Quality assessment for microscopic parasite images

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Abstract

Microscopy lens distortion will cause errors during parasites image acquisition for water sample inspection. Since water sample inspection is crucial for treated water monitoring, the quality of microscopic parasite images such as Giardia and Cryptosporidium need to be monitored as well to avoid errors in treated water inspection. In this work, the subjective and objective evaluation of parasite images were performed. The parasite species studied were Cryptosporidium and Giardia (oo)cysts. Parasite image database consisting of 20 reference images and 360 distorted images were used in the evaluation. The distorted images were generated from the reference images by applying distortion to the reference images with Gaussian White Noise and Motion Blur, at 9 levels of distortions. Twenty subjects were selected to assess the distorted images for the subjective evaluation. The scores obtained from the subjects were transformed into Mean Opinion Score (MOS). In the objective evaluation, six Full Reference-IQA (FR-IQA) metrics, namely MSSIM, SSIM, FSIM, IWSSIM, GMSD and VIF were used to evaluate the distorted images. The subjective MOS scores were used as the benchmark to determine the most suitable objective IQA to assess parasite images. The relationship between the subjective MOS and objective IQAs are examined using performance metrics namely PLCC and RMSE. It was found that MSSIM is the most suitable IQA to assess parasite images distorted with Gaussian White Noise and Motion Blur.

Keywords: Parasite images, Giardia, Cryptosporidium, Full-Reference Image Quality Assessment (FR-IQA).

1. Introduction

Inspection via object recognition has become the topic of interests for many researchers in image processing fields that apply automation to replace human expert. Inspection of treated water sample under microscope requires good quality of images in order to count average number of parasites like Giardia and Cryptosporidium that captured in the sample which determine the safety of the treated water[1]. For robust object recognition performance, good quality of images is required for both manual and automatic inspection. To date, many image quality assessment models have been developed. However, image quality assessment of microscopic images especially for Giardia and Cryptosporidium parasites, has not been reported yet to the best of our knowledge.

This work carries significant contribution as many researchers investigated and reported on distortion correction of a microscopy lens system which causing non-uniform geometric distortion, displacement errors and others[2][3][4][5]. However, the focus of these works and reports was only on the distortion correction. Our work focused on image quality assessment on microscopic parasite images for Giardia and Cryptosporidium, which eventually will open more interests on other microscopic images as well for further studies. Generally, Image Quality Assessment (IQA) has two categories which are subjective and objective evaluations. Subjective evaluation setup is done when the images are evaluated by human, who provides rating based on their visual assessment on the image quality. For objective evaluation setup, the rating calculation for the images is conducted via mathematical algorithms. For justification, the gold standard of IQA is subjective evaluation by human, however, human always has fatigue eyes which eventually lead to errors, as well as cost and time consumption [6]. Hence, objective assessment is the way forward for improvement of treated water inspection process.Recently, IQA objective assessment, has evolved from Full Reference-IQA(FR-IQA) to No-Reference-IQA(NR-IQA) [7][8]. FRIQA is an objective evaluation by comparing the image with its reference image. Meanwhile, Reduced Reference-IQA(RR-IQA) is an objective evaluation using partial information of the reference image. On contrary, NR-IQA is an objective evaluation without information of reference image.

To this study, six Full Reference-IQA (FR-IQA) metrics, namely Structural Similarity Index (SSIM)[9], Multiscale SSIM (MS-SSIM)[9], Feature SIMilarity (FSIM)[10], Visual Information Fidelity (VIF)[11], Information Weighted SSIM (IW-SSIM)[12] and Gradient Magnitude Similarity Deviation (GMSD) [13]. These metrices are chosen as they are widely used to study the image quality of various types of images such as MRI, wood, underwater and natural images [14][15][16][17]. After investigation of these objectives assessment, the performance are measured using human mean opinion scores(MOS) and metrics which in our study, Pearson's Linear Correlation Coefficient (PLCC) [18] and Root Mean Square Error (RMSE) [19] were used.

2. Methods

2.1. *Parasite Images*

Twenty parasite images from two parasite species, namely Giardia and Cryptosporidium. The images were obtained from Department of Parasitology, University of Malaya, 50603 Kuala Lumpur, Malaysia. The twenty parasite images are shown in Fig. 1. The images were converted to grayscale and the pixel values were normalized to the range 0 - 255 for ease of applying the same levels of distortion across all the reference images. The images consisted of a matrix of 1376 x 1320 pixels. These twenty reference parasite images were the distorted by Gaussian white noise and motion blur, which represent image distortions typically encountered in parasite images. Gaussian white noise often arises in during acquisition of parasite images by the capturing apparatus [20]. On the other hand, parasite images are subjected to motion blur when there is a relative motion between the capturing apparatus namely microscope lens and the parasite specimen [21]. These distortions cause the quality of the parasite image to be low [21]. Thus, the features of the parasite could not be differentiated. This could cause misclassification of the parasite species as the feature extractor will not be able to extract distinctive features from the parasite texture images effectively [21]. The Gaussian white noise with standard deviation, σ_{GN} and motion blur with standard deviation, σ_{MB} were applied to the reference images at nine levels of distortion of the reference images, i.e.: σ_{GN} = 10, 20, 30, 40, 50, 60, 70, 80 and 90 for Gaussian white noise and σ_{MB} = 10, 20, 30, 40, 50, 60, 70, 80 and 90 for motion blur. This produces 380 parasite images, twenty reference images, 180 images distorted by Gaussian White Noise and 180 images distorted by Motion Blur.

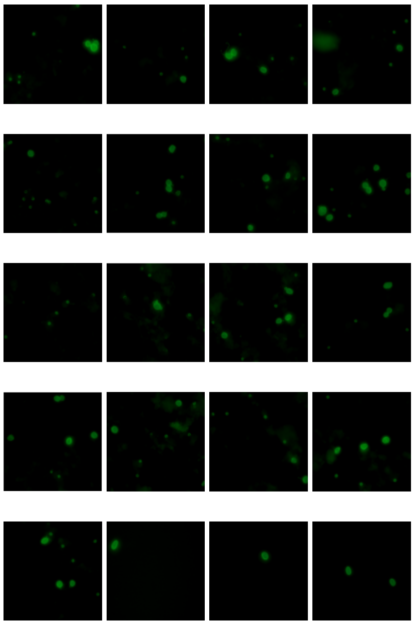

Fig. 1. Twenty reference Giardia and Cryptosporidium parasite images

2.2. *Subjective Evaluation*

Twenty students aged 20-25 years from the Department of Electrical and Electronics Engineering from Manipal International University (MIU) and University of Malaya, Malaysia volunteered to evaluate the parasite images. The evaluation was performed based on the procedures recommended in Rec. ITU-R BT.500-11 [22] in an office environment using a 21 inch LED monitor with resolution of 1920 x 1080 pixels. Uncorrected near vision acuity of every subject was checked using the Snellen Chart before the subjective evaluation in order to confirm their fitness to perform the evaluation task. The subjective evaluation was performed based on the Simultaneous Double Stimulus for Continuous Evaluation (SDSCE) methodology [15,22]. Here, the reference and distorted images are displayed on the monitor screen side-by-side, where the reference image is displayed on the left and the distorted image is displayed on the right. Each subject evaluates the distorted image by comparing the quality of the images (right side) with its reference image (left side). The subject rates either Excellent (5), Good (4), Fair (3), Poor (2) or Bad (1) for each image displayed. The numerical scores were not revealed to the subjects as it could cause bias between the subjects [23] . The evaluation process takes 15 to 20 minutes. The ratings obtained from the subjects were used to calculate MOS [23].

2.3. *Objective Evaluation*

The MOS is compared with six FR-IQA metrics: Structural Similarity Index (SSIM) [9], Multiscale SSIM (MS-SSIM) [9], Feature SIMilarity (FSIM) [10], Visual Information Fidelity (VIF) [11], Information Weighted SSIM (IW-SSIM) [12] and Gradient Magnitude Similarity Deviation (GMSD) [13]. The FR-IQA metrics are descripted in Table 1.

Table 1. FR-IQA Metrics used in this study

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.

2.4. *Performance Evaluation*

Two well established performance metrics were used to study the correlation between the objective IQA and subjective MOS values. The first performance metric chosen is PLCC. The PLCC values between the FR-IQA metrics and MOS were calculated after the nonlinear regression. The second performance metric is RMSE. RMSE is a statistical metric commonly used to evaluate a model's performance [24]. Similar to PLCC, the RMSE values were calculated after the nonlinear regression.

3. Results and Discussion

The relationship between MOS and ten distortion levels of Gaussian white noise and Gaussian blur were shown in Fig. 2 (a) and (b). Generally, as the distortion levels increase, the quality of the image will be poorer. As the quality of the images gets poorer, the MOS value decreases.

Based on the scatter plot in Fig. 2 (a), the MOS scores decreased at the range of 4.3 to 1.6 as the gaussian white noise's distortion levels increased from 10 to 90. This shows that the human subjects could differentiate images with different distortion levels. In Fig. 2 (b), the MOS scores did not deviate much even when the level of Gaussian blur increased from 10 to 90. This shows that there are no significant changes in the quality of parasite images when the images were blurred.

The calculated PLCC and RMSE values between MOS, FR-IQA metrics (FSIM, IWSSIM, MSSIM, GMSD, SSIM and VIF) and NR-IQA metrics (BRISQUE, NIQE and PIQE) are shown in Table 2. PLCC values close to 1 indicate that the MOS correlates well with the IQA metric, whereas lower RMSE values indicate that the MOS correlates with the IQA metric. Table 2 shows that the highest PLCC and lowest RMSE values for Gaussian white noise and the overall database were obtained for the MSSIM. The highest PLCC and lowest RMSE were obtained for BRISQUE for Gaussian Blur.

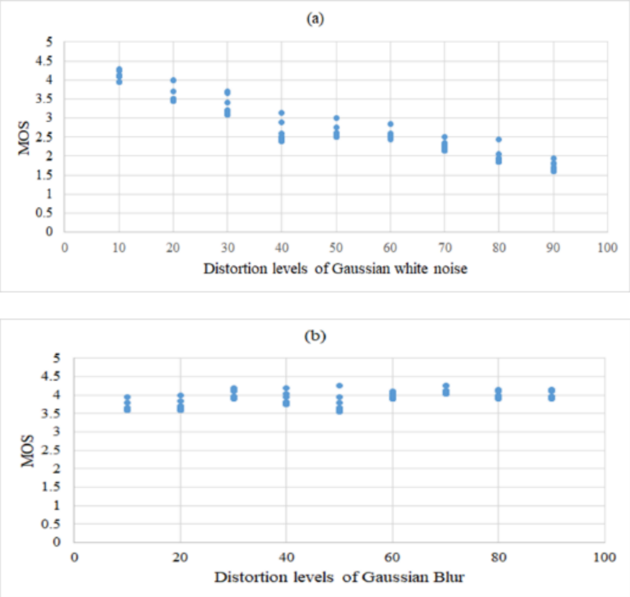

Fig. 2. Scatter plot of MOS versus (a) Gaussian white noise, (b) Gaussian blur.

Table 2. PLCC and RMSE values between MOS, FR-IQA and NR-IQA.

		FSIM	IWSSIM	MSSIM	GMSD	SSIM	VIF
PLCC	**GWN**	**0.939**	**0.966**	**0.975**	**0.755**	**0.957**	**0.881**
	MB	**0.294**	**0.060**	**0.047**	**0.056**	**0.048**	**0.104**
	All	**0.946**	**0.960**	**0.961**	**0.866**	**0.955**	**0.936**
RMSE	**GWN**	**0.256**	**0.191**	**0.165**	**0.488**	**0.216**	**0.352**
	MB	**0.170**	**0.177**	**0.177**	**0.177**	**0.177**	**0.176**
	All	**0.263**	**0.228**	**0.224**	**0.407**	**0.240**	**0.287**

4. Conclusions

A database which consists of 380 parasite images (20 reference and 360 distorted images) was generated. The reference images were distorted with Gaussian White Noise and Motion Blur which commonly occur during the acquisition of parasite images. The database also contains the subjective MOS, six types of objective FR-IQAs and three NR-IQAs' evaluation.

The relationship between the subjective MOS and objective IQAs are examined using performance metrics namely PLCC and RMSE. Both performance metrics showed that MSSIM is the most suitable IQA to assess parasite images. This is because MSSIM is a more direct way to compare the structures of the reference and the distorted parasite images as it measures the structural information change between the reference and distorted images. This study has also shown that IQA is important in assessing parasite images as feedback method prior to inspection procedure.

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