Automatic Recognition of Frame Quality Degradation For Inspection of Surveillance Camera

Yi-Chong Zeng*, Miao-Fen Chueh† and Chi-Hung Tsai‡
*Advanced Research Institute, Institute for Information Industry, Taipei, Taiwan
E-mail: yichongzeng@iii.org.tw Tel: +886-2-66072958
†Smart Network System Institute, Institute for Information Industry, Taipei, Taiwan
E-mail: miuchueh@iii.org.tw Tel: +886-2-66073500
‡Advanced Research Institute, Institute for Information Industry, Taipei, Taiwan
E-mail: brick@iii.org.tw Tel: +886-2-66072922

Abstract— **When surveillance camera is broken down, it will degrade frame quality directly. Sometimes, quality degradation happens occasionally, it is difficult for people being aware it immediately. With the aim to automatically inspect surveillance camera, we propose an automatic method to recognize frame quality degradation. Seven features are extracted based on four kinds of measures, i.e. mean of structure similarity, variation of intensity difference, minimum of block correlation, and average color. Those measures have different reactions to different degradations. Subsequently, linear discriminant analysis (LDA) applied to the extracted features is able to train classifiers. Six classes of degradations are recognized in this work, including signal missing, color missing, local alternation, global alteration, periodic intensity change, and normal status. After implementing degradation recognition, we determine whether surveillance camera works normally or not. The experiment results demonstrate that the proposed method is capable of recognizing degradation as well as inspecting surveillance camera.**

I. INTRODUCTION

In recent years, digital camera is popular for surveillance application. However, it is inevitable that surveillance camera will be broken down one day. When camera is malfunctioned, frame content is corrupted, and meantime frame quality is degraded. The most serious quality degradation is that video signal is cut off. Consequently, terminal monitor displays white noise or full-black frames. People are not aware of the phenomenon of quality degradation immediately, for example, gradual change of intensity. Therefore, developing an automatic method for detection/recognition of quality degradation is helpful to inform people that camera is abnormal.

Basically, imaging sensor, image processing unit and control unit play an important role in digital camera. Charge-coupled device (CCD) and complementary metal-oxide-semiconductor (CMOS) are two common techniques in imaging sensor, which transfers light to digital signal. Image processing unit is multi-functional. For instance, it computes image blurriness and then communicates control unit to adjust position of camera lens in order to acquire an in-focus image.

We suppose that once camera component is broken down, different component leads to different quality degradation. If we can assess frame quality by using diverse measures, it would be helpful to recognize degradations as well as inspect camera. Many kinds of quality measures have been presented for image and video, e.g. mean squared error (MSE), peak signal-to-noise ratio (PSNR), structural similarity (SSIM) [1, 2], mean opinion score (MOS) [3], and Czenakowski distance (CZD) [4, 5], etc. MSE is a common measure to quantify difference between two signals. Small MSE represents that those signals are similar to each other. PSNR is derived from MSE, and it is frequently used to evaluate quality of restored image/frame. For instance, if decompressed image is similar to raw image, it will meet a large PSNR between those two images. SSIM is a noticeable measure, and it has better consistency with human eye perception than PSNR. When a group of people score image quality, MOS is defined as the average of all scores, and MOS is a subjective fidelity criterion.

Some researchers addressed the issue of measuring image sharpness/blurriness in [6-13]. In [6], Crete et al. computed luminance differences in order to represent degree of image blurriness. In [7], Tsomko et al. calculated means and variances of luminance, and then classified blurriness into three levels: globally sharp, average quality, and globally blurry. Wee and Paramesran modeled sharpness problem as generalized eigenvalue problem [8]. They traced the several large eigenvalues to represent sharpness by implementing singular value decomposition (SVD) to image. In [9], Vu and Chandler combined spectral-based sharpness map and spatial-based sharpness map to be an overall perceived sharpness map, which is used for sharpness assessment. In [10, 11], the authors computed blur metric by analyzing edges. Some sharpness/blurriness metric was computed based on transform coefficients [12, 13], such as discrete cosine transform (DCT), Wavelet transform.

This paper introduces an automatic quality degradation recognition method for inspection of surveillance camera. First, we extract seven features based on four kinds of measures which are mean of structure similarity (MSSIM), variation of intensity difference, minimum of block correlation, and average color. Subsequently, linear discriminant analysis (LDA) is applied to the extracted features for training of multiple classifiers. We classify quality degradations into six classes: signal missing, color missing, local alternation, global alternation, periodic intensity change, and normal status. After implementing degradation recognition, we determine whether surveillance camera works normally or not. The

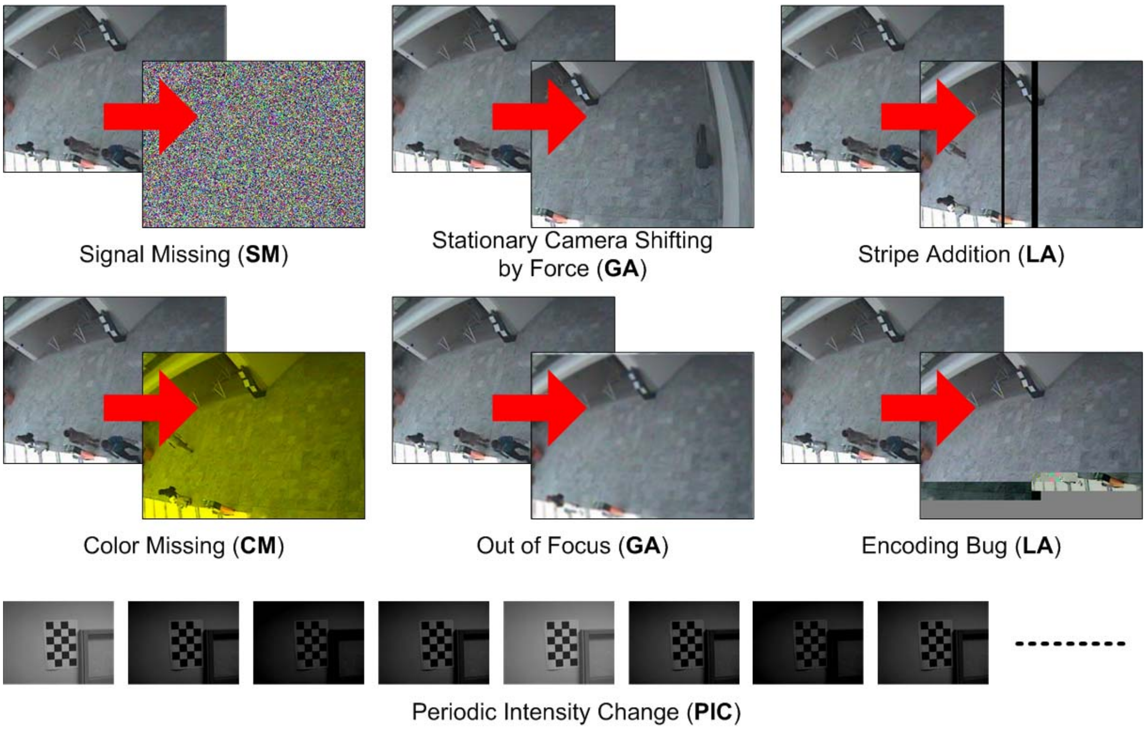


Fig.1 Effects of seven quality degradations

proposed method is compared with two existing approaches (i.e. [6] and [7]), and the experiment results demonstrate that our method achieves the best recognition performance among three approaches. The rest of this paper is organized as follows: the characteristics of degradations and measures are described in Section II. In Section III, we introduce the proposed method how to train classifiers and recognize degradations. Experimental results will be shown in Section IV, and the concluding remarks will be drawn in Section V.

II. The Characteristics of Quality Degradations and Measures

A. The Characteristics of Quality Degradations

Facing a variety of quality degradations, it is difficult to recognize degradation accurately. For this reason, we only emphasize on the common quality degradations and classify them into six classes: signal missing (SM), color missing (CM), local alternation (LA), global alteration (GA), periodic intensity change (PIC), and normal status (NS). Fig.1 depicts the effects of seven quality degradations. Fig.2 shows the simplified block diagram of surveillance camera, and the influences of broken camera components to degradations are listed in Table I.

A.1. Global Alternation

Global alteration represents frame content is corrupted globally. In this case, the common degradations include blurring and content inconsistency. Several situations that cause frame blurring, e.g. dirty camera lens, out of focus, over-quantization, and motion blurring.

When quantizer in an encoder is malfunctioned, it will remain low-frequency DCT coefficients, and decoded frame becomes blocky and blurry. Over-quantization is equivalent to spatial blurring. Once stationary camera is shifted by force, content of two consecutive frames is inconsistency, and meantime motion blurring occurs at frame. One function of digital image processing unit is to measure blurriness, and then communicates control unit to iteratively adjust position of lens until an in-focus frame is acquired. Therefore, when digital image processing unit is broken down, frame will be out of focus.

TABLE I
INFLUENCES OF BROKEN CAMERA COMPONENTS TO DEGRADATIONS

Degradation / Component	Global Alternation	Local Alternation	Signal Missing	Color Missing	Periodic Intensity Change
Lens	●	●			
Color Filter Array				●	
Imaging Sensor	●	●	●		●
Digital Image Processing	●				
Encoder	●	●		●	
Channel			●		

A.2. Local Alternation

The major difference between local and global alterations is size of altered area. Local alteration affects parts of frame,

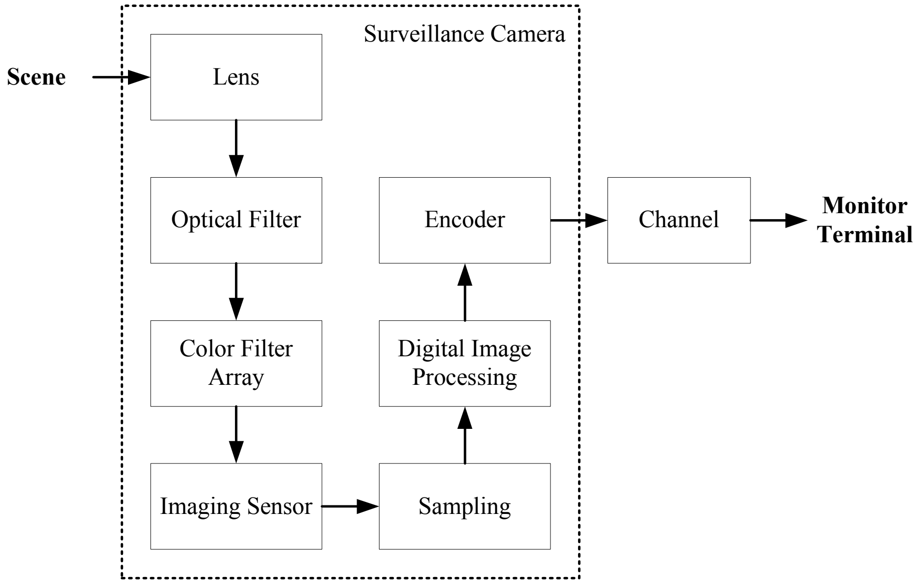


Fig.2 Simplified block diagram of surveillance camera

the rest of areas are unaltered. In this case, the common degradations include stains addition, stripe addition, and encoding bug.

Once stain sticks on camera lens, a part of frame is nothing. Stripe artifact is generated with respect to imaging sensor. Furthermore, when bug exists in encoder, it makes rear part of frame is decoded incorrect, but the front part of frame is normal as show in Fig.2. Therefore, encoding bug is considered as local alternation.

A.3. Color Missing

There are many types of color models, such as RGB, YUV, and YCbCr. When one of chromatic signals loses, frame is displayed in limited range of chromaticity. For instance, if blue component loses, frame tends to yellow display. In this case, the serious quality degradation is once color frame becomes gray scaling. Broken color filter array and encoding bug possibly results in color missing.

A.4. Signal Missing

Signal missing is the most serious quality degradation, and it occurs due to acquisition component is malfunctioned or delivery channel is cut off. Meanwhile, terminal monitor will display white noise or full-black frames.

A.5. Periodic Intensity Change

The function of imaging sensor is to transfer light intensity into digital signal. When imaging sensor is broken down, it affects accuracy of transferring light intensity. Human vision system is very sensitive to rapid change of intensity, but is blunt to gradual change of intensity. It is difficult to detect intensity change in a single frame. For this reason, a sequence of frames is analyzed in order to determine whether periodic intensity change adds to those frames or not.

A.6. Normal Status

If frame quality is not degraded, we consider it as normal status, and surveillance camera works normally.

TABLE II
RELATIONSHIP BETWEEN QUALITY DEGRADATIONS AND FEATURES

Feature \ Degradation	Global Alternation	Local Alternation	Signal Missing	Color Missing	Periodic Intensity Change
First MSSIM (f_1)	●		●	●	●
Second MSSIM (f_2)		●	●		
Variation of Intensity Difference (f_3)	●		●		●
Minimum of Block Correlation (f_4)		●	●		
Average Colors (f_5, f_6, f_7)				●	●

B. The Characteristics of Measures

In this work, features are extracted based on four kinds of measures: mean of structure similarity (MSSIM), variation of intensity difference (VID), minimum of block correlation (MBC), and average color (AC). In what follows we shall introduce the characteristics of those measures. The relationship between degradations and features are listed in Table II.

B.1. Mean of Structure Similarity

In [1, 2], researchers computed MSSIM for several applications, e.g. image quality assessment, and object tracking, etc. Due to structure similarity (SSIM) is a full-reference quality metric, a reference image is needed during SSIM computing. We design two ways for reference frame selection. First, one of the front frames in video is chosen as the reference, which is abbreviated as X_r. Let X_{k-1} and X_k be the (k-1)-th and the k-th frames, respectively. In the second way, X_{k-1} is treated as the reference to X_k.

When the i-th frame quality is degraded, X_i should be different from X_r, the MSSIM between X_i and X_r will be low. On the contrary, MSSIM is close to 1 when X_i is similar to X_r. This measure is helpful to recognize several degradations, including global alternation, signal missing, color missing, and periodic intensity change.

If X_{k-1} and X_k are degradation-free frames, those two frames should be similar to each other, and the MSSIM between X_{k-1} and X_k is close to 1. If X_{k-1} and X_k are noisy-like frames, those two frames are totally different to each other and the MSSIM is very low. Therefore, this measure is used to recognize local alternation, and signal missing.

B.2. Variation of Intensity Difference

There are many causes of frame blurring, such as motion blurring, spatial blurring, out of focus. Blurring effect makes a large difference between a sharp edge and its blurred one. But there is a slight difference between an unsharp edge and its blurred one. Under these circumstances, we analyze intensity differences between frame and its blurred ones, and then measure VID. This measure is suitable to represent degree of frame blurriness, and it is used for recognitions of global alternation, signal missing, and periodic intensity change.

B.3. Minimum of Block Correlation

In order to detect local alternation, a frame is divided into several non-overlapping blocks. We compute block correlation between two blocks at the current frame and the previous frame. As a part of the current frame is altered, one block in the current frame is different to the corresponding block in the previous frame. Thus, block correlation will be low for two different blocks. MBC is measured for recognition of local alternation.

B.4. Average Color

Color is an important feature that is helpful to detect degradation of color missing. We compute the averages of three primary colors. When average color is zero, it means the corresponding primary color missing. The conflicting situation is that frame becomes full-black due to signal missing, but it could be misrecognized as color missing. Due to intensity is highly associated with color, average color is capable of detecting periodic intensity change.

III. The Proposed Method

In this section, we shall introduce how to detect and recognize degradations. Our method consists of three phases: features extraction, degradation classification, and detection of periodic intensity change.

A. Features Extraction

As we mentioned above, the seven features are extracted based on four kinds of measures The detail of feature extraction is described in the followings.

A.1. Mean of Structure Similarity

Referring to [1, 2], MSSIM is formulated as follows:

$$\begin{cases} \mathrm{MSSIM}(X,Y) = \frac{1}{HW}\sum_{i=1}^{W}\sum_{j=1}^{H}\mathrm{SSIM}(\Omega_{i,j},\Psi_{i,j}), \\ \mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}, \end{cases} \tag{1}$$

where H and W are, respectively, the height and the width of frame. $\Omega_{i,j}$ and $\Psi_{i,j}$ represent the (i,j)-th blocks in the frame X and the frame Y, respectively. Moreover, μ_k and σ_k represent the mean and the standard deviation of pixels' value to the k-th block, respectively. c_1 and c_2 are two small values to prevent the denominator of SSIM zero. Two features based on MSSIM are defined as,

$$\begin{cases} f_1 = \mathrm{MSSIM}(X_r, X_k), \\ f_2 = \mathrm{MSSIM}(X_{k-1}, X_k), \end{cases} \tag{2}$$

where X_r and X_k are, respectively, the reference frame and the k-th frame.

A.2. Variation of Intensity Difference

Assuming that I_0 is the initial intensity of the frame X, it is filtered with three average kernels, which is defined as $I_m=I_0*\Phi_m$ and $m=\{1, 2, 3\}$. I_m represents the m-level blurred intensity, and Φ_m is a two-dimensional average kernel of sized $(2m+1)\times(2m+1)$. The m-level difference (δ_m) between two intensities is formulated as,

$$\delta_m = \frac{1}{\sqrt{HW}}\|I_m - I_{m-1}\|_2, \text{and } m = \{1,2,3\}, \tag{3}$$

where $\|x\|_2$ is the $L2$-norm of variable x.

Fig.3(a) shows a test image and its blurred image, and the test image is sharper than the blurred one. Fig.3(b) illustrates the intensity difference curves of two images, which are plotted by the blue solid lines. The approximate straight lines are plotted by the red dotted lines. It is obvious that the test image has the steeper curve than the blurred one does. Therefore, image blurriness is positively associated with slope of approximate line.

The approximate line is formulated as, $y = s\cdot x + t$, where x and y correspond to the half width of average kernel (i.e. x=m) and the intensity difference (i.e. y=δ_m), respectively. Using least square approximation (LSA), the slope (s) is calculated by the following equation,

$$f_3 = s = \frac{-\sum_{m=1}^{3} m\sum_{m=1}^{3}\delta_m + 3\sum_{m=1}^{3} m\delta_m}{3\sum_{m=1}^{3} m^2 - (\sum_{m=1}^{3} m)^2}. \tag{4}$$

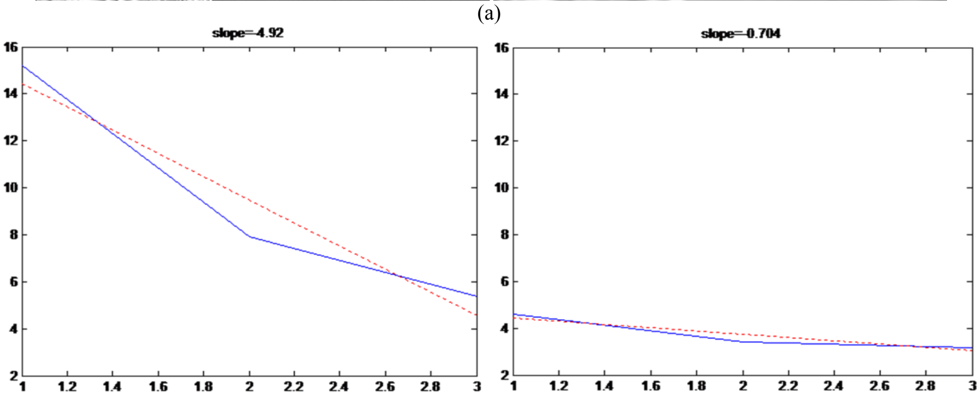
In Fig.3(b), the slopes are, respectively, -4.92 and -0.70 for the test image and the blurred image. Analyzing the results, the small slope corresponds to the sharp image; the large slope corresponds to the blurred image. Consequently, the slope is treated as the third feature to represent degree of frame blurriness.

A.3. Minimum of Block Correlation

An intensity frame is divided into 4×4 non-overlapped blocks. We compute correlation between two blocks in two consecutive frames, and find the minimum of block correlation as defined below,

$$\begin{cases} f_{4,k} = \min_{1\le i,j\le 4}|r_{i,j,k}|, \\ r_{i,j,k} = \frac{E[(B_{i,j,k-1}-B_{i,j,k-1})(B_{i,j,k}-B_{i,j,k})]}{\sqrt{E[(B_{i,j,k-1}-\mu_{i,j,k-1})^2]}\sqrt{E[(B_{i,j,k}-\mu_{i,j,k})^2]}}, \end{cases} \tag{5}$$

(a)



(b)

Fig.3 Blurriness Measure: (a) The test image and its blurred one, and (b) the curves of intensity difference (solid lines) and the approximate lines (dotted lines). The slopes of approximate lines are, respectively, –4.92 and –0.70 for the test image and the blurred image.

where $E(x)$ denotes the expectation of variable x. $B_{i,j,k}$ represents the the (i,j)-th block in the k-th intensity frame. $r_{i,j,k}$ is the correlation between $B_{i,j,k\text{-}1}$ and $B_{i,j,k}$, and it will be the fourth feature.

A.4. Average Color

The averages of three primary colors are formulated as follows:

$$\begin{cases} f_5 = \mu_{\mathrm{R}} = \frac{1}{HW}\sum_{m=1}^{HW} R(m) \ , \\ f_6 = \mu_{\mathrm{G}} = \frac{1}{HW}\sum_{m=1}^{HW} G(m) \ , \\ f_7 = \mu_{\mathrm{B}} = \frac{1}{HW}\sum_{m=1}^{HW} B(m) \ , \end{cases} \tag{6}$$

where R, G, B represent the red, the green, and the blue components, respectively. μ_i denotes the average of the i-th primary color, where $i\in\{\mathrm{R, G, B}\}$, and those three average colors will be the fifth, the sixth, and the seventh features.

B. Degradation Classification

In order to recognize degradation successfully, we train multiple classifiers and find the proper parameters for every classifier, so that degradation in one class is distinct from the other degradations. Let $\mathcal{G}_1$ and $\mathcal{G}_2$ be two groups. $\mathcal{G}_1$ includes only one class of degradation, and the rest of degradations are clustered in $\mathcal{G}_2$. Assuming that F_{x_i} is the feature set of the i-th degradation x_i. Linear discriminant analysis is exploited to find an appropriate weight vector (A) and a threshold (τ), so that the degradation x_i in $\mathcal{G}_1$ meets the condition: ${F_{x_i}}^{\mathrm{T}}A \geq \tau$, and the degradation x_i in $\mathcal{G}_2$ meets the condition: ${F_{x_i}}^{\mathrm{T}}A < \tau$. The procedures of classifier training are described in the followings:

Step 1: All degradations are separated into two groups in advance. Let $\mathcal{G}_i^t$ be the i-th group at the t-th layer. $\mathcal{G}_1^1$ includes SM, and $\mathcal{G}_2^1$ includes CM, LA, GA, and NS. We adopt all seven kinds of features to estimate the weight vector A_1 and the threshold τ_1 for the first-layer classifier.

Step 2: $\mathcal{G}_2^1$ is separated into two sub-groups, $\mathcal{G}_1^2$ and $\mathcal{G}_2^2$ further. $\mathcal{G}_1^2$ includes CM, and the $\mathcal{G}_2^2$ includes LA, GA, and NS. Similarly, all features are used to estimate the weight vector A_2 and the threshold τ_2 for the second-layer classifier.

Step 3: $\mathcal{G}_2^2$ is separated into two sub-groups $\mathcal{G}_1^3$ and $\mathcal{G}_2^3$, where $\mathcal{G}_1^3$ includes LA, and $\mathcal{G}_2^3$ includes GA and NS. Only two kinds of features, f_3 and f_4, are used to estimate the weight vector A_3 and the threshold τ_3 for the third-layer classifier.

Step 4: The function of the final classifier is to distinguish GA from NS. Two kinds of features, f_1 and f_3 are used to estimate the weight vector A_4 and the threshold τ_4.

After implementing training process, we have four weight vectors and four thresholds. The procedures of degradation recognition are described as follows:

Step 1: The recognition criterion of SM is defined as,

$$S_1 = \begin{cases} 1 & {F_{x_i}}^{\mathrm{T}}A_1 \geq \tau_1 \\ 0 & {F_{x_i}}^{\mathrm{T}}A_1 < \tau_1 \end{cases} \tag{7}$$

As S_1=1, the degradation x_i is considered as signal missing. Otherwise, degradation recognition is incomplete, and then goes to Step 2.

Step 2: The recognition criterion of CM is defined as,

$$S_2 = \begin{cases} 1 & F_{x_i}{}^{\mathrm{T}} A_2 \geq \tau_2 \\ 0 & F_{x_i}{}^{\mathrm{T}} A_2 < \tau_2 \end{cases} \tag{8}$$

As S_2=1, the degradation x_i is considered as color missing. Otherwise, degradation recognition is incomplete, and then goes to Step 3.

Step 3: The recognition criterion of LA is defined as,

$$S_3 = \begin{cases} 1 & F_{x_i}{}^{\mathrm{T}} A_3 \geq \tau_3 \\ 0 & F_{x_i}{}^{\mathrm{T}} A_3 < \tau_3 \end{cases} \tag{9}$$

As S_3=1, the degradation x_i is considered as local alternation. Otherwise, degradation recognition is incomplete, and then goes to Step 4.

Step 4: The recognition criterion of GA is defined as,

$$S_4 = \begin{cases} 1 & F_{x_i}{}^{\mathrm{T}} A_4 \geq \tau_4 \\ 0 & F_{x_i}{}^{\mathrm{T}} A_4 < \tau_4 \end{cases} \tag{10}$$

As S_4=1, the degradation x_i is considered as global alternation. Otherwise, x_i is considered as normal status as S_4=0.

C. Detection of Periodic Intensity Change

Periodic intensity change cannot be detected in a signal frame. For this reason, we extract a sequence of L frames every time and then analyze them. Five kinds of features are computed for all L frames, i.e. f_1, f_3, f_5, f_6 and f_7. Subsequently, discrete Fourier transform (DFT) is applied to those features, $\mathbf{F}_k = \mathcal{DFT}\{f_{k,1}, \cdots, f_{k,j}, \cdots, f_{k,L}\}$, where $f_{k,j}$ represents the k-th feature of the j-th frame. Analyzing the magnitudes within the half of the DFT spectrum, the biggest magnitude at AC frequency is found and defined as,

$$\begin{cases} i_k^* = \operatorname{argmax}_{1 \leq i \leq \frac{L}{2}} |F_{k,i}| \,, \\ \beta_{1,k} = |F_{k,i_k^*}| \,, \end{cases} \tag{11}$$

where $|F_{k,i}|$ and $\beta_{1,k}$ denote the magnitude of the i-th AC coefficient and the biggest magnitude for the k-th feature. Subsequently, we find the little big magnitude met the following conditions,

$$\begin{cases} j_k^* = \operatorname{argmax}_{\substack{1 \leq j \leq \frac{L}{2} \\ |i_k^* - j| \geq 3}} |\mathcal{F}_{k,j}| \,, \\ \beta_{2,k} = |\mathcal{F}_{k,j_k^*}| \,, \end{cases} \tag{12}$$

where $\beta_{2,k}$ represents the little big magnitude. The difference between the frequencies of $\beta_{1,k}$ and $\beta_{2,k}$ must be larger than or equal to 3 (i.e. $|i_k{}^* - j_k{}^*| \geq 3$) in this work. The cause of this condition is to prevent the frequency of the little big magnitude is too close to that of the biggest one. The threshold of 3 is decided by referring numerous experiment results.

When PIC adds to a video, a biggest magnitude locates at DFT spectrum, which is very much larger than the second large magnitude. In addition to magnitude, the frequencies of the biggest magnitudes for the selected features should be the same. Thus, the recognition criterion of PIC is based on the rate of two magnitudes and the frequency of the biggest magnitude, which is formulated as (13). i_k^* denotes the frequency of the biggest magnitude for the k-th feature. t_1 and t_2 are two thresholds and are set to t_1=2.44 and t_2=4.52 in the experiments. As S_5=1, the video is degraded by PIC.

IV. Experiment Results

A. Recognition of Single Degradation

First, we adopted 270 videos over nine quality degradations to train classifiers as well as estimate parameters. Those degradations are normal status, over-quantization, out of focus, stationary camera shifting by force, stripe addition, encoding bug, color missing, signal missing, and periodic intensity change. In the experiments, we tested another 630 videos. Every video consists of 300 frames of sized 288×384 with frame rate of 25 frame/sec (fps). All videos were downloaded from CAVIAR [14].

In the first experiment, we focus on recognition of signal degradation occurs at video. Table III lists the recognition rates of five classes of degradations. The average recognition rate of 99.86% demonstrates that the proposed method is efficient in degradation recognition. Moreover, Table IV lists the recognition rates of non-PIC and PIC over 630 videos. It is obvious the recognition rate of PIC is 87.14% demonstrates the proposed method is capable of distinguishing PIC from

TABLE III
RECOGNITION RATES OF FIVE CLASSES OF DEGRADATIONS OVER 630 VIDEOS (UNIT: %)

		Class of Degradation				
		SM	CM	LA	GA	NS
Experiment	SM	**100**	0	0	0	0
	CM	0	**100**	0	0	0
	LA	0	0.01	**99.63**	0.23	0.13
	GA	0	0	0	**99.89**	0.11
	NS	0	0	0.02	0	**99.98**

TABLE IV
RECOGNITION RATES OF NON-PIC AND PIC OVER 630 VIDEOS (UNIT: %)

		Class of Degradation	
		Non-PIC	PIC
Experiment	Non-PIC	99.82	0.18
	PIC	12.86	87.14

$$S_5 = \begin{cases} 1, & \text{if } \frac{\beta_{1,3}}{\beta_{2,3}} \geq t_1 \text{ and } \frac{\beta_{1,5}}{\beta_{2,5}} \geq t_2 \text{ and } \frac{\beta_{1,6}}{\beta_{2,6}} \geq t_2 \text{ and } \frac{\beta_{1,7}}{\beta_{2,7}} \geq t_2 \text{ and } \left\lfloor i_1^* / 2 \right\rfloor = i_3^* = i_5^* = i_6^* = i_7^* \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

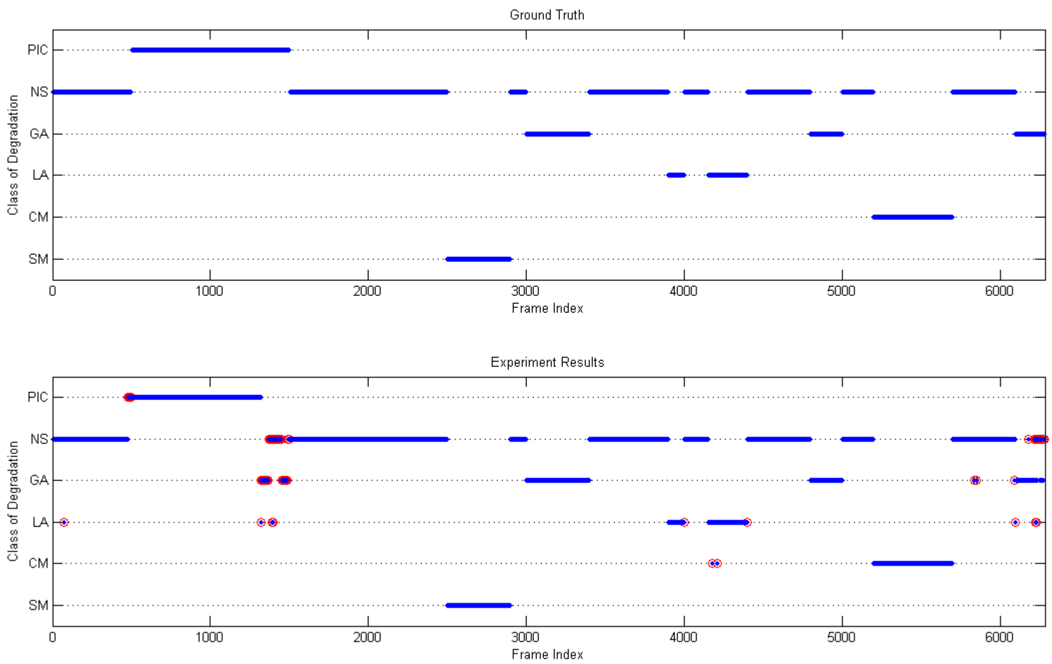


Fig.4 The ground truth and the experiment results of degradation recognition. Red circle in the bottom figure represents incorrect result.

non-PIC.

B. Recognition of Multiple Degradations

A big challenge to this work is how to detect/recognize multiple degradations on surveillance video. In the second experiment, we tested three surveillance videos with frame rate of 10 fps, and video length is 10 minutes averagely. The nine quality degradations mentioned above were randomly imposed on videos. For recognition of PIC, we used a shift window to extract 300 frames every time, analyzed those frames, and determined whether PIC adds to video or not. For the other degradations, (7), (8), (9) and (10) were available.

Fig.4 shows the ground truth and the recognition results. The test video consists of 6283 frames, and the nigh degradations are set as follows:

i. Periodic Intensity Change: 501st to 1500th frames;
ii. Signal Missing: 2501st to 2900th frames;
iii. Out of Focus: 3001st to 3400th frames;
iv. Stripe Addition: 3901st to 4000th frames;
v. Encoding Bug: 4151st to 4400th frames;
vi. Over-quantization: 4801st to 5000th frames;
vii. Color Missing: 5201st to 5700th frames;
viii. Stationary Camera Shifting by Force: 6101st to 6283rd frames;
ix. Normal Status: the rest of frames.

In the bottom of Fig.4, the red circle represents incorrect recognition result. Table V lists the recognition rates of five classes of degradations in the test video, and the average recognition rate is 96.02%. Table VI lists the recognition rates of non-PIC and PIC for the test video, and the recognition rate of PIC is 82.12%.

C. Comparisons

In the third experiment, we emphasized on performance of

TABLE V
RECOGNITION RATES OF FIVE CLASSES OF DEGRADATIONS FOR THE TEST VIDEO (UNIT: %)

		Class of Degradation				
		SM	CM	LA	GA	NS
Experiment	SM	**100**	0	0	0	0
	CM	0	**100**	0	0	0
	LA	0	0.57	**99.43**	0	0
	GA	0	0	0.38	**95.15**	4.47
	NS	0	0	0.12	0.09	**99.79**

TABLE VI
RECOGNITION RATES OF NON-PIC AND PIC FOR THE TEST VIDEO (UNIT: %)

		Class of Degradation	
		Non-PIC	PIC
Experiment	Non-PIC	99.55	0.45
	PIC	17.88	82.12

blurred frame detection using three methods. In our study, frame blurring is equivalent to global alternation, such as out of focus, over-quantization, motion blurring (i.e. stationary camera shifting by force). Under this circumstance, blurred frame is defined as frame degraded by global alternation. If a frame is normal status or degraded by local alternation (i.e. stripe addition and encoding bug), signal missing, or color missing, we consider it as a non-blurred frame. There were 62790 blurred frames and 104650 non-blurred frames of sized 288×384 tested, and our method compared with two existing approaches: Crete et al.'s method [6] and Tsomko et al.'s method [7]. All of the two existing methods and ours are

TABLE VII
RECOGNITION RATES OF BLURRED AND NON-BLURRED FRAMES BY THREE METHODS (UNIT: %)

	The Proposed Method	Crete et al.'s Method [6]	Tsomko et al.'s Method [7]
Blurred Frame	99.89	99.89	59.30
Non-blurred Frame	99.85	97.19	75.28

implemented by referring to pixel difference. Furthermore, three methods need 1 to 2 seconds for recognition of a blurred frame or a non-blurred frame, which are faster than another method.

Using Crete et al.'s method to compute blurriness in advance, Bayesian classification is applied to the computed blurriness in order to identify frame as either blurred frame or non-blurred frame. The threshold is set to 0.7227 for Bayesian classifier. Tsomko et al's method detected blurry frame and assessed blurriness at three levels: globally sharp, average quality and globally blurry. 'Globally sharp' is obviously distinct from 'globally blurry'. According to the authors' description, an average quality image may contain blurry parts or exposures insufficiently. In the experiment, if blurred frame is classified as average quality image, we consider it is blurry. On the contrary, if non-blurred frame is classified as average quality image, we consider it is not blurred.

Table VII lists the recognition rates of blurred and non-blurred frames by three methods. It is obvious the proposed method has the best performance among three approaches, and the recognition rates are above 99%. The experiment results demonstrate our method is efficient in recognitions of blurred and non-blurred frames.

V. CONCLUSIONS

In this paper, an automatic degradation recognition method is proposed for inspection of surveillance camera. Seven features are extracted based on four kinds of measures, and degradation is recognized into six classes: signal missing, color missing, local alternation, global alternation, periodic intensity change, and normal status. The recognition rates of normal status, signal missing, color missing, local alternation, and global alternation are above 95% averagely, and the recognition rate of periodic intensity change is above 82%. Moreover, the proposed method has the best performance among three methods to distinguish blurred frame from non-blurred one, and our method can achieve high recognition rate over 99%.

REFERENCES

[1] Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Trans. Image Processing*, vol.13, no.4, pp.600-612, April 2004.

[2] A. Loza, L. Mihaylova, N. Canagarajah, and D. Bull, "Structural similarity-based object tracking in video sequences," *IEEE Int'l Conf. on Information Fusion*, pp.1-6, July 2006.

[3] ITU-T, Methods for subjective determination of transmission quality, Aug. 1996.
http://www.itu.int/rec/T-REC-P.800-199608-I/en

[4] İ. Avcıbaş, B. Sankur, and K. Sayood, "Statistical evaluation of image quality measures," *Journal of Electronic Imaging*, vol.11, no.2, pp.206-223, April 2002.

[5] B. Bing, 3D and HD broadband video networking, Artech House Inc., Norwood, MA, USA, 2010.

[6] F. Crete, T. Dolmiere, P. Ladret, and M. Nicolas, "The blur effect: Perception and estimation with a new no-reference perceptual blur metric," in *Proc. SPIE—Electronic Imaging Symp. Conf. Human Vision and Electronic Imaging*, San Jose, CA, 2007, vol. XII, p. EI6492–16, 2007.

[7] E. Tsomko, H. J. Kim, J. Paik, and I.-K. Yeo, "Efficient method of detecting blurry images," *Journal of Ubiquitous Convergence Technology*, vol.2, no.1, pp.27-39, May 2008.

[8] C.-Y. Wee, R. Paramesran, "Measure of image sharpness using eigenvalues," *Information Sciences*, vol.177, no.12, pp.2533-2552, June 2007.

[9] C. T. Vu, D. M. Chandler, "S3: a spectral and spatial sharpness measure," *MMEDIA*'09, pp.37-43, 20-25 July 2009.

[10] P. Marziliano, F. Dufaux, S. Winkler, T. Ebrahimi, and G. Sa, "A no-reference perceptual blur metric," in *Proc. IEEE Int. Conf. Image Process.*, pp. 57–60, 2002.

[11] Y. C. Chung, J. M. Wang, R. R. Bailey, S. W. Chen, and S. L. Chang, "A non-parametric blur measure based on edge analysis for image processing applications," in *Proc. IEEE Conf. Cybern. Intell. Syst.*, vol. 1, pp. 356–360, 2004.

[12] J. Caviedes, F. Oberti, "A new sharpness metric based on local kurtosis, edge and energy information," *Signal Processing: image communication*, vol.19, no.2, pp.147-161, Feb. 2004.

[13] L. Debing, C. Zhibo, M. Huadong, X. Feng, and G. Xiaodong, "No reference block based blur detection," in *Proc. Int. Workshop QoMEx*, 2009, pp. 75–80.

[14] CAVIAR Test Case Scenarios,
http://groups.inf.ed.ac.uk/vision/CAVIAR/CAVIARDATA1/