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Research Article

Image Quality Assessment (IQA) for Parasites

Muhammad Amirul Aiman Asri[1], Norrima Mokhtar[1], Heshalini Rajagopal[2], Wan Amirul Wan Mohd Mahiyiddin[3], Yvonne Ai Lian Lim[4]

[1]*Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Lembah Pantai, Kuala Lumpur, Malaysia, Malaysia*
[2]*Institute of Computer Science and Digital Innovation (ICSDI), UCSI University, Kuala Lumpur, Malaysia*
[3]*Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Lembah Pantai, Kuala Lumpur, Malaysia, Malaysia*
[4]*Department of Parasitology, Faculty of Medicine, University of Malaya, Lembah Pantai, Kuala Lumpur, Malaysia.*

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ABSTRACT

Distorted images due to microscopy lens distortion can cause errors when acquiring images of parasites in water samples during inspection. Given the critical nature of inspecting treated water, it is important to monitor the quality of microscopic parasite images to prevent errors during inspection. To this end, this study involved both subjective and objective evaluations of parasite images, specifically Cryptosporidium and Giardia (oo)cysts. The evaluation utilized a parasite image database comprising 380 images where 20 are reference images and 360 are distorted images. For the subjective assessment, 20 subjects assessed the distorted images, and Mean Opinion Scores (MOS) were obtained. To perform an unbiased evaluation, six Full Reference-IQA (FR-IQA) metrics and three Blind-IQA metrics were employed to appraise the distorted images. The Mean Opinion Scores (MOS) were used as a reference point to ascertain the most appropriate objective IQA method for evaluating the parasite images. The study analyzed the relationship between the MOS ratings and the objective IQA techniques using PLCC and RMSE as performance metrics. The results of the investigation revealed that the MSSIM method was the most effective IQA approach for evaluating parasite images affected by Gaussian White Noise (GWN) and Gaussian Blur (GB).

1. Background

Many researchers in image processing are interested in using object recognition for inspection, with the goal of automating tasks that were previously done by human experts. To ensure the accurate counting of parasites such as Giardia and Cryptosporidium in treated water samples, high-quality images are necessary when inspecting them under a microscope. These parasites play a crucial role in determining the safety of the treated water [1]. While numerous image quality assessment models have been developed, to the best of our knowledge, no studies have reported on the assessment of image quality in microscopic images, particularly those of Giardia and Cryptosporidium parasites. The significance of this work lies in its substantial contribution, considering the multitude of researchers who have focused on addressing and reporting on the correction of distortion in microscopy lens systems. These systems can result in problems such as asymmetrical geometric distortion and displacement errors [2], [3], [4], [5]. Unlike previous works and reports that solely addressed distortion correction, our study's focus was on evaluating the image quality of microscopic parasite images, with a particular emphasis on Giardia and Cryptosporidium. This work could potentially generate more interest in studying other microscopic images as well. Image Quality Assessment (IQA) is broadly classified into two types: subjective and objective quality assessments. Subjective evaluation involves visual assessment and rating of the image quality based on humans' perception, while objective assessment utilizes statistical set of rules to determine the ratings. While subjective evaluation serves as the benchmark for IQA, it is prone to errors caused by human fatigue and is both time-consuming and expensive [6]. In order to enhance the treated water inspection process, the adoption of objective assessment methods is necessary. Image Quality Assessment (IQA) has progressed towards Blind IQA methods in recent times [7], [8]. The Objective IQA metrics are illustrated in Fig. 1.

Corresponding author E-mail: norrimamokhtar@um.edu.my URL: www.um.edu.my

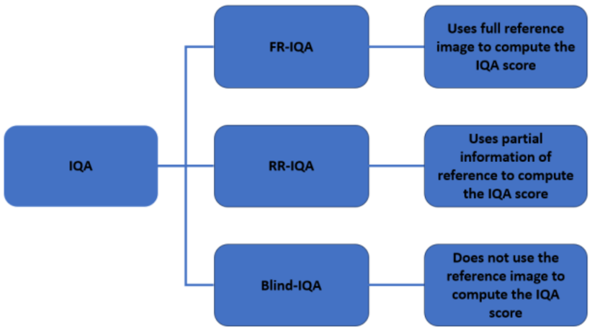


Fig. 1. IQAs

In this study, six FR-IQA metrics, SSIM [9], MS-SSIM [9], FSIM [10], VIF [11], IW-SSIM [12] and GMSD [13]. In addition, three Blind-IQA, namely BRISQUE [14], NIQE [15] and PIQE [16]. These metrics were selected because they are frequently utilized to assess the image quality of diverse image categories, such as medical, wood species, underwater, and natural images. [17], [18], [19], [20]. After examining these objective assessments, their efficacy was measured using Mean Opinion Scores (MOS) from human raters, as well as metrics. Pearson's Linear Correlation Coefficient (PLCC) [21] Root Mean Square Error (RMSE) [22] were the metrics utilized in our study to assess their performance.

2. Methodology

2.1. *Parasite Species Images*

The Department of Parasitology at the University of Malaya, Malaysia provided us with a collection of twenty images featuring 2 parasite species, Giardia and Cryptosporidium Fig. 2 displays the parasite images. The grayscale images were normalized to facilitate the application of uniform levels of distortion across all the reference images. The size of each image is 1376 x 1320. In order to replicate typical image distortions observed in parasite images, GWN and GB were applied to the original parasite images. GWN can arise during image acquisition by the capturing apparatus [23]. GB is a well-known blurring method used to correct for background and staining effects in parasite images [24]. The presence of such distortions can lead to a decrease in the quality of the parasite image [25]. Consequently, the distinctive characteristics of the parasites may not be discernible, potentially resulting in misidentification of the species. This is because the feature extraction process may not be able to accurately capture the distinguishing features from the textured parasite images [25].

Nine levels of GWN and GB distortion were applied to the reference images in the range of 10 to 90.

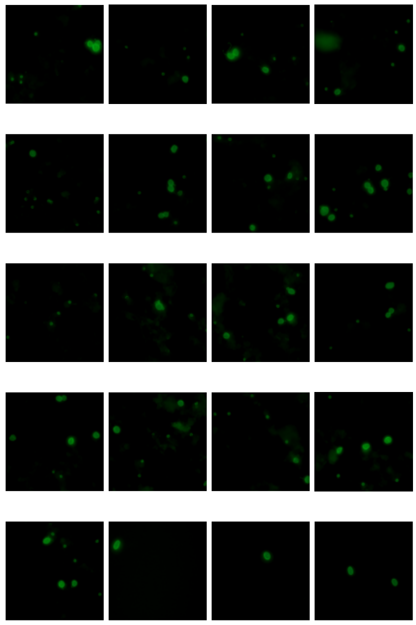


Fig. 2. Reference parasite images

2.2. *Subjective IQA*

The parasite image evaluation involved twenty participants between the ages of 20 and 25. The assessment was conducted following the Rec. ITU-R BT.500-11 guidelines [26]. The SDSCE methodology was employed for the subjective evaluation, which involves the simultaneous presentation of reference and distorted images for continuous evaluation [15], [26]. The SDSCE methodology was employed for the subjective assessment, whereby each subject compared the quality of the reference and distorted images displayed side-by-side on the monitor screen. The reference image was displayed on the left and the distorted image was displayed on the right. Using a scale of 1 (Bad) to 5 (Excellent), each subject evaluated the distorted image relative to its reference image without knowing the numerical scores. The ratings were used to calculate MOS without revealing the scores to the subjects in order to prevent bias. Before the evaluation, the vision acuity of every subject was checked using the Snellen Chart to ensure their suitability for the task [27].

2.3. *Objective IQA*

The MOS is compared to nine IQA metrics. The metrics used in this study is explained in Table 1. In order to investigate the relationship between subjective MOS values and objective IQA, two well-established performance metrics were employed. The first metric, known as PLCC, entailed computing PLCC values through non-linear regression between the FR-IQA metrics and MOS. The second metric utilized was RMSE, a commonly used statistical measure for assessing model performance [28].

Table 1. IQA metrics

IQA Algorithm	Description
Structural Similarity Index Metrics (SSIM)	Captures the loss in the structure of the image.
Multiscale SSIM (MS-SSIM)	Mean of SSIM that evaluates overall image quality by using a single overall quality.
Feature SIMilarity (FSIM)	A low-level feature-based image quality assessment which used two types of features: Phase Congruency (PC) and Gradient Magnitude (GM).
Visual Information Fidelity (VIF)	Measures image information by computing two mutual information quantities from the reference and distorted images.
Information Weighted SSIM (IW-SSIM)	Obtained by combining content weighting with MS-SSIM.
Gradient Magnitude Similarity Deviation (GMSD)	Computes the pixel-wise similarity between the gradient magnitude maps of the reference and distorted images to create a Local Quality Map (LQM) of the distorted image.
Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)	Computes two types of Gaussian distribution functions to accommodate the varying characteristics of MSCN coefficients: Generalized Gaussian Distribution (GGD) and Asymmetric Generalized Gaussian Distribution (AGGD)
Naturalness Image Quality Evaluator (NIQE)	Measures the distance between the NSS-based features calculated from image to the features obtained from an image database used to train the model. The features are modelled as multidimensional Gaussian distributions
Perception based Image Quality Evaluator (PIQE)	Calculates the no-reference quality score for an image through block-wise distortion estimation

3. Results and Discussion

Fig. 3 explains relationship between MOS and nine levels of GWN and GB. Scatter plot is being used to show the MOS scores are given by different individuals. In general, the quality of an image tends to degrade as the level of distortion increases, leading to a decrease in the MOS value as shown in the scatter plot and its trending line. This suggests that human subjects were capable of distinguishing between images that had varying degrees of distortion. The findings depicted in Fig. 3 (b) reveal that the MOS scores remained relatively constant despite an increase in the level of GB from 10 to 90, indicating that the blurring effect had not much impact on the quality of the parasite images.

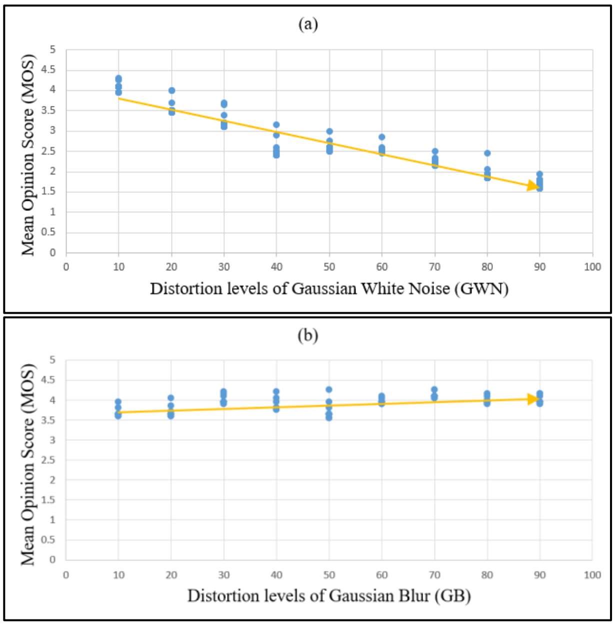


Fig. 3. Relationship between (a) GWN, (b) GB levels and MOS

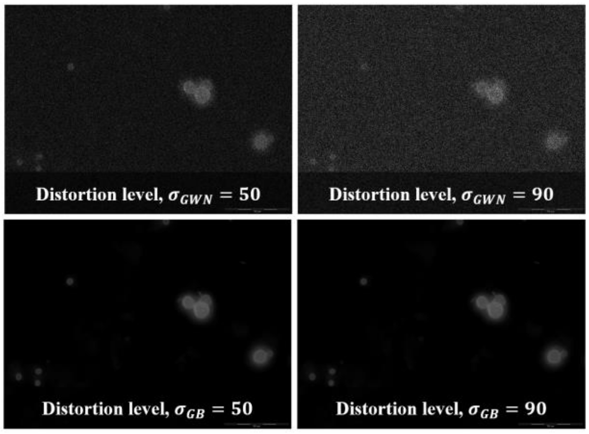


Fig. 4. Image comparison between 50 and 90 distortion level for GWN (Top) and GB (Bottom)

A noticeable image quality change for GWN when applying a distortion level from 50 to 90 as shown in Fig. 4. This indicates that the higher the degrees of distortion, the noisier the images become. The image for GB, however, seems to have very minute changes in its image quality. Distortion description and its level is explained in Table 2.

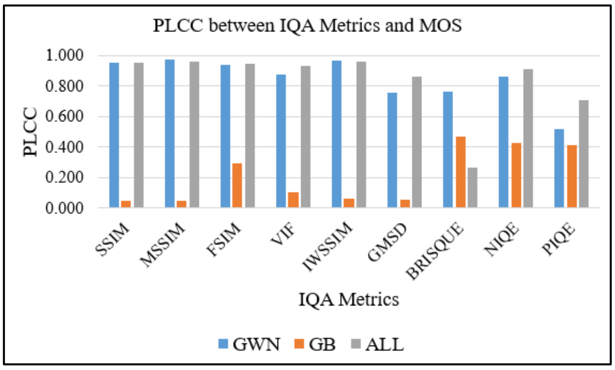
Table 2. Distortion type

Distortion type	Description	Distortion levels
Gaussian White Noise (GWN)	Gaussian White Noise distribution with standard deviation, σ_{GWN}. Formula: GWN_im = Ref_im + σ_{GWN} *randn (size (Ref_im))	σ_{GWN}: 10, 20, 30, 40, 50, 60, 70, 80, 90
Gaussian Blur (GB)	3σ sized square kernel window with Gaussian kernels of standard deviation, σ_{GB}. Formula: GB_im = fspecial('gaussian',[3 3], σ_{GB})	σ_{GB}: 10, 20, 30, 40, 50, 60, 70, 80, 90

Where Ref_im represents the reference image, GWN_im represents the Gaussian white noised image and GB_im represents the Gaussian blurred image.

Fig. 5 presents histograms that display the computed values of PLCC and RMSE, reflecting the correlation between MOS and IQA metrics.

(a)



(b)

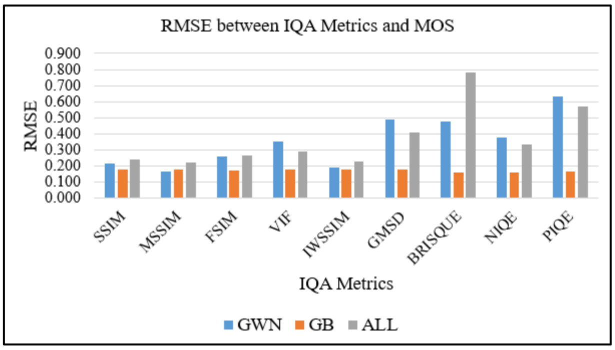


Fig. 5. Histogram of (a) PLCC (b) RMSE values between IQA metrics and MOS.

A higher PLCC value suggests a stronger correlation between MOS and IQA metric, whereas a lower RMSE value indicates a better correlation. The results show that MSSIM produced the highest PLCC and lowest RMSE values for WN and the entire dataset. Conversely, BRISQUE demonstrated the highest PLCC and lowest RMSE values for GB.

4. Conclusions

By introducing GWN and GB, which are typical distortions encountered during the acquisition of parasite images, a database of 380 images was established, comprising 20 reference images and 360 distorted images. To evaluate these images, six types of objective FR-IQAs and three Blind IQAs, alongside the subjective MOS, were utilized. Performance metrics such as PLCC and RMSE were employed to determine the correlation between the subjective MOS and objective IQAs. The study concluded that MSSIM was the most effective IQA for assessing parasite images, as it directly compares the structure of the reference and distorted images, measuring the variation in structural information between them. This study highlights the importance of IQA in assessing parasite images and its potential as a feedback mechanism before the inspection procedure.

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Authors Introduction

Mr. Muhammad Amirul Aiman Bin Asri

He received the B.E (Electrical) from the Department of Electrical Engineering, University of Malaya, Malaysia in 2020 Currently, he is a Research Assistant in University of Malaya, Malaysia. His research interest includes image processing, artificial intelligence and machine learning.

Dr. Norrima Mokhtar

She received the Bachelor of Engineering (B. Eng) degree in Electrical Engineering from University of Malaya in 2000. She was appointed as a lecturer to serve the Department of Electrical Engineering, University of Malaya immediately after graduating with her Master of Engineering. As part of her career development, she received SLAB/SLAI scholarship to attain her Ph.D. in 2012. She is now serving Department of Electrical Engineering, University of Malaya.

Dr. Wan Amirul Bin Wan Mohd Mahiyidin

He received the M.Eng. degree from the Imperial College London in 2009, the M.Sc. degree from University of Malaya in 2012, and the Ph.D. degree from University of Canterbury in 2016. He is currently a senior lecturer at the Department of Electrical Engineering, University of Malaya. His research interests are multiple antennas system, cooperative MIMO, channel modelling and positioning system.

Dr. Heshalini Rajagopal

She received her PhD and Master's degree from the Department of Electrical Engineering, University of Malaya, Malaysia in 2021 and 2016, respectively. She received the B.E (Electrical) in 2013 Currently, she is an Assistant Professor in UCSI University, Kuala Lumpur, Malaysia. Her research interest includes image processing, artificial intelligence and machine learning.

Dr. Yvonne Lim Ai Lian

She is a professor at the Department of Parasitology, Faculty of Medicine, Universiti Malaya (UM), Kuala Lumpur and a council member of the Academy of Sciences Malaysia. She has taken on leadership roles as the Deputy Dean (Research) at the Faculty of Medicine and the Director of International Relations Office (IRO), Universiti Malaya. She has also served on the University Senate and was the former president of the Malaysian Society of Parasitology and Tropical Medicine (MSPTM). Her research focuses on host-parasite interactions and the epidemiology and control of neglected tropical diseases primarily among the indigenous communities. Universiti Malaya. She has also served on the University Senate and was the former president of the Malaysian Society of Parasitology and Tropical Medicine (MSPTM). Her research focuses on host-parasite interactions and the epidemiology and control of neglected tropical diseases primarily among the indigenous communities.