6.22| 4.86| 6.27| 4.67| 11.24|
|               | 256 × 256     | 7.48| 5.04| 4.69| 7.88| 8.86| 12.58|
|               | 512 × 512     | 8.72| 6.75| 6.17| 11.14| 6.87| 16.12|
| Global burr   | 240 × 320     | 7.07| 3.83| 2.58| 4.47| 5.03| 8.76|
|               | 256 × 256     | 7.46| 4.18| 3.03| 4.5 | 5.37| 8.78|
|               | 512 × 512     | 8.68| 6.25| 3.82| 7.94| 8.82| 8.01|

is high, BCOLTA shows preferable, and when image resolution increased, burr image denoising results are improved. In addition, compared with other traditional algorithms and DnCNN model by NR and FR IQA algorithms, BCOLTA has obvious advantages in image denoising effects and computational complexity.

4 | CONCLUSIONS

In this study, a block cosparsity overcomplete learning transform burr image denoising algorithm is proposed. The dataset of high-voltage copper contact and the model of burr are built. The parameter of the burr influences the penalty term and condition number of the algorithm. NR and FR IQA methods are used to evaluate the results of denoising images. Compared with other traditional algorithms and DnCNN algorithm on inherent and Gaussian noise by NR and FR IQA algorithms, experimental results of BCOLTA show SOTA in time complexity and image denoising results, and it is suitable for large and online image denoising.

TABLE 2 The execution time of different algorithms (240 × 320)

| Algorithm                                      | 5  | 10  | 20  | 25  | 30  | 50  |
|------------------------------------------------|----|-----|-----|-----|-----|-----|
| Block-matching 3D algorithm (BM3D)             | 63.6| 54.2| 53.4| 57.5| 52.8| 54  |
| K-means clustering singular value decomposition (K-SVD) | 1502| 852.5| 211.3| 118.1| 93.2| 44.8|
| LPA-ICI                                        | 2.7 | 2.9 | 2.9 | 2.9 | 2.7 | 2.8 |
| Multi-scale expected Patch Log Likelihood (EPLL) | 203.2| 204.1| 203.4| 201.2| 204.3| 206 |
| EPLL-HQS                                       | 55.4| 55.1| 55.3| 55.4| 55.6| 56.6|
| Variance stabilising transformations for iterative poisson Gaussian denoising filters (IterVST poisson) | 1.5 | 1.5 | 1.6 | 1.3 | 1.3 | 1.2 |
| DnCNN                                          | 72.4| 60.9| 60.6| 65.6| 61.1| 62.1|
| BCOLTA                                         | 2.2 | 2.1 | 2.2 | 2.1 | 2.3 | 2.4 |
TABLE 3  Full reference (FR) and no reference (NR) image quality assessment (IQA) algorithms are used for image denoising of different algorithms

| Algorithm   | PSNR | ADD-SSIM | ADD-GSIM | PSIM | SIQE | ASIQE | NFERM |
|-------------|------|----------|----------|------|------|-------|-------|
| BM3D        | 32.7266 | 0.9984 | 0.9962 | 0.9983 | 0.6322 | 0.6521 | 36.4979 |
| KSVD        | 33.0578 | 0.9920 | 0.9888 | 0.9967 | 0.6030 | 0.6270 | 42.9839 |
| LPA-ICI     | 33.7178 | 0.9964 | 0.9929 | 0.9973 | 0.6377 | 0.6518 | 50.1889 |
| Multi-scale EPLL | 28.5033 | 0.9942 | 0.9920 | 0.9975 | 0.6241 | 0.6426 | 34.4781 |
| EPLL-HQS    | 28.3633 | 0.9969 | 0.9935 | 0.9975 | 0.6062 | 0.6344 | 40.3074 |
| IterVST poisson | 22.7267 | 0.9936 | 0.9916 | 0.9967 | 0.5806 | 0.6163 | 64.1196 |
| DnCNN       | 32.0950 | 0.9974 | 0.9946 | 0.9978 | 0.6052 | 0.6331 | 39.2435 |
| BCOlTA      | 38.1367 | 0.9975 | 0.9960 | 0.9985 | 0.6328 | 0.6515 | 41.7303 |

ADD-SSIM, analysis of distortion distribution-based structural similarity metric; PSIM, perceptual similarity index; SIQE, screen image quality evaluator; ASIQE, accelerated screen image quality evaluator; NFERM, no reference free energy-based robust metric.

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