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Anticipatory Quality Assessment Metric for Measuring Data Hiding Imperceptibility

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Abstract. *Steganography is the art of writing concealed information in a way that it cannot arouse suspicion about its existence. The hidden data must not raise the attention of attackers to the existence of secret information in the host image. Therefore, ensuring high imperceptibility of the steganography is very essntial. Imperceptibility evaluation of the stego file can be determined by subjective or objective evaluation. Subjective evaluation is based on human judgment and opinion determining visual quality. This kind of evaluation, is not efficient as it is expensive, time consuming, and in any way cannot be referred to as an automatic system. On the other hand, objective metrics are based on mathematical concepts and might have poor correlation with subjective evaluation. This paper focuses on predicting the subjective quality using anticipatory objective Image Quality metric (IQM). The primary objective of this paper is to develop a systematic method of using HVS for image quality assessment. Moreover, the new metric method use a mathematical approaches for image quality measures predict the image quality measure basing on human perception.*

Keywords: Steganography, Anticipatory quality assessment metric.

1. **Introduction.** Information security field is facing a great challenge; the capacity to hide data is a significant constraint obstructing the progress of steganography. Steganography is a scientific field that deals with the hiding of data within information in an appropriate secret file cover. These modes of hiding secret information reduce the threat of attackers. A file is produced which has all the hidden information o known as a stego file. This stego file must be identical to the original file. In order to achieve this, a steganographic system depends on factors that are detrimental to its functionality. These factors include: payload capacity; imperceptibility; and robustness. By hiding a secret message, noise may be introduced to the original cover file, but this introduced noise must not be seen and detected by any human visual system or any statistical means.

There is a significant demand for steganographic approaches that can ensure imperceptibility of such information. Measuring the imperceptibility of the stego file is essential for most approaches dealing with image steganography. It can be determined by subjective or objective evaluation. The most accurate and reliable way to determine the visual quality of such stego file would be by human visual evaluation (subjective evaluation) [14, 15]. However, this type of evaluation is, time consuming, expensive, and can not be part of an automatic system. For these reasons, researchers used objective evaluation for assessing quality of the image as it based on mathematical equations and provides faster results.

However, there are a limited corresponding evaluation parameters available. Most of the studies use the Peak Signal to Noise Ratio (PSNR) as a metric for imperceptibility evaluation, although it could provide less accurate results than the Human Visual System (HVS) evaluation.

The simplest and most extensively utilized objective quality assessment parameter is the Mean Squared Error (MSE), calculated by averaging the squared concentration alterations of cover and stego image pixels. MSE and PSNR are attractive parameters since they are modest to compute, have pure physical connotations, and are statistically suitable in the perspective of optimization. However, PSNR measures the mathematical differences between the cover image and the stego image and does not take into account the characteristic of human visual system (HVS). Therefore, they have poor correlation with the perceived quality by the Human Visual System (HVS) [9, 10]. In the last few decades, extensive work has gone into developing advanced quality assessment methods that effectively use the features of (HVS).

The authors of this article have analyzed the correlation between subjective and objective evaluation [13]. On these experiments, a comparative study of the existing image quality metrics is performed for the steganographic images. The image quality score for commonly used objective quality metrics in the field of steganography has been compared with the subjective assessment performed by 500 observers. It was found that the selected objective metrics has a poor correlation with the subjective assessment, and may fail to accurately evaluate the performance of a steganographic algorithm. The HVS based metrics have better correlations compared to the standard pixel based metrics such as MSE and PSNR; this shows the effectiveness of using features of HVS in the quality assessment metrics. Figure 1 plots the main image quality metrics (objective evaluations) with Mean Opinion Score (subjective evaluation) conducted by 500 observers for degradation evaluation. Poor correlations were obtained between MOS and error based metrics such as PSNR and MSE. However, the objective quality metrics derived from the HVS features have a good relationship with the subjective assessment as compared to standard MSE and PSNR [1,2,13]. The outstanding quality of the image index depicted has the greatest correlation to the subjective score because of its loss of cover and stego images. This is due to the capacity to detect luminance distortion. In addition, the study concludes, that the human eye is depicted to be less sensitive to a blue color and more sensitive to green [13]. Therefore, it is significant to involve the human perception characteristics to assess the performance of any quality assessment metric. As such, not only color sensitivity should be considered but also brightness, contrast and image complexity are important factors.

Based on this analysis, it is essential to develop a predictive quality metric that is objectively assess the image quality on a similar way to the subjective evaluation. This paper focuses on predicting the subjective quality using an anticipatory objective. Anticipatory Quality Assessment Metric (AQAM) is an objective assessment metric that simulates the judgment of human perception. The primary objective of this paper is to develop a systematic method of using HVS for image quality assessment.

2. **Anticipatory Quality Assessment Metric.** The Anticipatory Quality Assessment Metric (AQAM) parameters determine the quality of the image by applying the underlying principles of Human Visual System (HVS). AQAM emphasizes distortion which can be identified by a human observer. Therefore, this method creates a model using the local image properties based on the strategies implemented by HVS. The intensity and edge point of zero-crossing based on wavelets are the main strategies of this study. The intensity of the image is identified from the sharp regions. The details which are found in the sharp

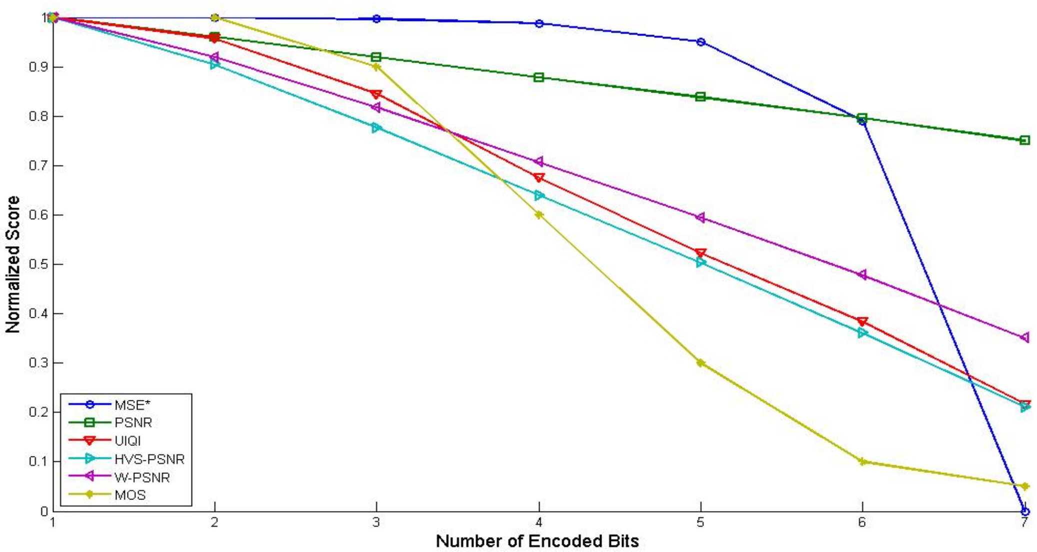

FIGURE 1. Normalized subjective and objective score

region of that photo is resolvable at multiple levels determining the sharp variations in image edge points.

The distortions impact on the contrast points in the photo changing structural data contact. The Noise Visibility Function (NVF) is applied to achieving edge areas in any image analyzed in the multi-level wavelet domain. It generates the information containing various sub-bands.

Zero crossing is a local structure categorized by a set of pixels demonstrating the sharp intensity of variations in the neighborhood. To achieve this, the edge data is extracted from the photo by applying the Laplacian Methods or a gradient. The main function of NVF is the estimation of the regional complexity by carrying out analysis in every region of the local image. The method that is proposed here estimates the quality of the perceptual image by using local image and intensity properties in the wavelet domain.

Frequency data is used for the quality perception of the linear spatial that is mined from the three levels of wavelet. Calculations are made for logging energies of the sub-bands and a weighted geometric mean provide a base for the sharpness estimation. Finer scales (high frequency bands) deliver a bigger result with the reduction in the sharpness numerical value. The intensity of the cover and the stego image is achieved through calculation. In order to find the accurate information of the whole process the similarity in sharpness of the cover and stego images are estimated.

Consequently, the wavelet of the image provides the high frequency sub-bands at i^{th} level as:

$\{W_{LH}^i, W_{HL}^i, W_{HH}^i\}$.

The sub-band power of $i \in 1, 2, 3$ are computed as:

$$\alpha_x^i = \log_{10}(1 + \frac{\delta(x)}{\varphi_x^i}) \tag{1}$$

$\delta(x)$ is the value achieved by summing up the square off coefficients x, where x belong to $W_{LH}^i, W_{HL}^i, W_{HH}^i$. φ_x^i is the total coefficient of sub-band x which related to level i. The number of strength at each stage is measured as:

$$\alpha^i = \frac{\mu(\alpha^i_{W_{LH}} + \alpha^i_{W_{HL}}) + \eta.\alpha^i_{W_{HH}}}{\mu + \eta} \tag{2}$$

In the above mentioned equation the constant and variable have some assigned values as follows:

Constant μ is specified a value 0.3, η is assigned as 3. Note: η is allocated to higher value to provide larger weighting for the HH sub-band that has the high frequency mechanism.

The general intensity of a given image in the Equation 3 ensures lower measures of low value wavelets. For stego and cover image, intensity are assumed by γ_C and γ_S. The sharpness likeness of the stego and cover images is shown in Equation 4. ψ can be any value use for the avoidance of denominator being zero.

$$\gamma = \overset{[}{i} = 1]3 \sum 2^{3-i} \alpha^i \tag{3}$$

$$\omega = \frac{2\gamma_C \gamma_{S+\psi}}{\gamma_C^2 \gamma_{S+\psi}^2} \tag{4}$$

The cover image is referred to as a quality reference image at hand, using the current point of view. By applying the Equation 5 and **6,** the edge match of each sub-bands of the stego and cover is assessed. It is seen that the higher the alteration, the higher the difference of the edge. The data will remain in the edge points which are normally not displaced due to distortions.

The difference is seen in the Gaussians (DoG) logical model which was anticipated by many in vision science; these are in the receptive fields of X-cells in the Lateral Geniculate Nucleus (LGN) in the thalamus, [3,7]. The CSF was later deployed in the band pass filters within frequency domain, called the weighted sum of DoG (or SDoG). The result is to make DoG the creator of bandwidth of the CSF, taking the visual system as a multi-scale analyzer together with ON/OFF cells with required size and Enroth-Cugell Christina and Robson receptive fields [3]. The equation referring weighted sum of DoG will be:

$$E(C) = \sum_k Th_k \lfloor G^+_{\sigma k} - G^-_{\sigma k} \rfloor (C) \tag{5}$$

$$E(S) = \sum_k Th_k \lfloor G^+_{\sigma k} - G^-_{\sigma k} \rfloor (S) \tag{6}$$

In the above equation, C and S are considered as the stego and cover images (in luminance units) respectively; G_σ is the normalized Gaussian operator, Standard Deviation (SD) σ, σ^+ and σ^- are the SD of the positive and negative parts of a DoG ($\sigma^- = \lambda\sigma^+$); and Th is embedding threshold use for illustration in the next part.

A DoG is not seen only as a second derivative but it is also used for achieving edge detection with the same superiority as with $\nabla^2 G$ expressed in the forms of coefficient and localization of the negative and positive weights; they are to be same as per equation (as in Equation 5 and 6).

The edge points numerical value of the stego and cover images are viewed as$E(C)$ and $E(S)$ correspondingly. The cover and stego image edge show structural similarity and are computed as given in equation E_s.

$$E_{s_x} = \frac{\mathrm{sum}(E_x(C) \cap E_x(S))}{\sqrt{\mathrm{sum}(E_x(C)} \sqrt{\mathrm{sum}(E_x(S)}} \tag{7}$$

The final relationship of zero-crossing is shown in equation

$$\Delta = \Pi_x E_{s_x} \tag{8}$$

In this context, the two features that are the edge and intensity point of zero-crossing are unavoidable for the image quality evaluation. Therefore, the newly born AQAM metric use to asses the perceptual image quality. The proposed quality metric can be calculated as:

$$AQAM = \Delta^{\nu} \cdot \omega^{\nu} \tag{9}$$

The value of ν has been taken as 0.8, for it to give the greater geometric weight to intensity since it is the most powerful feature that captures human attention in early vision.

3. **Experimental Results.** Validating the performance of proposed quality metric subjectively is a primary phase. Mean Opinion Score (MOS), may be used for measuring the subjective evaluation. High MOS values indicates that the image is of good quality and nearly identical to the original image. It is worth noting that in this experiment we used MOS as our benchmark to measure the correlation between selected MOS and IQM. For this reason we selected TID2013 (Tampere Image Database 2013) which is a publicly available database [5]. The MOS on the other hand was obtained from the result of 500 experiments that were conducted by 500 observers, delivering MOS which ranges from 1 to 5. The TID2013 consists of 25 cover images, producing 150 stego images from five different steganography approaches. Table 1 shows list of steganography approaches used in the experiment.

The measurements or values produced by each of the selected image quality metrics were correlated with MOS using two different performance measures: Spearman Cank Order Correlation Coefficient Spearman Rank Order Correlation Coefficient (SROCC) [6] and Pearson Linear Correlation Coefficient Pearson Linear Correlation Coefficient (PLCC) [4]. PLCC was the most commonly used delivering accurate predictions. The prediction accuracy can be quantified by two ways; either by measuring the average error between the algorithms predictions and MOS values or by measuring how well an algorithms predictions correlates with the MOS values. SROCC was employed to assess prediction monotonicity. Thereafter, the prediction monotonicity specifies how well an algorithm predicts the rank ordering of the opinion scores.

The overall PLCC results are obtained from the experiment for the test images and are presented in the scatter plot graph in Figure 3. From Figure 3, it is clearly seen that PLCC of PSNR, SSIM, and UIQI metric were positively correlated with MOS. While, the scatter plot graph of AQAM shows a negative correlation between these two variables. The results in Table 2 depict a value which is almost equal to -1. From this point of view, we can conclude that the AQAM metric has the highest correlation with MOS readings compared to the other metrics. The main reason why the graph is negative correlates to how the AQAM metrics are calculated. From this it is concluded that the lower the quality of an image, the higher is the AQAM score. Meanwhile, MOS assigns a lower score for lower image quality and a higher score for better image quality. It is seen that the AQAM demonstrated high prediction performance because of the two modeling strategies used by the HVS and by adapting these strategies based on the amount of distortion.

Moreover, Figure 2 illustrates the relationship between PSNR, MSE, wPSNR, PSNR-HVS, UIQI and AQAM with MOS based on 500 observers. Most of the metrics deliver good results when the number of encoded bits were low. However, with the increase of the encoded bits, wPSNR, UIQI and PSNR-HVS follow the MOS trajectory in some degree while AQAM perfectly matched the MOS.

Table 1. Steganography approaches

Distortion	Steganography approach
1	Least Significant 4 Bits (2-LSB)
2	Least Significant 4 Bits (4-LSB)
3	Pixel Value Differences (PVD)
4	Steganography method proposed in [11]
5	Steganography method proposed in [12]

Table 2. Performance Comparison using PLCC and SROCC

Assessment Metric	PLCC	SROCC
PSNR	0.72896	0.75415
SSIM [8]	0.81562	**0.93415**
UIQI [9]	0.85952	0.91597
AQAM	**-0.95295**	0.92987

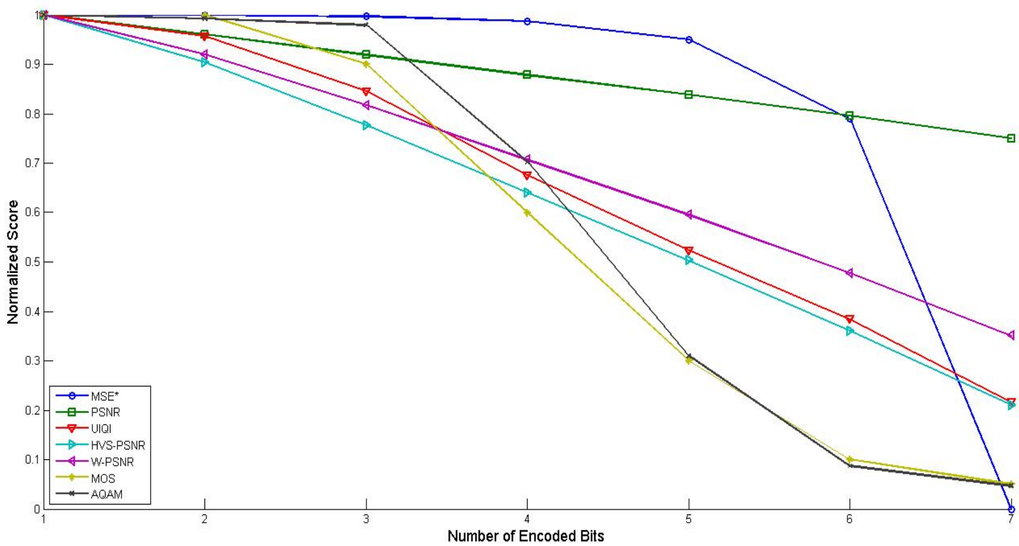

Figure 2. Normalized image metrics with subjective evaluation

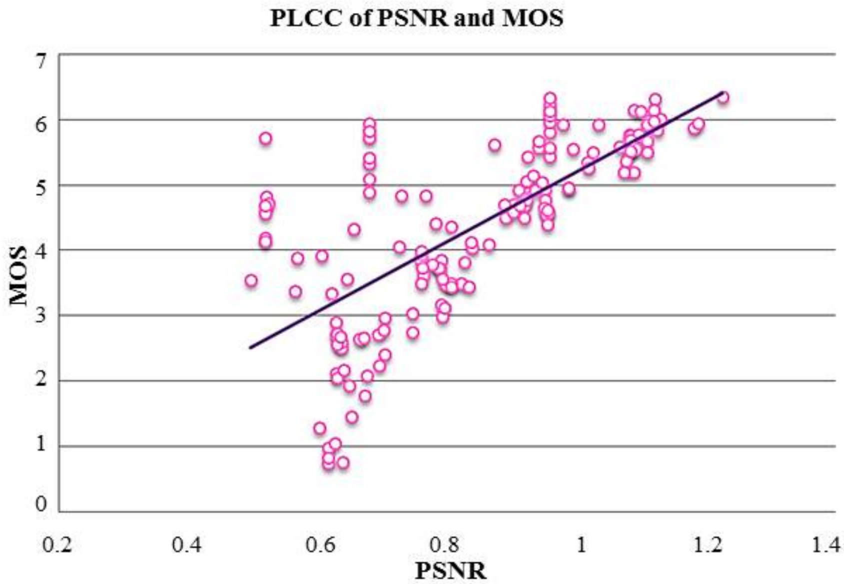

FIGURE 3. PLCC of PSNR and MOS

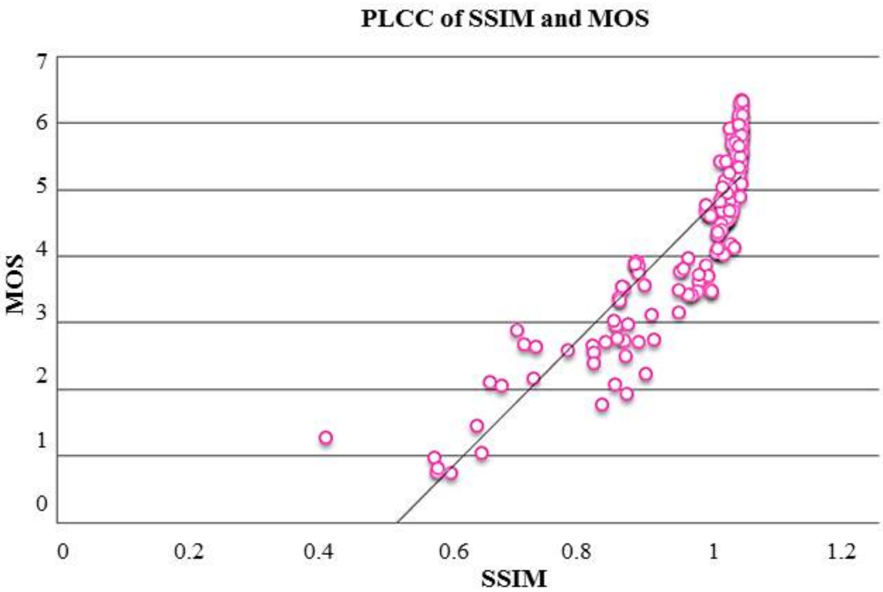

FIGURE 4. PLCC of SSIM and MOS

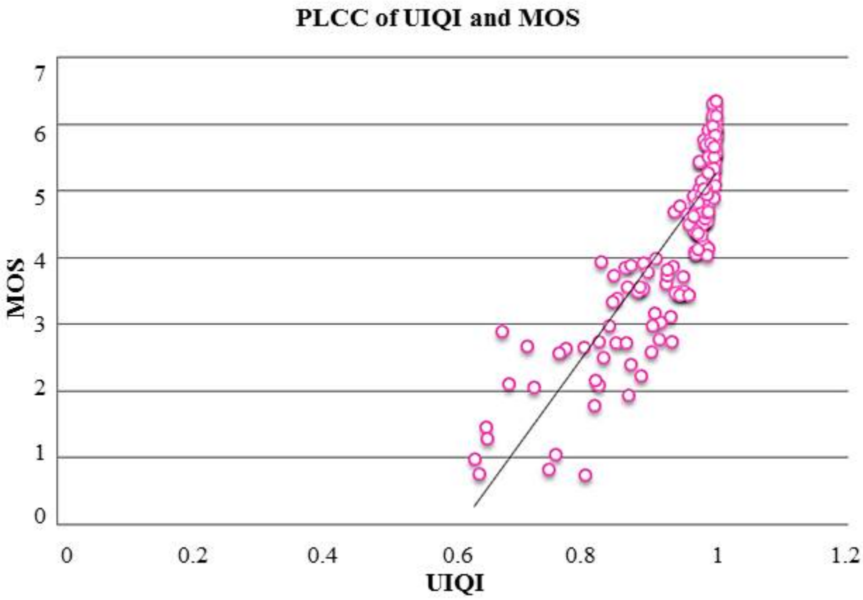

Figure 5. PLCC of UIQI and MOS

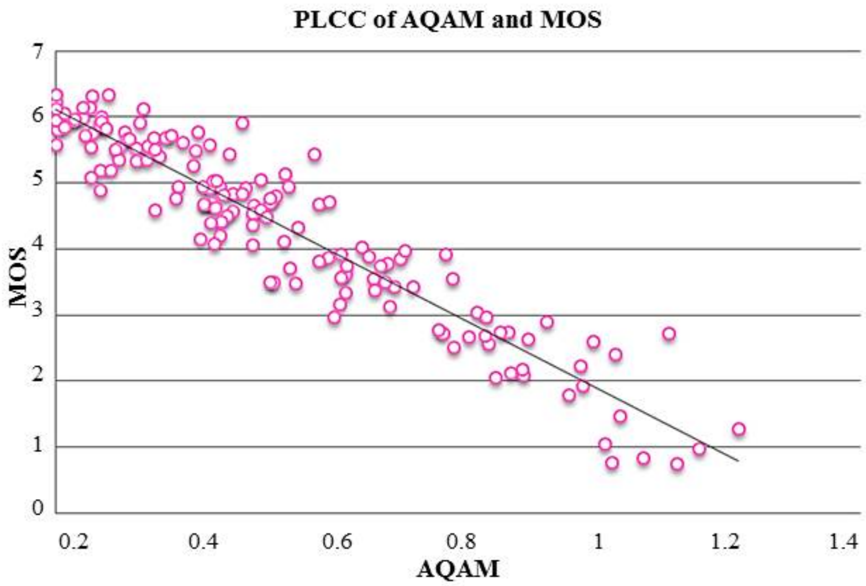

Figure 6. PLCC of AQAM and MOS

4. **Conclusion.** In conclusion, the work presented in the paper depicts a simple method used in image quality assessment; it accounts for the most significant features regarding image structural data, the edge point and intensity. From the research conducted, the AQAM method proved to be efficient in the comparative analysis with the other three publicly available image quality assessment databases.

Furthermore, the overall capability of the image quality index (IQM) to predict the quality of image depends on the type of image content and also the level of degradation present. Each IQM has its limitation and strength on estimating image quality. On the other hand AQAM metric provides an excellent correlation with MOS based on PLCC whilst SSIM is the best performing algorithm based on SROCC. The PSNR metric gave the poorest result using both SROCC and PLCC. From the analysis, we conclude that the best metric for the method that uses the properties of HVS is achieved through AQAM whereas SSIM is the best method based on the principle of image structure. Alternatively, the performance of SROCC for SSIM is the best, the SROCC of AQAM is acceptable and very close to SSIM performance. It was seen that there were strong monotonic correlations between AQAM and SSIM with MOS. Both of the metrics also demonstrated that they could perform as well as a subjective evaluation process in assessing image quality.

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