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Evaluation of Laparoscopic Video Quality Using Statistical Dependencies of Spatial and Texture Measures

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Introduction

Uneven illumination is a spatial distortion arising when details in video content is lost due to imbalanced illumination of scene content. Mis-diagnosis due to loss of intricate details is a major problem in the medical field. Quality assessment (QA) techniques can help ensure that sufficient perceptual video quality is maintained to aid in diagnostic procedures.

Hypothesis

To gather quality-related information from a perceptual scene, the human visual system relies upon different spatial, textural, and temporal features. The statistical dependency between frame-level spatial and texture features can be used to determine the visual quality of a video. For this purpose, a luminance map and a local binary pattern (LBP) map are used here. Luminance map yields spatial information on the perceptual brightness and contrast in a scene, and LBP map effectively provides textural information.

Methods

In this work, a video QA model is developed using 10 reference and 40 unevenly illuminated (UE) videos from the publicly available Laparoscopic Video Quality database. The dataset provides mean opinion scores (MOS) for the subjective study involving experts and non-experts. The frame-level luminance and LBP maps are generated and decomposed using a steerable pyramid. The subband coefficients are modeled using bivariate generalized Gaussian distribution, and the mean, median, and standard deviation of model parameters are computed. This is used as input to a support vector regression network with the video-level MOS as the training labels. The average of the predicted frame quality scores gives the final video quality.

Results

Figure 1 shows the reference and distorted frames of the videos in increasing levels of distortion severity and their corresponding luminance and LBP maps. The model performance is evaluated using Pearson's Linear Correlation Coefficient (PLCC) and Spearman's Rank Order Correlation Coefficient (SROCC) values, tabulated in table 1. The observed results are: PLCC = 0.98793, SROCC = 0.88849 (for expert MOS labels) and PLCC = 0.96706, SROCC = 0.82513 (for non-expert MOS labels). The predicted scores are found to be highly correlated with the subjective scores. Additionally, the Root

Mean Square Error (RMSE) value is also computed in table 2. The lower RMSE values (RMSE = 0.38453 for expert MOS labels) indicate good model prediction accuracy.

Conclusion

All the performance metrics show improved values for expert labels, which reinforces the belief that experts are perceptually more tuned to finer scenic details compared to non-experts. The proposed model can be successfully used to perform a quality evaluation of unevenly illuminated videos.

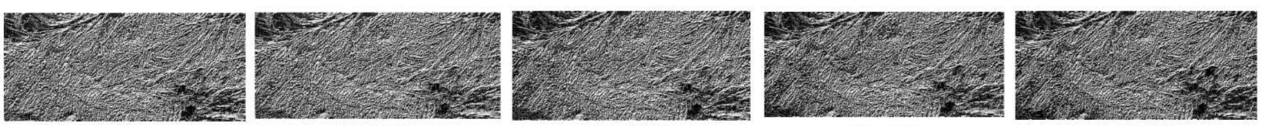
Figure(s)

(a) Reference (b) UE1 (c) UE2 (d) UE3 (e) UE4

Figure – 1: Illustration of the 100th frame of the pristine and uneven illumination distortion videos in increasing order of distortion severity, respectively

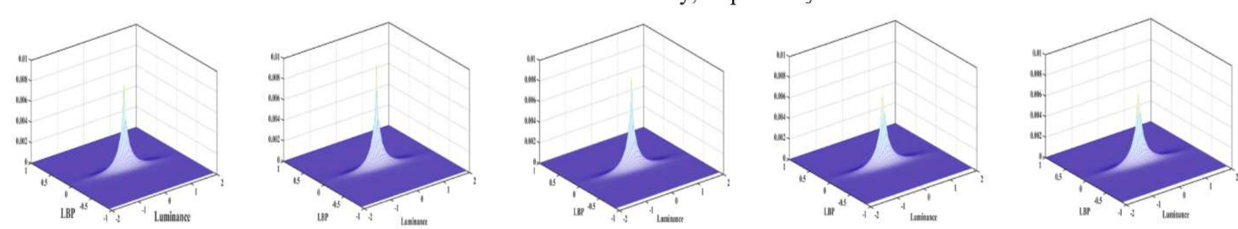
(a) Reference (b) UE1 (c) UE2 (d) UE3 (e) UE4

Figure – 2: Illustration of the luminance maps of the 100th frame of the pristine and uneven illumination distortion videos in increasing order of distortion severity, respectively



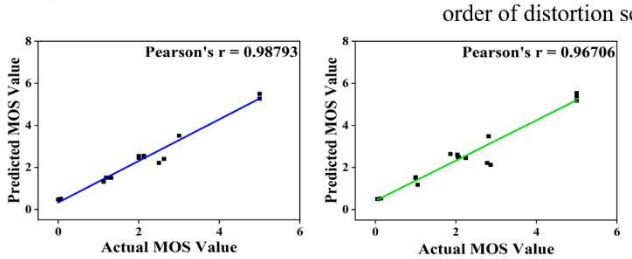
(a) Reference (b) UE1 (c) UE2 (d) UE3 (e) UE4

Figure – 3: Illustration of the LBP maps of the 100th frame of the pristine and uneven illumination distortion videos in increasing order of distortion severity, respectively



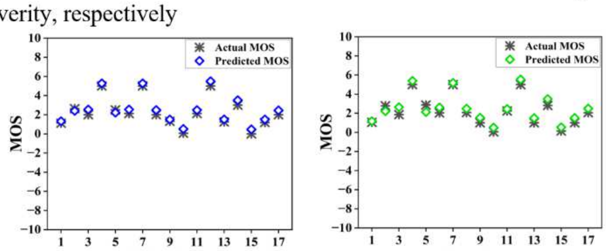
(a) Reference (b) UE1 (c) UE2 (d) UE3 (e) UE4

Figure – 4: Illustration of BGGD plots of the 100th frame of the pristine and uneven illumination distortion videos in increasing order of distortion severity, respectively



(a) Expert MOS (b) Non - expert MOS

Figure – 5: Best linear plots for predicted video quality scores using proposed method



(a) Expert MOS (b) Non - expert MOS

Figure – 6: Scatter plots for showing distribution of the actual MOS and predicted scores for test videos

Table – 1: Performance of proposed algorithm represented in terms of PLCC and SROCC metrics (the best performance value for each column is indicated in bold)

Model Name	**PLCC**		**SROCC**	
	Expert MOS	**Non – expert MOS**	**Expert MOS**	**Non – expert MOS**
PSNR	0.9452	0.9561	0.9530	0.9372
SSIM	0.9847	**0.9926**	**0.9580**	**0.9502**
VIF	0.9878	0.9919	0.9534	0.9391
BRISQUE	0.2973	0.3142	0.2634	0.2980
NIQE	0.6655	0.6618	0.5605	0.5416
VIIDEO	0.4035	0.3983	0.4281	0.3888
Proposed	**0.98793**	0.96706	0.88849	0.82513

Table – 2: RMSE comparison for export MOS and non-expert MOS training labels

Metric	**Expert MOS**	**Non – expert MOS**
RMSE	0.38453	0.50214

Keywords

Artificial Intelligence/Machine Learning; Emerging Technologies; Imaging Research; Quality Improvement & Quality Assurance