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An Algorithm for Real-Time Blind Image Quality Comparison and Assessment

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ABSTRACT

This research aims at providing means to image comparison from different image processing algorithms for performance assessment purposes. Reconstruction of images corrupted by blur and noise requires specialized filtering techniques. Due to the immense effect of these corruptive parameters, it is often impossible to evaluate the quality of a reconstructed image produced by one technique versus another. The algorithm presented here is capable of performing this comparison analytically and quantitatively at a low computational cost (real-time) and high efficiency. The parameters used for comparison are the degree of blurriness, information content, and the amount of various types of noise associated with the reconstructed image. Based on a heuristic analysis of these parameters the algorithm assesses the reconstructed image and quantify the quality of the image by characterizing important aspects of visual quality. Extensive effort has been set forth to obtain real-world noise and blur conditions so that the various test cases presented here could justify the validity of this approach well. The tests performed on the database of images produced valid results for the algorithms consistently. This paper presents the description and validation (along with test results) of the proposed algorithm for blind image quality assessment.

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1. INTRODUCTION

In this article an approach to fast blind quality assessment of images for target recognition and identification has been described. The blind quality assessment of an image finds many NASA, DoD, FAA, NOAA, and DHS applications such as target detection, pattern recognition, and remote sensing. Given that in most imaging applications the target is an unknown variable, having a tool to measure the quality of the reconstructed images of that target has a significant value. To add to the complication, in most imaging applications, the image itself suffers from several physical phenomena such as atmospheric noise (of several different kinds), time, phase, and frequency shifts, and other clutter caused by interference and speckles. The proposed tool should also be able to measure the level of deterioration of the signal due to environmental effects. Therefore, evaluation of a processed image is not an easy task. It requires a good understanding of the processing methods used and the types of clutter affecting the image. On the other hand, for a meaningful comparison, some effective parameters have to be chosen and qualitatively and quantitatively measured across reconstructed versions of the same image. Finally, any algorithm capable of handling these tasks has to be efficient, fast, and simple to qualify for "real-time" applications.

This research is aimed at assigning a value to the visual quality of several images reconstructed from the same target image processed by different algorithms. In doing so, we have identified some of the important parameters that affect the quality of an image and ways in which they can be measured quantitatively. The remainder of this paper is organized as follows: Section II gives the reader a little background on the requirements and components for this research and some of the challenges in blind quality assessment of reconstructed images; Section III discusses the methodology and the innovative techniques used in this research to overcome some of the challenges in blind image quality assessment; Section IV describes the results obtained from this research; and Section V is reserved for conclusive remarks for this research and the direction of the future work in this field.

2. BACKGROUND

In many advanced image processing applications information from multiple sensors or processors is combined to create images with higher resolution [12],[13],[14]. One major disadvantage of this technique is that collective channel noise, speckles, and other artifacts from different sensors degrade the image quality making the task of target reconstruction, restoration, detection, recognition, and classification much more difficult [15],[16]. While many image reconstruction and restoration techniques have been developed to obtain true target images from the raw observed data, many of these methods suffer from a range of issues such as computational involvement of algorithms to suppression of useful information [17],[18],[27]. Each of these image reconstruction and restoration techniques has varying degrees of dire side-effects on the image quality. Therefore, there is a need for a tool that could perform a quality comparison of reconstructed images from the same scene using different image analysis techniques. Since most reconstructed images mainly suffer from clutter, noise, data loss, and phase/pixel shifts, we have based our blind quality assessment algorithm on these parameters [19],[20]. As depicted in Figure 2 below, the proposed algorithm consists of several modules, each unique in its design and purpose, while applicable to a broad range of images. These modules are described below:

2.1. De-noising filter banks

A noisy image can be simply modeled as S(i,j) = f(i,j) + σe(i,j). Where S is corrupted image with noise e, and σ is the noise level. To de-noise is to remove σe(i,j) and recover f(i,j). Noise is a wide-band phenomenon. Therefore, de-noising would require a delicate balance of high, low, and mid band filters with proper threshold[26] that would minimize interference with the main signal. The proposed filters in this research use a combination of wavelet based filter banks and Wiener/Gaussian filters as a means of multiband noise suppression and wide band noise reduction, respectively.

The Wiener filters are specialized in (additive) noise smoothing (compression low-pass filter) and blur inversion (deconvolution highpass filter) while reducing the mean square error. In the Fourier transform domain the Wiener filters can be expressed as Equation 1:

$$W(f_{1,}\, f_2) = \frac{H^*(f_{1,}\, f_2)\, S_{xx}(f_{1,}\, f_2)}{\left|H(f_{1,}\, f_2)\right|^2 S_{xx}(f_{1,}\, f_2) + S_{nn}(f_{1,}\, f_2)} \qquad (1)$$

Where $S_{xx}(f_{1,}\, f_2)$ and $S_{nn}(f_{1,}\, f_2)$ are power spectrum of the original image and noise, respectively and $H(f_{1,}\, f_2)$ is the blurring filter[6].

The Gaussian filters perform signal smoothing by applying convolution (blurring) and therefore removing high frequency noise (mean filtering). The 2D Gaussian filter can be expressed as Equation 2:

$$G(x,y) = \frac{1}{2\pi\sigma^2}\, e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (2)$$

Where the standard deviation (σ) determines the degree to which the image is smoothed. The Gaussian filters smooth the image more gently than the mean filter and preserve the edges better. Therefore, the Gaussian filter is not only better for edge detection due to its sharp cutoff frequency, but also it is the perfect pair for Wiener filter as it neutralizes the blur effect of these filters and reduces the noise in bands that Wiener filter is not effective [3],[4],[5].

Wavelet de-noise and decomposition method is proven to be one of the most effective methods [1],[2]. This method involves three steps. First, a mother wavelet is used to generate the discrete wavelet transform (DWT) which in turn is employed to decompose the image. Then hierarchical DWT representations of the image make it possible to determine de-noise layer number by a proper soft threshold and threshold function algorithm. The threshold is chosen automatically by the algorithm by combining the type of image and its decomposed image scale coefficients. Finally, reconstructing the image by applying the threshold coefficients and inverse discrete wavelet transform (IDWT), reconstructs the de-noised image. Wavelet transforms are the result of translation and scaling of a finite-length waveform known as mother wavelet. A wavelet divides a function into its frequency components such that its resolution matches the frequency scale and translation. To represent a signal in this fashion it would have to go through a wavelet transform. Application of the wavelet transform to a function results in a set of orthogonal basis functions which are the time-frequency components of the signal. Due to its resolution in both time and frequency wavelet transform is the best tool for decomposition of signals that are non-stationary or have discontinuities and sharp peaks. In this work the wavelet transform has been used to de-noise and decompose images. Wavelet de-noising and decomposition method involves three steps. First, the mother wavelet is used to generate the discrete wavelet transform (DWT) which in turn is employed to decompose the image. The approach consists of decomposing the signal of interest into its detailed and smoothed components (high-and low-frequency). Then, the hierarchical DWT representations of the image make it possible to determine de-noised and decomposed layer numbers by the proper soft threshold function. The detailed components of the signal at different levels of resolution localize the time and frequency of the event. Therefore, the wavelet filter can extract the "short-time", "extreme value", and "high-frequency" features of the image. Finally, the threshold coefficients and inverse discrete wavelet transform (IDWT) are used to reconstruct the de-noised image. Usually, the subset of the discrete threshold coefficients can be generated from the discrete version of the generating function (Equation 3):

$$\psi_{m,n} = a^{-\frac{m}{2}}\psi(a^{-m}t - nb) \qquad (3)$$

Where a and b are scale and shift, and *m* and *n* represent the number of levels and number of coefficients used for scaling and shifting of wavelet basis, respectively. Applying a subset of this set to a function *x* with finite energy will result in wavelet transform coefficients from which one can closely approximate (reconstruct) *x* using the coarse coefficients of this sequence [1],[2] as shown in Equation 4:

$$x(t) = \sum_{m\in Z}\sum_{n\in Z}\langle x,\psi_{m,n}\rangle \,.\, \psi_{m,n}(t) \qquad (4)$$

2.2. Sharpness and edge detection

The proposed blind image quality assessment approach is based on immediate human visual factors such as lighting, contrast, tone, noise, and blurriness. These parameters have been carefully simplified, filtered, merged, and optimized to result in a quantitative measure for quality of a broad range of images. As part of the filtering and simplification process, the edge detection and sharpening filters have been employed.

The sharpness filtering or un-sharp masking can be used to remove uneven pixels and noise from an image while preserving the original data and avoiding deformity and shrinkage. This is done by applying linear or non-linear filters that amplify the high frequency components of the image and therefore give the impression of an image with a higher resolution. This technique increases the sharpness effect of an image by raising the contrast of small brightness changes. The image appears more detailed, since the human perception is aligned to the recognition of edges and lines. Un-sharp masking could increase the detail contrast in general and amplify image interference of the original and therefore result in very bumpy and unnatural image effects. In fact, too much masking could cause "halo" effect (light or dark outlines near edges). It can also bring in slight color shifts by emphasizing certain colors while diminishing others. By setting automatic thresholds that limit the sharpness of unwanted elements in image (such as image grains), the proposed filters in this research have been carefully designed to optimize masking without causing “halo” effect and to emphasize luminance channel rather than color to avoid any color shift [7].

Edge detection is an essential part of any feature detection or extraction in image processing or computer vision algorithms. The technique consists of recognizing the points at which the brightness of a digital image changes abruptly (points of discontinuity). These changes could be an indication of important incidents in an image such as sudden changes in depth or surface orientation, properties of material, or illumination of the scene. Despite different techniques presented to solve this non-trivial problem, one of the early ones by Canny is considered an state-of-the-art edge detector. In his approach, Canny considered an optimal smoothing filter given the criteria of detection, localization, and minimizing multiple responses to a single edge. He proved that this filter can be implemented as the sum of four exponential terms and approximated by first-order derivatives of Gaussians. He used central differences as a gradient operator to estimate input image gradients [10],[11]: using Equations 5a,b:

$$L_x(x,y) = -\frac{1}{2}\,.\,L(x-1,y) + 0.\,L(x,y) + \frac{1}{2}.\,L(x+1,y) \qquad (5a)$$

$$L_y(x,y) = -\frac{1}{2}\,.\,L(x,y-1) + 0.\,L(x,y) + \frac{1}{2}.\,L(x,y+1) \qquad (5b)$$

The gradient magnitude and orientation then can be computed as shown in Equations 6a,b:

$$|\nabla L| = \sqrt{L_x^2 + L_y^2} \qquad (6a)$$

$$\theta = Atan2(L_y, L_x) \qquad (6b)$$

2.3. Quantitative quality analysis

For the purposes of comparison and assessment of various images reconstructed from a degraded original version, it is desired to have a quantitative measure based on human visual system which can be measured using parameters involved in signal transformation. In this research, the ideal quantitative measure has been analytically calculated based on a delicate balance between the signal to noise ratio (SNR) and norm of the reconstructed image. Furthermore, important factors in human visual system such as scene lighting, contrast, and edges have been considered to come up with these parameters. As depicted in Figure 2, a cluttered image is de-noised to an optimal level (measured by SNR) and then using the un-sharp masking its useful information has been extracted to realize a factor that is an indication of the portion of the true image that is embedded inside the cluttered version. The closer this number is to one, it shows a higher portion of the true image inside the reconstructed version. A number larger than one (as shown in the case of exceptional images in Table 3) is an indication that the image has picked up a few extra pieces in addition to what was intended in the original image.

SNR is a measure of how well a signal is preserved as it travels through a noisy environment. It is the ratio of signal power to background noise power measured in dB. It is calculated in Equation 7:

$$SNR = 10\ \log_{10}\frac{P_s}{P_n} = 20\ \log_{10}\frac{A_s}{A_n} \qquad (7)$$

Where P_s and P_n are signal and noise power, and A_s and A_n are signal and noise amplitude, respectively.

Since all data acquisition systems suffer from environmental noise, SNR can be partially improved by limiting the amount of noise injected into the system from the environment. This can be done by reducing the sensitivity of the system and/or filtering out the noise. Another type of noise (additive noise) is introduced to the system at the quantization phase. This type of noise is non-linear and signal-dependent and therefore, requires more selective filtering for noise cancellation. The filters used in this research for noise reduction are a delicate balance between Weiner, Gaussian, and wavelet filter banks which optimally adjust themselves to the level of noise in signal and noise frequency bands for maximum noise cancellation and minimum signal deterioration [8]. Figure 2 shows the details as well as the order of these filters.

Thinking of an image as a two dimensional matrix, norm can be used to measure the “size” of the image or the “distance” or “difference” between two images. 1-Norm of a vector is given by Equation 8:

$$\|\vec{X}\|_1 = \sum_{i=1}^{n} |x_i| \qquad (8)$$

Accordingly, Equation 9 shows the 1-norm of a matrix

$$\|A\|_1 = max_j\left(\sum_i |a_{i,j}|\right) \qquad (9)$$

This amounts to the maximum of column sums. Following the same pattern, the 2-norm of a vector is shown in Equation 10:

$$\|\vec{X}\|_2 = \sqrt{\sum_{i=1}^{n} |x_i|^2} = \sqrt{\langle\vec{X},\vec{X}\rangle} \qquad (10)$$

Which amounts to matrix 2-norm in Equation 11 being

$$\|A\|_2 = \sqrt{Largest\ eigenvalue\ of\ A^*A} \qquad (11)$$

Otherwise known as singular value of matrix A [9].

3. RESEARCH METHOD

Figures 1 and 2 below show the placement of the proposed algorithms in a given image processing setup and its functional block diagram. Ideally, the proposed algorithms should be able to analyze an image received from a transmitter, that is cluttered with various noise and blur effects of the channel, compare it to the outcome of various image processing algorithms (A1, A2, and A3) for the same image (Image 1, Image 2, and Image 3), and decide which processed image is a better representative of the original image being transmitted. Since there is no prior knowledge about the original image in hand at the receiver side, this comparison and analysis is done blindly. As such, to validate the capability of the proposed algorithms in assessing and comparing the quality of processed images, it must be tested with known images compared to their cluttered and processed versions.

The algorithm starts processing each image by first reading it into the work space of the computer. Then a set of cascaded filter banks (wavelet, Gaussian, and Weiner) are applied to the image to remove noise from the image. Each type of filter in this stage requires special parameters to be extracted from the image. Therefore, every image would go through some pre-processing to compute these parameters. After noise removal, each image is tested for a predetermined SNR global thresholding and unsharp masking to make sure that the quality of the signal has not been degraded in the noise removal process and that noise level is not going to affect the assessment process. Next, an image edge detection algorithm is applied to reduce the image to a sub-image consisting of important information that can be measured quantitatively. Finally, the norm of the sub-image is calculated based on the singular values of the matrix of image pixels. The results of these computations are listed for a set of sample images in Table 1.

Furthermore, to achieve a comprehensive model for an algorithm that can handle a wide-range of imaging applications, we have used a large database of images (240 faces and landscapes) which contain original image, original images cluttered with noise, original image corrupted with blur, and original image with both noise and blur. This set represents a wide range of variety in image quality and resolution from close-up (face) images all the way to far-away (landscape) images. The noise in this case consists of Gaussian, salt and pepper, and shot noise [26]. The blur consists of different levels of pixel displacements and angular rotations. We have used a variety of the most prevalent techniques recommended in the literature to include noise and blur in the images [21],[22]. Wavelet transforms have been employed for analyzing noise in image data as suggested by relevant literature [1],[2], [23],[24],[25].

Figure 3 shows the block diagram of the validation approach combined with the details of the proposed algorithms shown in Figure 2. Consistency in quality measure figures is the key to the successful validation of this approach and its applicability to a wide range of images from different sensors. The objective is to have one algorithm that works with images from different set of sensors. To show consistency in results, the tests have been repeated with the original image (O), original image plus noise (O+N), original image plus blur (O+B), and original image plus noise and blur (O+N+B) and the results have been shown for all cases in Table 1.

4. RESULTS AND ANALYSIS

As mentioned earlier, the proposed algorithm for blind image quality assessment is more robust, more efficient, faster, and less computationally involved than similar algorithms introduced in the literature. The advantage of this algorithm is that it works on an effective subset (edge) of the image. Therefore, due to less computational overhead and more reliable data (effective edges) it is more efficient. Table 1 shows examples of images from the image database used for this experiment. Figure 4 shows examples of the validation results for this research as depicted in section III of the paper. As shown in Figure 3, the set of images for this experiment were cluttered in 3 different ways (Table 1) and all processed with the proposed blind image quality assessment algorithm. Quantitative results prove to be consistent for each and every image type tested. Here are some observations from these test results:

a. The algorithm consistently rates the original better than the noisy (O+N), blurry (O+B), and noisy-blurry (O+N+B). The qualitative measure obtained is also rating the O+N and O+B consistently. In all cases, as the quality of the image is degraded from blur t noise, the quality measure keeps decreasing. The consistency here has also triggered comparison to human visual system (HVS).
b. The proposed algorithm also shows consistency in grading the quality of O+N+B images compared to O, O+N, and O+B. The O+N+B images are qualitatively graded lower than the other types of images and this is consistent with our expectations.
c. The results also indicate that the proposed quality assessment measure is a robust and reliable one based on limited visual parameters for a fast convergence suitable for real-time applications with limited sensor data. The measure has proven to differentiate between different versions of the same image very

accurately. Accordingly, it is designed to detect the quality of the image in the same way that human eye can.

The authors plan to further examine the validity of this algorithm in comparison to human visual system (HVS). Additionally, the algorithm will be tested for different grades of blur and noise to find the resolution thresholds of the proposed method. Both these are rather important tasks as they find applications in many automated systems in which human observation and validation is part of the process (radar, remote sensing, manufacturing, etc.). Once validated, the algorithm will be matched to relevant applications in the real world.

5. CONCLUSION

Target image extraction, recognition, and processing are of great interest to many science and engineering fields such as remote sensing, target detection, radar processing, and meteorology. The long-term goal of this research is to enable increased autonomy and quality of image processing systems, with special emphasis on automated processing, validation, and reconfiguration. The overall theme of this work is automatic extraction and processing of high-resolution images by adding a real-time blind image quality assessment algorithm. Wiener, Gaussian, un-sharp masking, and Multi-resolution wavelet filter banks have been proposed to enable an efficient and fast solution to this problem. A delicate balance of these filters in the proposed algorithm is capable of recognizing the quality of an image in comparison to corrupted versions of it. This research has led to accelerate research in theories, principles, and computational techniques for blind quality assessment in image processing. The results obtained indicate that the proposed algorithm can effectively assess the quality of any given image from a wide range of extremes in an image database. Furthermore, the algorithm can differentiate between a regular image and its corrupted versions. Additionally, the proposed algorithm is fast, efficient, and robust and can be implemented in hardware for real-time applications.

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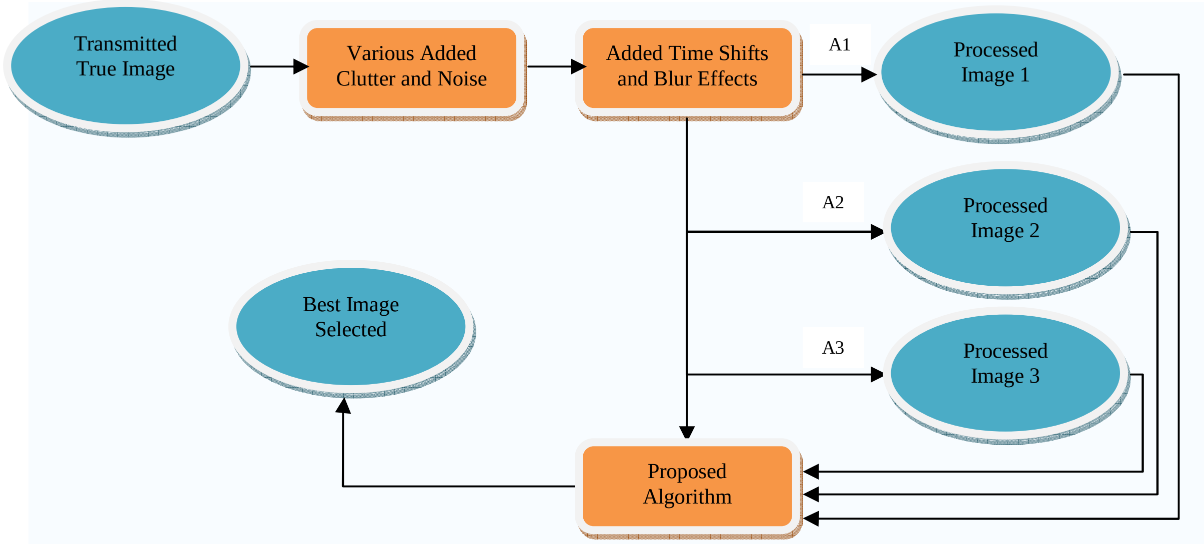


Figure 1. The general path for an image from transmitter to receiver, the alternative paths for processing, and the proposed algorithm for image quality assessment

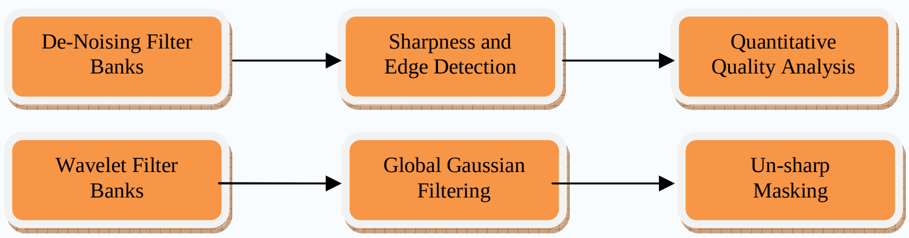


Figure 2. Components of the proposed edge detection algorithm for image quality assessment and details of the de-noising filter banks

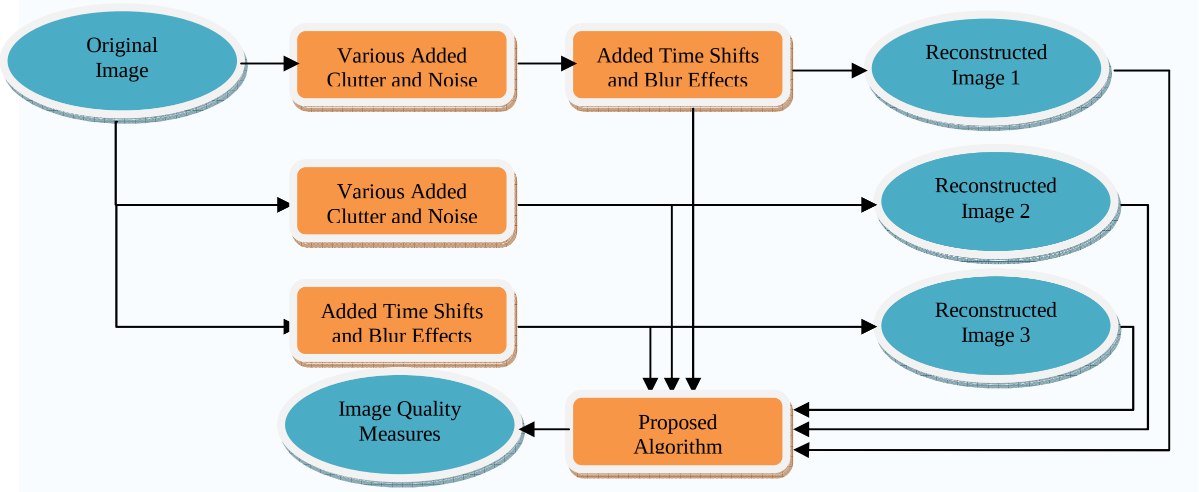
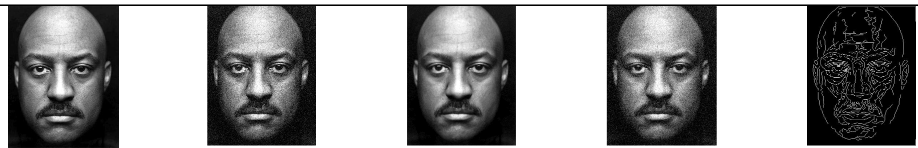
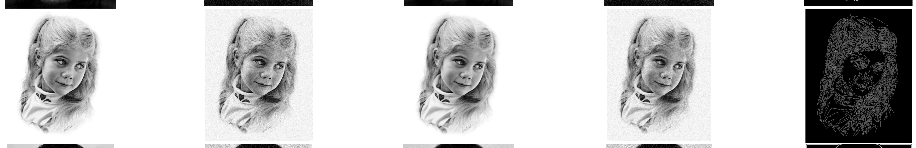
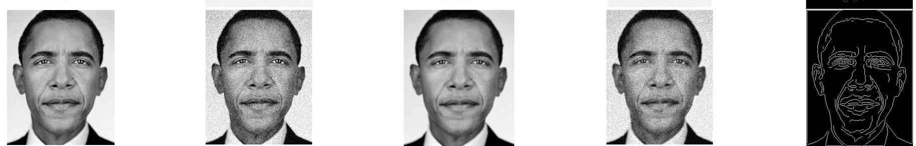
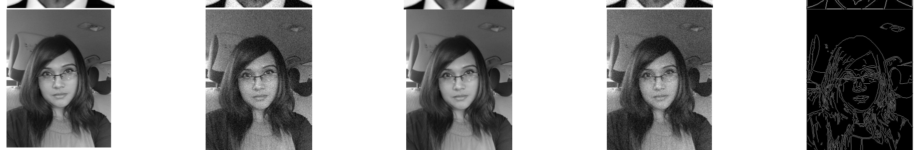
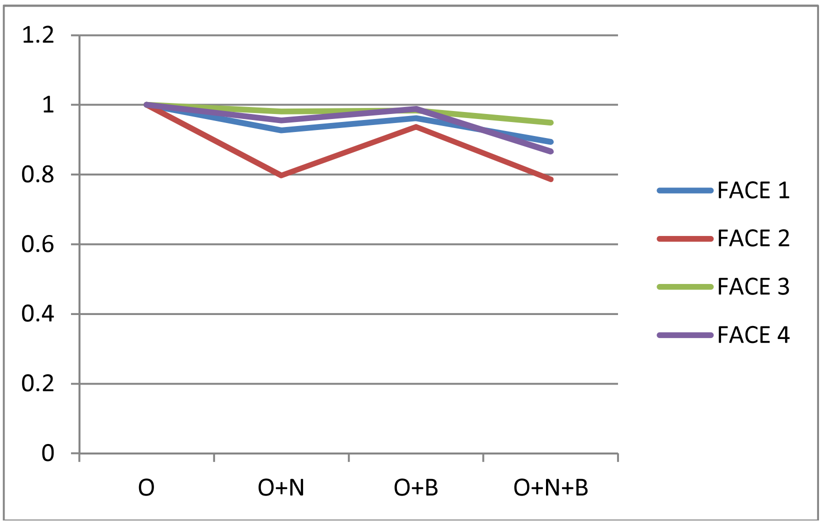


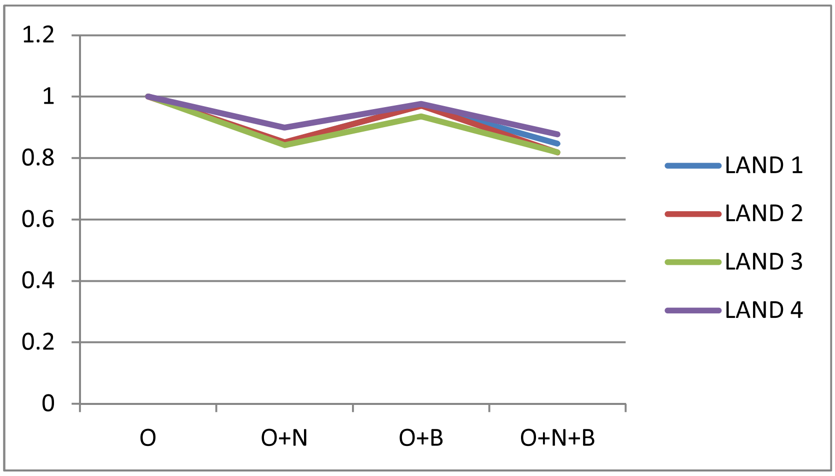
Figure 3. The validation approach functional block diagram for the proposed algorithm for blind image quality assessment

Table 1: Examples of images used for validation of the proposed algorithm for blind image quality assessment. The algorithm has been tested with original image (O), original image plus noise (O+N), original image plus blur (O+B), and original image plus noise and blur (O+N+B). Examples of images with exceptional conditions are shown in the last two rows.

Examples of Images	O	O+N	O+B	O+N+B	Image Edge
Face1					
Face2					
Face3					
Face4					
Landscape1					
Landscape2					
Landscape3					
Landscape4					



a. Examples of the normalized validation results for the proposed algorithm for blind image quality assessment of face images. The algorithm has been tested for original image (O), original image plus noise (O+N), original image plus blur (O+B), and original image plus noise and blur (O+N+B).



b. Examples of the normalized validation results for the proposed algorithm for blind image quality assessment of landscape images. The algorithm has been tested for original image (O), original image plus noise (O+N), original image plus blur (O+B), and original image plus noise and blur (O+N+B).

Figure 4. Examples of the normalized validation results for the proposed algorithm for blind image quality assessment

BIBLIOGRAPHY OF AUTHORS

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