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*Original research article*

# Image Quality Assessment Using Variational Mode Weighted Index

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## ABSTRACT

The prime objective of an image quality assessment model is to assess the image quality consistently based on the whole image information. However, human perception does not match with the same philosophy. Based on this hypothesis, subjective and objective measures are commonly used for measuring image quality. Moreover, subjective evaluation is a time-consuming process so objective quality measures are used in the majority of image processing applications. In this paper, a new objective measure (variational mode quality index (VMQI)) is proposed to determine the quality of the image. Initially the reference image and the processed image are decomposed separately to four-level 2-D decomposition using the Variational Mode Decomposition (VMD). Then, the structural similarities between the four decomposed modes are evaluated using SSIM. Separate weighting values are computed for each SSIM based on either energy or entropy of each mode of the original image. Finally, the VMQI is evaluated using the weighting and the SSIM values. The performance of the proposed quality measure, VMQI, is evaluated using the publicly available image database. The experimental result reveals that the VMQI has a higher correlation coefficient (CC) 0.996 as compared to other existing measures such as SSIM and MSE which have correlation values of 0.9566 and 0.9715.

**Keywords:** Correlation coefficient; Image quality assessment; SSIM; Variational mode decomposition; VMQI

## 1. Introduction

Image quality has been widely investigated for various image processing applications such as image restoration, image compression, and image transmission [1]. For these applications, the referral quality of the processed image should be high in order to ensure its correctness for further assessment. But, the quality of the reconstructed image may be degraded during these processing techniques. Estimating the loss of image information is a challenging task in the aforementioned image processing techniques. Different proposed methods, such as subjective and objective measures, are available for quality assessment.

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Typically, the subjective measure has been used to estimate the image quality in various applications [2]. However, subjective image evaluation has limitations such as being time-consuming and requiring image processing experts to assign the score for a reconstructed or processed image [2]. To overcome these limitations, in the literature, various objective measures are commonly employed to evaluate the quality of the processed image [3].

The widely accepted objective quality measures are peak signal-to-noise ratio (PSNR) and mean square error (MSE) as these measures have low computational complexity for evaluating the quality of the image with clear physical meanings. The shortcomings of MSE and PSNR are that these measures are evaluated based on the pixel-to-pixel difference and have less correlation with subjective evaluation techniques [4]. Moreover, to overcome the limitations of both MSE and PSNR measures, Wang et al. [3] have proposed an image quality assessment method which is based on the structural similarity index (SSIM) between original and reconstructed images. The SSIM has advantages such as being capable of reflecting the visual quality of the image based on the pixel intensity from luminance, contrast, and structure, and being well correlated with human perception [2, 3]. In other applications, the multi-scale SSIM and three-component weighted structural similarity (three-SSIM) have been used. These measures have higher assessment accuracy values with respect to subjective measures [5, 6]. In three-SSIM, three different weights are assigned based on the local information such as texture, smooth area, and edge of the image. Zhang et al. [7] have proposed a shifting technique based SSIM, such as PP-SSIM, for image quality assessment. However, this algorithm has a limitation on assessing quality for the cross-distortion image. Most of the quality assessment methods reported in the literature have been using entire image information for estimating the quality [8-10]. However, human evaluators use a certain region of an image for assessing the quality or degradation [11-15]. Hence, it is required to develop an objective measure which can consider the local information of an image for evaluating quality and can match with the human perception. Moreover, the wavelet-based objective measures have been proposed to correlate with a human visual system for assessing images [16-19]. Fang et al. [20] have proposed the multi-scale weighted structural similarity index in which the wavelet transform has been used for obtaining the sub-bands from both original and reconstructed images. In this method, the differences between the SSIM values for different sub-bands of original and reconstructed images are evaluated. Moreover, several other wavelet-based measures such as complex wavelet SSIM (CW-SSIM) [21] and weighted wavelet distortion measure (WWDM) [22] have also been reported for evaluating the quality of the processed image. Despite their benefits, the wavelet-based image decompositions have one drawback: they are not totally signal dependent because they require a basis function to breakdown the image.

In the year 2014, Dragomiretskiey et al. [23] proposed the variational mode decomposition (VMD) method for computing different modes of a signal. The different modes are extracted using a Fourier isometry-based optimization technique and assigned a central frequency [23, 24]. Since then, the VMD has been used in different applications such as signal processing, image enhancement, denoising, etc. [25, 26].

The VMD has several advantages, including being totally image-specific and not being dependent on a basis function like the wavelet transform [24].

This motivated us to design an image dependent quality assessment method using the properties of VMD, SSIM and entropy.

The remaining parts of the paper are structured as follows. The image quality measure which is proposed in this work is described in Section 2. Different image processing methods are described in Section 3 for testing the effectiveness of the proposed image quality measure. In Section 4, we have presented the research findings with proper justification. The conclusions with future scope are presented in Section 5.

## 2. Proposed Image Quality Measure

Different spatial frequencies have different reciprocations in the human visual system. In these conditions, multi-resolution analysis has a significant impact on image processing. It means that low resolution and high resolution might have seen the general structure and details, respectively. Based on the above perusal, the block diagram in Fig. 1 depicts the step-by-step procedure to evaluate the proposed image quality measure. As a consequence, the original and processed images are decomposed into four modes with the use of VMD, and the images are subdivided into multi-scale spatial frequency sub bands. Then, SSIM is used to estimate the structural similarity between the modes.

The weighting of the different sub modes is determined by evaluating the feature with an energy or entropy metric. The variational mode quality index (VMQI) takes into account all of the spatial frequencies that affect image quality, so it is more accurate than the existing SSIM metric, especially when evaluating cross- distortion. The following are detailed descriptions of each stage of Fig. 1.

### 2.1 Variational mode decompositions

The objective of the two-dimensional VMD is to decompose the input image into K number of sub-images or modes based on the formulation of an optimization problem which is given by [23]

$$\min_{\{X_k\}\{\omega_k\}} \left\{ \sum_{k=1}^{K} \alpha_k \left\| \nabla \left[ X_{AS,K}(n) e^{-j\langle \omega_k n \rangle} \right] \right\|_2^2 \right\}$$

$$\text{Subject to} \quad \sum_{k=1}^{K} X_{AS,K}(n) = Y. \qquad (2.1)$$

In Eq. (2.1), the Fourier transformation of image $X_{AS,K}(n)$ is $\tilde{X}_{AS,K}(\omega)$. The mathematical relation between the above two signals is

$$X_{AS,K}(n) = \left[1 + \operatorname{sgn}\left(\langle \omega, \omega_k \rangle\right) \tilde{X}_{AS,K}(\omega)\right].$$

The modes are evaluated by solving Eq. (2.1) using the augmented Lagrangian and Fourier isometry for iterative estimation of modes [24].

The parameters used for image mode extraction are α (bandwidth constant), $K$ (number of modes), tol (tolerance), and the center frequencies.

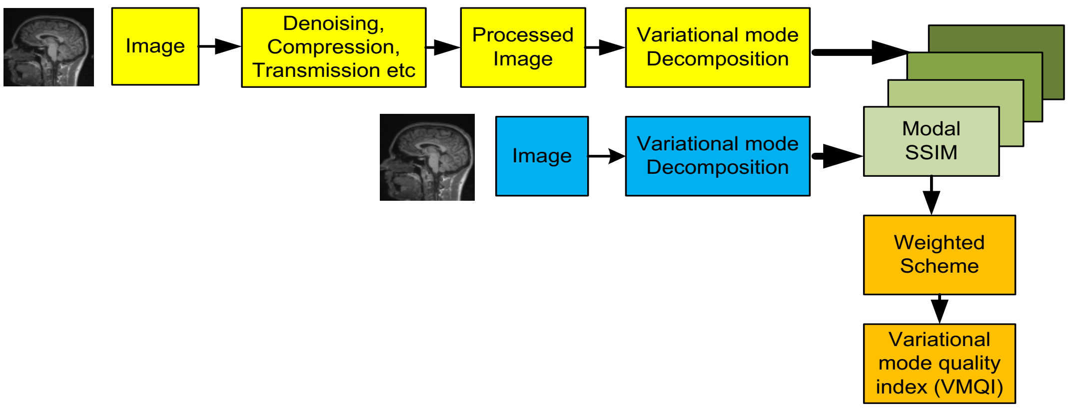


**Fig. 1.** Flow-chart for the evaluation of proposed image quality measure (VMIQ).

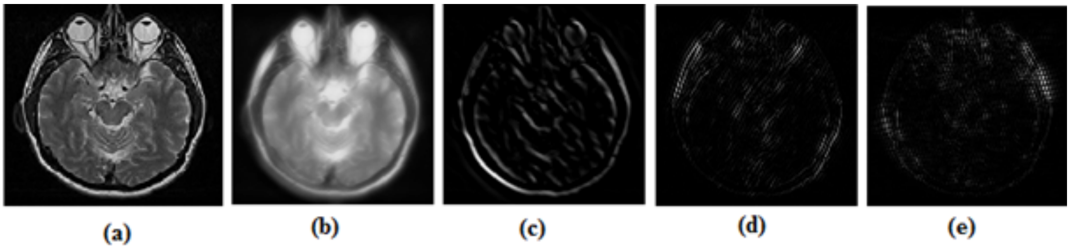


**Fig. 2.** (a) Original image, The VMD decomposed images are as (b) Mode1(c) Mode2 (d) Mode3 (e) Mode4.

Various values of alpha, such as 500 and 1000, for decomposition of an image are tested. It is evident that for alpha equals 1000, the average execution time is obtained as 294.79 sec whereas the execution time is 302.04 sec for alpha 500. This value of $\alpha = 1000$ is lower than the execution time of VMD by considering the α value as 500. Similarly, when the number of modes has been increased from four to eight, the execution time increases. Therefore, we have chosen the alpha value as 1000 and number of modes as 4 for VMD based decomposition of image into modes.

In this present study, we have considered $K = 4, \alpha = 1000$, and tol = 10-5, respectively [26]. Fig. 2 depicts the modes of the original image using the VMD technique for visual representation. The original image data, as shown in this figure, is divided into several modes based on the frequency content, which ranges from low to high. The information for vertical, horizontal, and diagonal edges is captured in modes 2, 3, and 4, whereas mode 1 captures the low-frequency part of the original image. Henceforth, the quality measure calculated by considering the modal details of the images will be helpful for quantifying the losses of image information.

## 2.2 Evaluation of VMQI measure

In this work, the original digital image X is composed of L discrete bins. Y is narrated as the processed image from digital image X. Both images, X and Y, are decomposed into K modes using VMD. The structural similarity between the modes of original and reconstructed images for $i^{th}$ mode is denoted as $SSIM_i$ with $i = 1, 2, ..., K$. The weight value for $i^{th}$ mode is evaluated based on either entropy or energy metric as

$$W\left(Entropy\right)_i = \frac{Entropy_{Mi}}{\sum_{k=1}^{K} Entropy_{Mi}}, i \in \left(1, 2, ..., K\right), \tag{2.2}$$

$$W\left(Energy\right)_i = \frac{Energy_{Mi}}{\sum_{k=1}^{K} Energy_{Mi}}, i \in \left(1, 2, ..., K\right), \tag{2.3}$$

where $Entropy_{Mi}$ and $Energy_{Mi}$ are the entropy and energy of $i^{th}$ mode [1]. The variational mode quantifies index (VMQI) is evaluated based on the mathematical expression as

$$\text{VMQI} = \sum_{k=1}^{K} W\left(Entropy\right)_i SSIM_i, i \in \left(1, 2, ..., K\right). \tag{2.4}$$

## 3. Image Processing Techniques

To rationalize the proposed image quality index model, three different processing techniques were considered: image denoising, image compression and image transmission. First, for image denoising, the median filter was applied to obtain the processed image [1]. Initially, the Gaussian noise and, the salt and paper noise with different values of signal-to-noise ratio (SNR) were added to the original image. The variations of the proposed quality measures with different SNR values of noisy image have been investigated. Second, an image compression algorithm has been implemented for evaluating the proposed image quality indices [27].

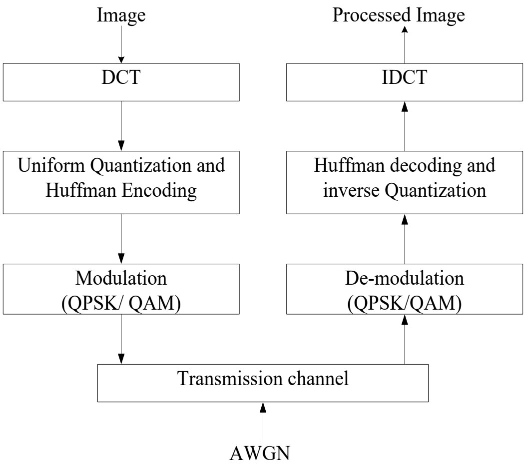


**Fig. 3.** Block diagram of the image transmission system.

This algorithm consists of the analysis of the image using discrete cosine transform (DCT), uniform quantization of the DCT coefficients of the image, and conversion of the quantized image into binary data or bit stream using Huffman coding. In the reconstruction part, the processed image is obtained from the bit stream using Huffman decoding, followed by inverse quantization and inverse DCT (IDCT). The Huffman technique is used because it is independent of the data type and does not lose any details during compression. The proposed quality measures are evaluated by varying the compression ratio.

Third, an image transmission framework as shown in Fig. 3 is considered for assessing the performance of the quality indices. From the image compression part, the bit stream is transmitted using either quadrature phase shifting keying (QPSK) or 16-bit quadrature amplitude modulation (QAM). In channel, the additive white Gaussian noise (AWGN) with different values of SNR is added. In the receiver part, the processed image is obtained using demodulation and image decompression. The proposed measures VMQI is evaluated by varying the SNR values of AWGN channel.

## 4. Results and Discussion

In this section the performance of the proposed variational mode quality index measure over image denoising, image compression and image transmission are evaluated. The correlation of the proposed distortion measure VMQI with subjective score is also investigated. This study is tested using the images from a publicly available Oasis MRI brain image database [28]. In the present work gray MRI images are used. These images are extracted by using RGB to gray conversion. All the images are resized to (512 × 512) before decomposition. The discussions of the results are given in the next section.

### 4.1 Performance of VMQI over image denoising

In this study, impulsive noise and additive noise are used to validate the proposed method. Impulsive noise, such as salt and pepper noise, is generally caused by errors in data transmission, failure in memory cells or analog-to-digital converter errors. On the other hand, Gaussian noise is the best example of additive noise. This noise is present in many applications, such as optical imagery, medical images from CT scans, the result of sensor limitations during image acquisition under low-light conditions, etc. Gaussian noise and salt and pepper noise are added to the original image with different variance values. The median filter has been applied to de-noise the image because it preserves the edges while removing noise [1].

Then, the performance of the proposed VMQI measure and various existing quality measure such as SSIM, MSE are evaluated. Fig.4 depicts the original image, noisy images (Gaussian noise and, salt and pepper noise with 0.06variance) (Fig. 4(b) and 4(d)) and filtered image (Fig. 4(c) and 4(e)). In the case of Gaussian noise, it was observed that the SSIM between original image (Fig.4(a)) and the filtered image (Fig.4(c)) is 0.567, whereas the proposed VMQI is 0.375.When the median filter is used, it is found that the VMQI is 0.816, whereas SSIM is 0.919. By minutely observing the texture of the images, we can observe that the SSIM is not able to quantify the local similarities, because it is a global measuring index. Whereas, in the case of VMQI, initially the image is decomposed into different modes.

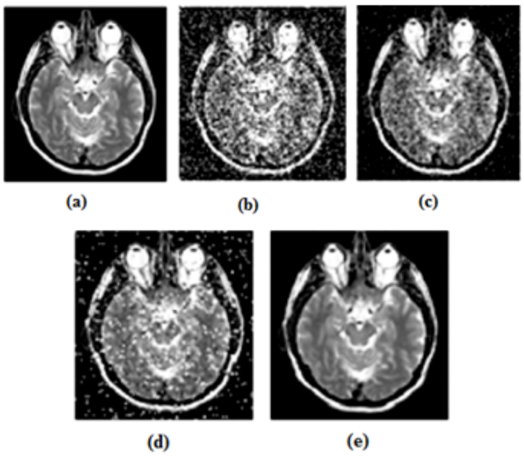

**Fig. 4.** (a) Original Image (b) Image with Gaussian noise (variance 0.06) (c) filtered image of fig. b (SSIM =0.567 and VMQI=0.375) (d) Image with Salt-and-pepper noise (variance 0.06) (e) Filtered image of Fig. 4(d) (SSIM=0.919 and VMQI=0.816).

The similarities between the modes are found using the SSIM and weights are assigned to the local similarities based on the information of the respective mode (calculated using either entropy or energy). Table 1 and Table 2 depict the performance of VMQI measure with different variance values of noise in image de-noising framework.

**Table 1.** Comparison of quality indices SSIM, MSE and VMQI in image denoising with entropy-based weighting scheme.

| System | Variance (mean=0) | SSIM | MSE | VMQI |
|---|---|---|---|---|
| Image denoising (Gaussian Noise) | 0.010 | 0.705 | 0.187 | 0.646 |
| | 0.015 | 0.664 | 0.208 | 0.589 |
| | 0.020 | 0.630 | 0.227 | 0.544 |
| | 0.025 | 0.659 | 0.246 | 0.507 |
| | 0.030 | 0.631 | 0.262 | 0.477 |
| | 0.035 | 0.589 | 0.275 | 0.456 |
| | 0.040 | 0.558 | 0.288 | 0.436 |
| | 0.045 | 0.541 | 0.304 | 0.418 |
| | 0.050 | 0.532 | 0.310 | 0.402 |
| | 0.055 | 0.527 | 0.328 | 0.388 |
| | 0.060 | 0.524 | 0.340 | 0.375 |
| Image denoising (Salt and pepper Noise) | 0.010 | 0.927 | 0.119 | 0.785 |
| | 0.015 | 0.926 | 0.120 | 0.784 |
| | 0.020 | 0.925 | 0.122 | 0.780 |
| | 0.025 | 0.924 | 0.123 | 0.775 |
| | 0.030 | 0.923 | 0.124 | 0.760 |
| | 0.035 | 0.922 | 0.126 | 0.755 |
| | 0.040 | 0.921 | 0.127 | 0.750 |
| | 0.045 | 0.920 | 0.128 | 0.744 |
| | 0.050 | 0.919 | 0.130 | 0.739 |
| | 0.055 | 0.918 | 0.132 | 0.728 |
| | 0.060 | 0.917 | 0.134 | 0.715 |

It is evident from the result that the VMQI measure decreases by increasing the noise variance for both Gaussian and, salt and pepper noise cases.

**Table 2.** Comparison of quality indices SSIM, MSE and VMQI in image denoising with energy-based weighting scheme.

| System | Variance (mean=0) | SSIM | MSE | VMQI |
|---|---|---|---|---|
| Image denoising (Gaussian Noise) | 0.010 | 0.646 | 0.188 | 0.794 |
| | 0.015 | 0.587 | 0.211 | 0.720 |
| | 0.020 | 0.545 | 0.229 | 0.716 |
| | 0.030 | 0.480 | 0.261 | 0.708 |
| | 0.040 | 0.439 | 0.294 | 0.690 |
| | 0.050 | 0.404 | 0.317 | 0.637 |
| | 0.060 | 0.376 | 0.337 | 0.604 |
| Image denoising (Salt and pepper Noise) | 0.010 | 0.926 | 0.119 | 0.891 |
| | 0.015 | 0.925 | 0.121 | 0.856 |
| | 0.020 | 0.924 | 0.122 | 0.825 |
| | 0.025 | 0.923 | 0.123 | 0.825 |
| | 0.030 | 0.922 | 0.125 | 0.824 |
| | 0.035 | 0.922 | 0.125 | 0.824 |
| | 0.040 | 0.921 | 0.127 | 0.823 |
| | 0.045 | 0.921 | 0.128 | 0.818 |
| | 0.050 | 0.920 | 0.130 | 0.815 |
| | 0.055 | 0.919 | 0.130 | 0.812 |
| | 0.060 | 0.918 | 0.132 | 0.808 |

### 4.2 Performance of VMQI over image compression

In this subsection, DCT is applied to the image and then the DCT coefficients are subjected for quantization and encoding [29]. Here, we have used the Huffman encoding for converting the quantized data into a bit stream. In the reconstruction part, the Huffman decoding, and inverse quantization methods are used for obtaining the processed DCT coefficients of each block. Then, the inverse DCT is used to produce the reconstructed image from the DCT coefficients of the blocks and the evaluation is performed using the original and processed images. Fig. 5 depicts the original image and reconstructed image with 10%, 30% and 70% as compression ratio values. The SSIM values of the reconstructed images are found as 0.175, 0.18 and 0.183, respectively. Whereas the proposed local similarities assess measure VMQI of the images are 0.367, 0.369 and 0.3655.

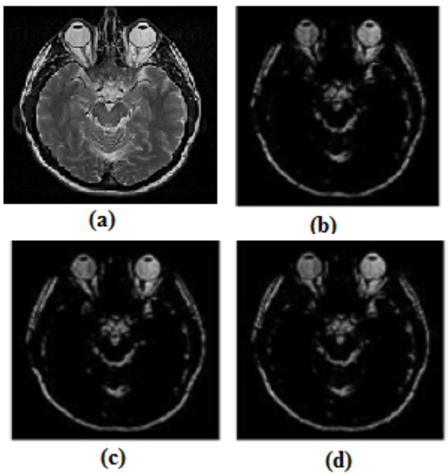


**Fig. 5.** (a) Original MRI Image (b) Reconstructed image with compression ratio 0.1 (SSIM=0.175 and VMQI=0.367) (c) Reconstructed image with compression ratio 0.3 (SSIM=0.1803 and VMQI=0.3694) (d) Reconstructed image with compression ratio 0.7 (SSIM=0.1832 and VMQI=0.3655 ).

These high values are due to the similarities of the modes of the images and the weights of the modes are 0.609, 0.186, 0.099 and 0.105. Experiments were conducted over several images with different compression ratios and the detailed results are presented in Tables 3 and 4.

**Table 3.** Comparison of quality indices SSIM, MSE and VMQI in image compression with entropy-based weighting scheme.

| System | Quality of compression | SSIM | MSE | VMQI |
|---|---|---|---|---|
| Image compression | 10 | 0.174 | 0.888 | 0.367 |
| | 20 | 0.179 | 0.884 | 0.371 |
| | 30 | 0.180 | 0.883 | 0.343 |
| | 40 | 0.181 | 0.882 | 0.374 |
| | 50 | 0.182 | 0.882 | 0.364 |
| | 60 | 0.183 | 0.881 | 0.364 |
| | 70 | 0.183 | 0.881 | 0.365 |
| | 80 | 0.184 | 0.880 | 0.380 |
| | 90 | 0.184 | 0.879 | 0.383 |

**Table 4.** Comparison of quality indices SSIM, MSE and VMQI in image compression with energy-based weighting scheme

| System | Quality of compression | SSIM | Norm MSE | VMQI |
|---|---|---|---|---|
| Image compression | 10 | 0.174 | 0.888 | 0.352 |
| | 20 | 0.179 | 0.884 | 0.354 |
| | 30 | 0.180 | 0.883 | 0.354 |
| | 40 | 0.181 | 0.882 | 0.358 |
| | 50 | 0.182 | 0.882 | 0.360 |
| | 60 | 0.183 | 0.881 | 0.362 |
| | 70 | 0.183 | 0.880 | 0.363 |
| | 80 | 0.184 | 0.880 | 0.365 |
| | 90 | 0.184 | 0.879 | 0.367 |

### 4.3 Performance of VMQI over image transmission

In this study, the digital image is compressed using DCT and converted to a bit stream using Huffman coding. Then the bit stream is transmitted using either quadrature phase shifting keying (QPSK) or 16-bit quadrature amplitude modulation (QAM) [30]. In the channel, different values of additive white Gaussian noise (AWGN) noise are added. In the receiver part, the process is reversed, and the image is reconstructed. Fig. 6 depicts the original image and the reconstructed image with compression and SNR as 50% and 15. SSIM and VMQI of the experimental result of 0.1818 and 0.3654. The VMQI quantifies the result more accurately as compared to SSIM. Experiments were conducted by varying the SNR of the channel and the quality measure was accessed. The details of the results are shown in Tables 5 and 6.

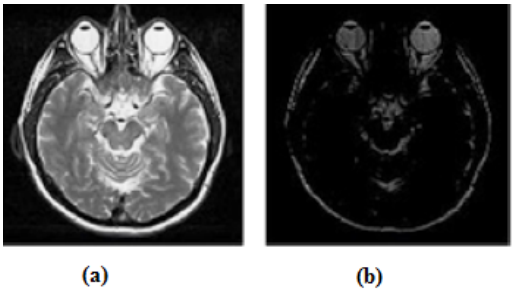

**Fig. 6.** (a) Original Image (b) Reconstructed image of QPSK modulated signal with compression ratio 0.5 and SNR-15(SSIM =0.1818 and VMQI=0.3654).

**Table 5.** Comparison of quality indices SSIM, MSE and VMQI in image transmission with entropy-based weighting scheme.

| System | SNR | SSIM | Norm MSE | VMQI |
|---|---|---|---|---|
| Image transmission ( 16 bit-QAM) | 1 | 0.151 | 0.769 | 0.277 |
| | 2 | 0.170 | 0.704 | 0.296 |
| | 3 | 0.190 | 0.644 | 0.303 |
| | 4 | 0.211 | 0.588 | 0.328 |
| | 5 | 0.234 | 0.537 | 0.347 |
| | 6 | 0.255 | 0.491 | 0.376 |
| | 7 | 0.282 | 0.448 | 0.464 |
| | 8 | 0.313 | 0.407 | 0.468 |
| | 9 | 0.351 | 0.365 | 0.508 |
| | 10 | 0.397 | 0.322 | 0.519 |
| Image Transmission (QPSK) | 1 | 0.173 | 0.849 | 0.251 |
| | 2 | 0.205 | 0.761 | 0.282 |
| | 3 | 0.245 | 0.656 | 0.309 |
| | 4 | 0.296 | 0.564 | 0.344 |
| | 5 | 0.371 | 0.456 | 0.449 |
| | 6 | 0.476 | 0.359 | 0.555 |
| | 7 | 0.607 | 0.270 | 0.662 |
| | 8 | 0.772 | 0.179 | 0.680 |
| | 9 | 0.893 | 0.118 | 0.750 |
| | 10 | 0.964 | 0.068 | 0.833 |

**Table 6.** Comparison of quality indices SSIM, MSE and VMQI in image transmission with energy-based weighting scheme.

| System | SNR | SSIM | Norm MSE | VMQI |
|---|---|---|---|---|
| Image transmission ( 16 bit-QAM) | 1 | 0.149 | 0.771 | 0.255 |
| | 2 | 0.171 | 0.708 | 0.301 |
| | 3 | 0.191 | 0.647 | 0.368 |
| | 4 | 0.212 | 0.589 | 0.370 |
| | 5 | 0.233 | 0.538 | 0.402 |
| | 6 | 0.256 | 0.492 | 0.436 |
| | 7 | 0.282 | 0.449 | 0.481 |
| | 8 | 0.310 | 0.406 | 0.489 |
| | 9 | 0.346 | 0.366 | 0.502 |
| | 10 | 0.393 | 0.324 | 0.521 |
| Image Transmission (QPSK) | 1 | 0.174 | 0.852 | 0.267 |
| | 2 | 0.204 | 0.756 | 0.322 |
| | 3 | 0.241 | 0.666 | 0.322 |
| | 4 | 0.300 | 0.556 | 0.436 |
| | 5 | 0.375 | 0.455 | 0.507 |
| | 6 | 0.482 | 0.361 | 0.562 |
| | 7 | 0.618 | 0.257 | 0.565 |
| | 8 | 0.773 | 0.178 | 0.732 |
| | 9 | 0.893 | 0.120 | 0.816 |
| | 10 | 0.956 | 0.066 | 0.845 |

### 4.4 Correlation of VMQI with subjective measure

The effectiveness of the proposed model is evaluated by investigating the correlation with subjective score [31]. The subjective evaluation is conducted by comparing the pair of images. The first image is the original image with good quality and the second one is the processed image.
The processed and original images have been given to the evaluators. Based on the visual similarity of the processed image with respect to the original image, each evaluator has assigned a score. The mean opinion score (MOS) is computed as the average values of these scores for each image using the number of evaluators. It is an ABC type subjective evaluation and is expressed as a single rational number, typically in the range of 1-5, where 1 denotes poor quality, and 5 is the best quality. It is calculated as the arithmetic mean of individual ratings ($R_i$) recorded by the experts for n samples and is demonstrated as

$$\text{MOS} = \frac{\sum_{i=1}^{n} R_i}{n}. \quad (4.1)$$

The difference in mean opinion score (DMOS) is calculated using the difference of the mean opinion score of the original image and processed image [32].

The performance of the proposed method is assessed by the popularly used evaluation criteria Pearson product-moment correlation coefficient (PPMCC). This technique was used to summarize the strength and direction of the two vectors with n samples each. Its range is from -1 to 1. PPMCC is a non-parametric rank order-based correlation metric and independent of the monotonic nonlinear metric between subjective and objective scores and can be defined as

$$\text{PPMCC} = \frac{1}{n}\sum_{i=1}^{n}\frac{(x_i - \bar{x})}{\sigma_x}\frac{(y_i - \bar{y})}{\sigma_y}. \quad (4.2)$$

The PPMCC is used for the qualitative analysis of the proposed image quality measure (VMIQ) and other existing measures (SSIM, MSE) with respect to the subjective test. The correlation coefficient (PPCC), the sum of squares of the error (SSE) and the root mean squared error (RMSE) measures are evaluated after performing the qualitative analysis. The qualitative analysis based on the curve fitting using least square method for SSIM Vs DMOS, norm MSE vs DMOS and proposed VMIQ vs DMOS is depicted in Fig.7.

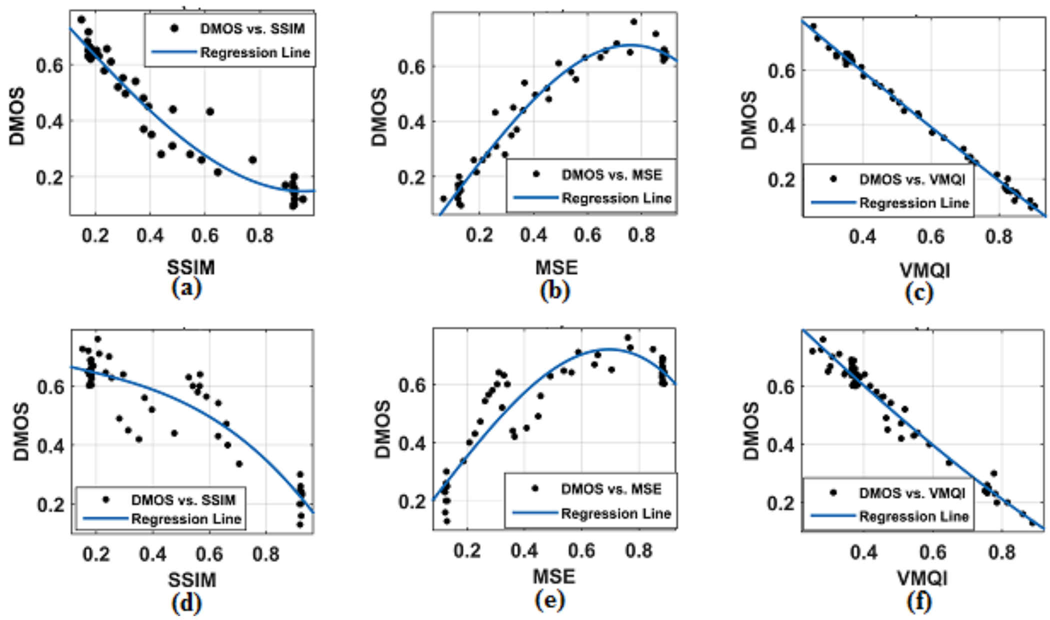


**Fig. 7.** (a)SSIM vs DMOS (b) MSE vs DMOS (c) VMQI vs DMOS with Wentrpy (d)SSIM vs DMOS (e) MSE vs DMOS (f) VMQI vs DMOS with Wmse.

It has been observed that, in energy based weighted system the VMQI has high correlation coefficient (PPMCC) value of 0.996 as compared to SSIM and MSE correlation values 0.9566 and 0.9715 respectively. The correlation value of SSIM and MSE with DMOS is 0.8681 and 0.8702 in energy based weighted method, whereas correlation value of VMQI is 0.973. The SSE and RMSE value in both the weighted method is much less compared to SSIM and MSE which supports the effectiveness of the proposed method. The evidence is recorded in Table 7.

The testing of VMQI measure over image compression technique is implemented using MATLAB software (version R2014a) and a desktop computer with configuration as Intel (R) i3-2120 CPU @ 3.30 GHz.,4 GB RAM. The average execution time for the evaluation of image quality using VMIQ is 530ms. The above observations from the work infers that the image quality measure is efficient to estimate the local similarities of processed image with respect to the original image.

**Table 7.** Correlation of the image quality measure with the DMOS.

| Weight | Parameters | SSIM | MSE | VMQI |
|---|---|---|---|---|
| | SSE | 0.1102 | 0.0723 | 0.009 |
| $W_{entropy}$ | PPMCC | 0.9566 | 0.9715 | 0.996 |
| | RMSE | 0.0456 | 0.0369 | 0.013 |
| | SSE | 0.2672 | 0.2629 | 0.054 |
| $W_{energy}$ | PPMCC | 0.8681 | 0.8702 | 0.973 |
| | RMSE | 0.06847 | 0.06792 | 0.030 |

## 5. Conclusion

In this paper, a new algorithm is proposed to quantify the similarity between the images. Several decomposition techniques such as discrete cosine transform (DCT), discrete wavelet transform (DWT) and Variational Mode Decomposition (VMD) are available for 2D decomposition purpose. VMD, which has an image-dependent property, is used in this work. The SSIM is used to find the similarity between the modes of the decomposed images instead of the total image. The weightage of the similarity is decided by the information contain of the individual modes. The overall similarity between the referral and processed image is recorded by taking the weighted average of individual modes. The proposed method is tested over various images using different image processed technique. The opinion score of the images for VMQI, SSIM and MSE are collected from image experts as well as common people. The correlation of the mean opinion score and the VMQI demonstrate the effectiveness of the proposed method.

The primary drawback of this approach is that it requires a referral image in order to deliver the quality. In the future, we will work on non-reference image quality measures by applying various machine learning techniques and SSIM to image modes. This will be a solution for the quality assessment of a blind image.

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