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A Weighted ROI-based Image Quality Assessment for WMSN

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Abstract: The major task of WMSN is image communication, which is really a challenge for resource constraint wireless sensors. WMSN should monitor the image distortion by image quality assessment (IQA) to take some adaptive precautions and thus guarantee application quality requirements. Most applications of WMSN require reliable transmission of Region of interest (ROI) in the image. However, little study has been taken on identifying how and to what extent ROI will influence IQA in WMSN. In this work, a simple method is proposed to estimate an image quality by considering the ROI of the image. Different weights are assigned to the primary ROI, secondary ROI and Non ROI parts of the image in the quality evaluation phase. The simulation results have shown that the proposed IQA has better performance than state-of-the-art IQA methods for WMSN.

Key words: Image quality assessment, region of interest, weighted PSNR, wireless multimedia sensor networks

INTRODUCTION

Wireless Multimedia Sensor Networks (WMSN) consist of wireless sensors embedded cameras and microphones, improving applications like surveillance, wildlife observation, traffic avoidance and industrial process control. The major task of WMSN is image communication, which is really a challenge. WMSN should monitor the image distortion to take some adaptive precautions and thus guarantee service quality requirements (Xiong *et al*., 2013). Image distortion in WMSN is mostly caused by image coding and transmission errors.

Region of interest (ROI) may hold more information than the other parts in the image. The image quality assessment (IQA) metric should reflect the effect of the ROI corruption on its evaluation result (Zhang *et al*., 2011). A common hypothesis is that the IQA should be correlated with ROI detection. However, little study has been taken on identifying how and to what extent ROI will influence IQA in WMSN. IQA methods can be categorized into subjective and objective methods. Subjective IQA methods are expensive and time consuming, which cannot be adapted for real time systems. The latter depends on the quantified parameters which are obtained from metrics. Results of a good objective IQA method should be statistically consistent with subjective methods (Moorthy and Bovik, 2011). The purpose of this research is to develop objective IQA algorithms for JPEG compressed images. Such algorithms must have the capability to effectively predict perceived JPEG image quality for WMSN.

The conventional metrics, such as the peak signal-to-noise ratio (PSNR) and the Mean-squared Error (MSE) do not correlate well with the subjective fidelity ratings. Human Visual System (HVS) based IQA metrics emphasize the importance of HVS' sensitivity to different visual signals (Sheikh and Bovik, 2006). The structural similarity (SSIM) index is designed to capture the loss of structure in the image (Wang *et al*., 2004). The multi-scale extension of SSIM (MS-SSIM) produces better results than SSIM (Wang *et al*., 2003). Sheikh *et al*. (2005) proposed the Information Fidelity Criterion (IFC) for IQA by quantifying the information shared between the distorted and the reference images. IFC was later extended to the Visual Information Fidelity (VIF) metric.

The image distortion in WMSN is a function of both the encoding bit rate and the power consumption. Pudlewski and Melodia (2010) propose a rate control scheme based on both analytical and empirical models, along with a joint video and channel encoder rate allocation scheme. He *et al*. (2008) develop an adaptive scheme to estimate the P-R-D model parameters and perform online energy optimization and control for real-time video compression. Sun *et al*. (2010) develop an online complexity control and energy minimization scheme for real-time video encoding over portable devices.

MATERIALS AND METHODS

We model the network as a tree graph, which consists of sensor nodes, inner nodes and a root node. Local image compression is performed at each sensor nodes. The architecture of WMSN is illustrated in Fig. 1.

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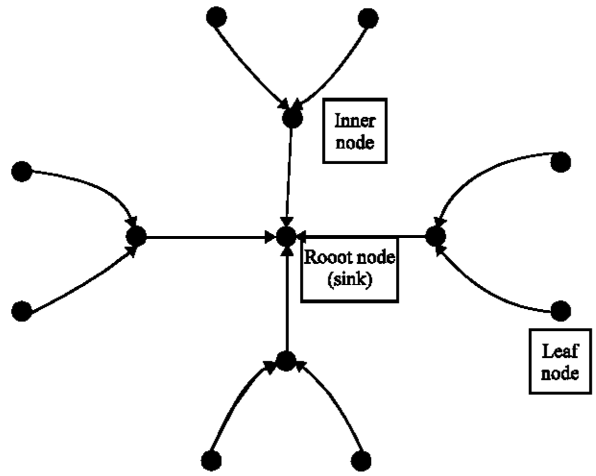

Fig. 1: WMSN consist of 12 nodes and 1 sink

General IQA metrics focus on distortions due to compression, dithering and printing. However, resource constraints and wireless channels influence the image quality for WMSN. Also, ROI may need more reliability for the application requirement in WMSN. Therefore, the communication distortion within these areas should be considered more severe than elsewhere. Hence, a simple image quality assessment method named Weighted Peak Signal to Noise Ratio (WPSNR) is proposed in this study.

The transmission of the background area may be required in order to analyze the full environment in detail. Each image was divided into three regions: First ROI, secondary ROI and non-ROI (background). A first ROI is the region containing the most interesting parts of the image; a secondary ROI is the region containing parts which were less interesting than the first ROI, but which contained subject matter that was still considered interesting. IQA method should consider this issue by assigning different weights to the first ROI, secondary ROI and Non ROI parts of the image. The weights were chosen to maximize the correlation between each modified metric and subjective ratings from the images. Weights were found for each region that maximized correlation to perceived fidelity.

For WPSNR, $x_{1st\text{-}ROI}$, $x_{2nd\text{-}ROI}$ and $x_{non\text{-}ROI}$ were computed via:

$$x_{1st-ROI} = 10\log_{10}\left(\frac{S}{D_{1st-ROI}}\right), \quad \text{where } D_{1st-ROI} = \frac{1}{N_{1st-ROI}} \sum_{i \in P_{1st-ROI}} E_i^2 \tag{1}$$

$$x_{2nd-ROI} = 10\log_{10}\left(\frac{S}{D_{2nd-ROI}}\right), \quad \text{where } D_{2nd-ROI} = \frac{1}{N_{2nd-ROI}} \sum_{i \in P_{2nd-ROI}} E_i^2 \tag{2}$$

$$x_{non-ROI} = 10\log_{10}\left(\frac{S}{D_{non-ROI}}\right), \quad \text{where } D_{non-ROI} = \frac{1}{N_{non-ROI}} \sum_{i \in P_{non-ROI}} E_i^2 \tag{3}$$

where, S denotes the signal energy and where E_i denotes a pixel in the error image E generated by each metric. $S = 255^2$ and $E = \tilde{I}-I$.

The augmented metrics were then taken as a weighted linear sum of $x_{1st\text{-}ROI}$, $x_{2nd\text{-}ROI}$ and $x_{non\text{-}ROI}$ as follows:

$$x = w_{1st-ROI}, x_{1st-ROI}+w_{2nd-ROI}\, x_{2nd-ROI}+w_{non-ROI}\, x_{non-ROI} \tag{4}$$

where, x denotes the augmented metric output and where, $x_{1st\text{-}ROI}$, $x_{2nd\text{-}ROI}$ and $x_{non\text{-}ROI}$ denote the weights constrained such that $w_{1st\text{-}ROI}+w_{2nd\text{-}ROI}+w_{non\text{-}ROI} = 1$ and $w_{1st\text{-}ROI}>0$, $w_{2nd\text{-}ROI}>0$, $w_{non\text{-}ROI}>0$.

RESULTS AND DISCUSSION

To examine the performance of proposed IQA algorithm, we have conducted comprehensive simulation experiments on IEEE International Workshop on Performance Evaluation of Tracking and Surveillance (PETS) 2000 and 2001's test datasets in MATLAB, as shown in Fig. 2.

The selection criteria of the test images are their suitability to the border surveillance applications. IQA metrics (PSNR, WSNR, SSIM, VIF and WPSNR) are applied on them to evaluate the performance. Four performance metrics are employed to evaluate the IQA metrics. The two are the Spearman Rank Correlation Coefficient (SRCC) and the Kendall Rank Correlation Coefficient (KRCC), which can measure the prediction monotonicity of an IQA metric. The other two metrics are Pearson Linear Correlation Coefficient (PLCC) and MAE. SRCC is defined as:

$$SRCC = 1 - \frac{6\sum_{i-1}^{N} d_i^2}{N(N^2-1)} \tag{5}$$

where, d_i is the difference between the ith image's ratings in objective and subjective evaluations. SRCC is a non-parametric rating-based correlation metric.

KRCC is another non-parametric rating correlation metric given by:

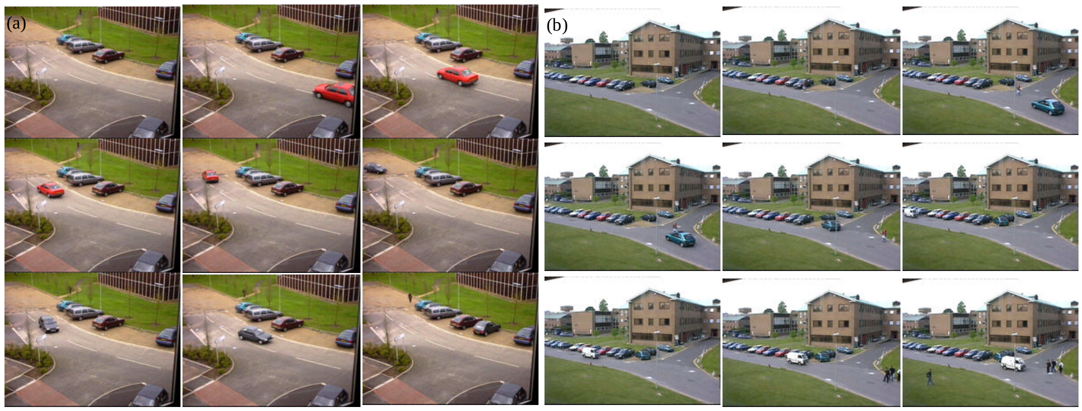

Fig. 2(a-b): (a) PETS'2000 and (b) 2001 test images

Table 1: Performance comparisons of 5 IQA algorithms on two image databases

Parameters	SRCC	KRCC	PLCC	MAE
PETS'2000				
PSNR	0.6189	0.4309	0.6347	0.1607
SSIM	0.8066	0.6058	0.8017	0.1209
MS-SSIM	0.8414	0.6478	0.8603	0.1007
VIF	0.6223	0.4589	0.6157	0.1397
WPSNR	0.9355	0.8031	0.9146	0.0809
PETS'2001				
PSNR	0.6132	0.4443	0.6329	0.7817
SSIM	0.8794	0.6939	0.8887	0.4386
MS-SSIM	0.8874	0.7029	0.8927	0.4328
VIF	0.9077	0.7315	0.9138	0.4038
WPSNR	0.9301	0.7704	0.9278	0.3647

$$\mathrm{KRCC} = \frac{N_c - N_d}{\frac{1}{2}N(N-1)} \tag{6}$$

where, N_c and N_d are the numbers of harmonious and discord pairs in the dataset.

PLCC is a nonlinear mapping between the objective and subjective ratings. For the ith image in the image dataset of size N, given its subjective score O_i and its raw objective score, we first apply a nonlinear function to given by:

$$q(r) = a_1\left\{\frac{1}{2} - \frac{1}{1+\exp\left[a_2(r-a_3)\right]}\right\} + a_4 r + a_5 \tag{7}$$

where, a_1 to a_5 are model parameters to maximize the correlations between objective and subjective scores. The PLCC value can then be computed as:

$$\mathrm{PLCC} = \frac{\sum_i (q_i - \bar{q}) * (o_i - \bar{o})}{\sqrt{\sum_i (q_i - \bar{q})^2 * (o_i - \bar{o})^2}} \tag{8}$$

MAE is computed using the alternated objective scores after the nonlinear mapping:

$$\mathrm{MAE} = \frac{1}{N}\sum |q_i - o_i| \tag{9}$$

The image errors occur on the image uniformly. Four performance metrics will be used here for algorithm verification and comparison. The characteristics of these six databases are summarized in Table 1.

KRCC and SRCC are used to evaluate prediction monotonicity and MAE and PLCC are employed to assess prediction accuracy. An excellent IQA measuring should have higher SRCC, KRCC and PLCC while lower MAE values. Table 1 shows our test results of 5 IQA metrics using the two datasets. It can be seen that WPSNR has higher SRCC, KRCC and PLCC while lower MAE values than other 4 IQA measures.

CONCLUSION

In this study, we proposed a novel weighted ROI-based IQA metric, namely WPSNR. It assigns different weights to the first ROI, secondary ROI and Non ROI parts of the image in the quality evaluation phase. To examine the performance of proposed algorithm, we have conducted comprehensive simulation experiments. Four performance metrics are employed to evaluate the IQA metrics. The results have shown that the proposed IQA has better performance than state-of-the-art IQA metrics for WMSN.

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