Journal of Information Hiding and Multimedia Signal Processing ©2011 ISSN 2073-4212
Ubiquitous International Volume **2**, Number **3**, July **2011**

An Efficient Contourlet-Transform-Based Algorithm for Video Enhancement

Yunbo Rao and Leiting Chen

School of Computer Science and Engineering,
University of Electronic Science and Technology of China, Chengdu, China, 611731
uestc2008@126.com

Received January 2011; revised May 2011

Abstract. *Since many activities of interest often occur in the dark environment, video enhancement has become increasingly important. In this paper, we focus on addressing two key issues for nighttime video enhancement: (1) we propose a contourlet-transform-based scheme to address the fusion problem of the same scene between daytime and nighttime videos. (2) Based on this, for further improving the perceptual quality of the moving objects, we propose an improved framework for nighttime video enhancement which can efficiently recover the unreasonable enhancement results due to imperfect moving objects extraction. Experimental results show that the proposed algorithm can obviously improve the visual quality from conventional methods.*
Keywords: Video enhancement, contourlet transform, moving objects extraction, fusion

---

1. **Introduction.** Video enhancement plays a crucial role in video processing applications, such as remote sensing, LCD display processing, highway surveillance, and scientific visualization [1]. There are several reasons for video enhancement: (1) the poor quality of the used video device and lack of expertise of the operator, (2) the obtained low quality video appear much noise, due to sensor noises or very low luminance, (3) due to low contrast, we cannot clearly extract moving objects from the dark background. Most color-based methods will fail on this matter if the color of the moving objects and that of the background are similar, and (4) high light or dark areas in which the scene information cannot be seen clearly by the observers. As a result, such images and videos may not reveal all the details in the captured scene, and may have a washed-out and unnatural look [2].

Traditional methods of video enhancement are to enhance the low quality video within itself and they do not embed any external high quality background information. Such as tone mapping, histogram equalization, and power low transform. Due to design or observational constraints a single video approach usually fails in proving the necessary enhancements. The method is usually applied to input images to obtain a superior visual representation of the image by transforming original pixel values using transform function of the form.

$$g(x, y) = T[r(x, y)] \tag{1}$$

where $g(x, y)$ and $r(x, y)$ are the output and input pixel values at image position (x, y) . T is transform function. Usually for correct enhancement it is desirable to impose certain restrictions on the transformation function [2, 3].

The other possible approach is to enhance nighttime video features by using the information gathered from high-quality video. This process is called image fusion. Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. The aim of image fusion is to integrate complementary and redundant information from multiple images to create a composite that contains a "better"description of the scene than any of the individual source images. An example review of the state of the art fusion algorithm can be found in [4, 5].

In video enhancement filed, fusion techniques focus on pixel-level including gradient pyramid [6], shift invariant discrete wavelet transform [7], weighted combination [8], and contourlet transform [9]. Pervious method in most real surveillance scenes are based on the following two assumptions [6-11]: (1) the camera is fixed and can observe the same scene all day long. (2) the scene model is coincident from daytime to nighttime. For example, in [11] propose a "denighting" method that combines the daytime background and the nighttime videos together. By using redundant information, the enhanced composite video has much improved accuracy as well as reliability. The algorithm adopt illumination ratio of the daytime background and nighttime background for enhancement, as in Eq.(2)

$$L_{eng}(x, y) = \frac{L_{DB}(x, y)}{L_{NB}(x, y)} L_{NF}(x, y) \tag{2}$$

where $L_{DB}(x, y)$ and $L_{NB}(x, y)$ represent illumination component of the daytime and nighttime background, respectively. $L_{eng}(x, y)$ is the illumination component of the final enhanced image, and $L_{NF}(x, y)$ represent illumination component of the input nighttime video. The illumination ratios $\frac{L_{DB}(x,y)}{L_{NB}(x,y)}$ of the daytime background images and the nighttime background images can be much smaller than 1. The enhanced results will lose the static illumination. (See Figure 8(a)).

To analyze the existing algorithms of fusion-based video enhancement, the algorithm of video enhancement is automatically combining images of a scene at different time intervals by image fusion. The fused image contains a comprehensive description of the scene which is more useful for human visual and machine perception. In this paper, we are combining daytime background image and nighttime video together, as shown in Figure 1. Based on this framework, a fast efficient contourlet-transform-based scheme to fuse video frames from high-quality daytime background and nighttime video is proposed. Meanwhile, for improving the perception quality of the moving objects, we further propose an improved framework for nighttime video enhancement which can efficiently recover the unreasonable enhancement results due to imperfect moving objects extraction.

The remainder of the paper is organized as follows. Section 2 describes contourlet-transform-based scheme and an improved framework for nighttime video enhancement. Experimental results are shown in section 3. Finally, the conclusion is given in section 4.

2. **The proposed algorithm.** The proposed algorithm is based on the fusion-based strategy using contourlet-transform-based scheme that introduces the daytime background information to help enhance the nighttime videos. For improving the perception quality of the moving objects, an improved framework for nighttime video enhancement is also proposed. The proposed algorithm can ensure better image reconstruction and color assignment. The flowchart of the proposed algorithm is shown in Figure 2. The proposed algorithm is composed of the following four components: (1) acquisition of clean daytime background images (i.e. daytime background in Figure 2(1)), (2) moving objects

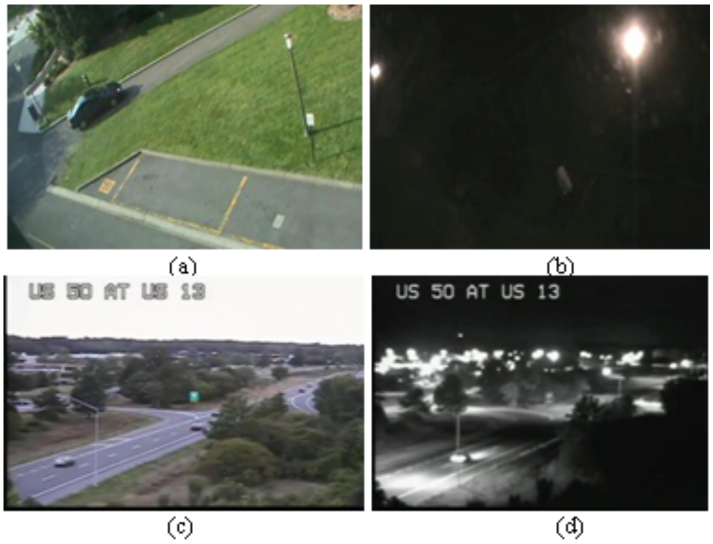

FIGURE 1. Frames from two typical surveillance video((a) campus and (c) highway). (a)and (c)daytime images, (b) and(d) nighttime images

extraction(i.e. in Figure 2(2)), (3) an improved framework for nighttime video enhancement(i.e. in Figure 2(3)), and (4) the final fusion and enhancement using contourlet-transform-based scheme algorithm (i.e. in Figure 2(4)).

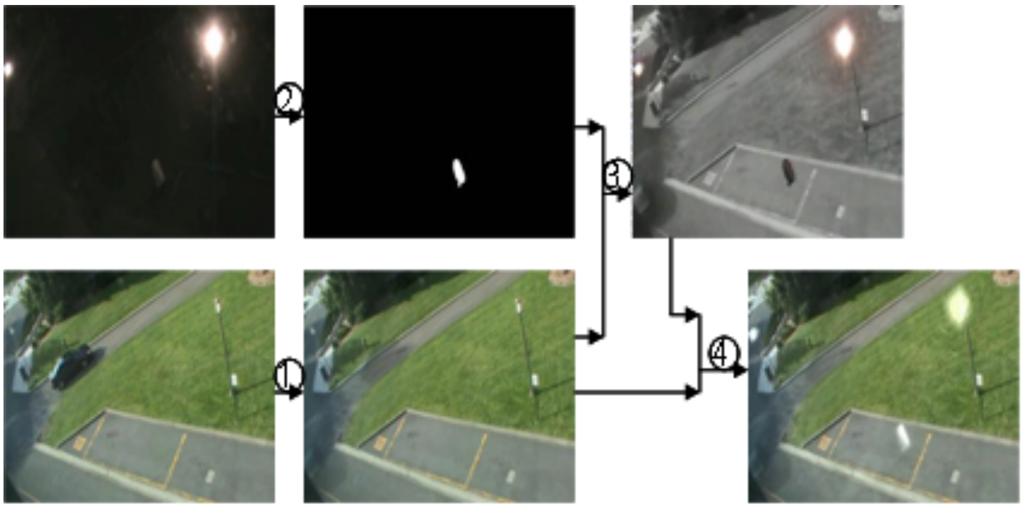

FIGURE 2. A block diagram of the proposed algorithm

The basic steps of our algorithm are described in Algorithm 1. First, we acquisitive clean daytime background images, it is desirable to have a clean daytime background without any moving objects. The daytime background images are obtained by averaging k frames of the input daytime videos. In components 2, due to the low contrast, we can not clearly extract moving objects from the dark background. Tone mapping approach is used to enhance the nighttime video frames and to separate an image into details and large scale features. The nonlinear mapping function with independent parameters is used to attenuate image details and to adjust the contrast of large scale features. Example results of the tone mapping is shown in Figure 7(c). Mixture of Gaussians method is used to extract moving objects. And our enhancement in components 3 is based on the illumination layer. The illumination layer is obtained by first decoupling the input frame

RGB into intensity and color components. For achieving the intensity component, in this paper, we use the CIE La*b*(CIELAB) model as the intensity and color since it is the most complete color model used to describe all the colors visible to the human eye. Then further decomposing it into the illumination layer $L(x, y)$ and the reflectance layer $R(x, y)$ using Retinex theory [12]. The input intensity image $I(x, y)$ is represented by the product of the illumination $L(x, y)$ and the reflectance $R(x, y)$ as follows:

$$I(x, y) = R(x, y) \times L(x, y) \tag{3}$$

After achieving the illumination layers, the enhanced frame is acquired by an improved framework for nighttime video enhancement. Finally, the enhanced image is reconstructed from the enhanced illumination and the reflectance and color of the input nighttime video. Components 4 use contourlet-transform-based scheme to fuse daytime background and nighttime video.

Algorithm 1 Basic algorithm

Input: nighttime video and daytime video with the same scene;
Procedure:
Step 1 Get background of daytime video from input video;
Step 2 Using tone mapping for input nighttime video;
Step 3 Moving objects extraction of nighttime video from step 2 video;
Step 4 Using improved framework for nighttime video enhancement;
Step 5 Fusion enhancements using contourlet-transform-based scheme of step (1) and (4).

Note that steps 1 and 2 in the proposed algorithm follow our previous work [10], more details can be found in ref [10]. Therefore, in this paper, we will focus on discussing steps 3, 4, and 5 of algorithm 1. These steps are described in detail as follows.

2.1. **Moving objects extraction.** The moving objects extraction step refers to segmenting the pixels associated with coherently moving objects or moving regions. In practice, moving objects extraction in the image space is difficult, especially when dealing with low contrast and noisy videos. In order to effectively extract moving objects from the dark background, we propose to introduce tone mapping functions for segmenting the nighttime video objects. In our moving objects extraction step, we first apply tone mapping function [13] to “pre-enhance” the videos. Mixture of Gaussians (MoG) method is used to extract moving objects, which tracks multiple Gaussian distributions simultaneously [14]. MoG allow the colour distribution of a given pixel to be multimodal. The MoG method can be described in the following.

We set $I_t(x, y)$ and $B_t(x, y)$ are used to denote the illumination pixel intensity and its background estimate at spatial location(x, y) and time t. The spatial coordinate(x, y) may be dropped if it is not relevant in the description. The pixel distribution $f(I_t = u)$ is modeled as a mixture of k Gaussians:

$$f\left(I_t = u\right) = \sum_{i=1}^{k} w_{i,t}.\eta(\mu, \mu_{i,t}, \delta_{i,t}) \tag{4}$$

Where $\eta(\mu, \mu_{i,t}, \delta_{i,t})$ is the $i{-}th$ Gaussian component with intensity mean $\mu_{i,t}$ and standard deviation $\delta_{i,t}$. $w_{i,t}$ is the portion of the data accounted for by the $i - th$ component. Typically, ranges from three to five, depending on the available storage. The parameters of the matched component are then updated as follows:

$$w_{i,t} = (1-\alpha)w_{i,t} + \alpha \tag{5}$$

$$\mu_{i,t} = (1-\rho)\mu_{i,t} + \rho I_t \tag{6}$$

$$\delta^2_{\mu_{i,t}} = (1-\rho)\delta_{\mu_{i,t-1}} + \rho(I_t - \mu_{i,t})^2 \tag{7}$$

Where α is a user-defined learning rate with $0 \le \alpha \le 1$. ρ is the learning rate for the parameters and can be approximated as follows:

$$\rho = \frac{\alpha}{w_{i,t}} \tag{8}$$

If no matched component can be found, the component with the least weight is replaced by a new component with mean I_t, a large initial variance δ_0 and a small weight w_0 . The rest of the components maintain the same means and variances, but lower their weights to achieve exponential decay:

$$w_{i,t} = (1-\alpha)w_{i,t-1} \tag{9}$$

To determine whether I_t is a foreground pixel, we first rank all components by values of $\frac{w_{i,t}}{\alpha_{i,t}}$. If $i_1, i_2, ..., i_k$ is the component order after sorting, the first M components that satisfy the following criterion are declared to be the background components:

$$\sum_{k=i}^{i_k} w_{k,t} \ge T \tag{10}$$

Where T is the weight threshold. In this paper T is set to 10. We convert the extracted moving objects results into binary object-masks for each frame. Morphological opening, closing, and connected component analysis are then performed on the binary masks to get rid of small and random noises, and to fill the holes. Experimental results of the moving objects extraction are shown in Figure 3.

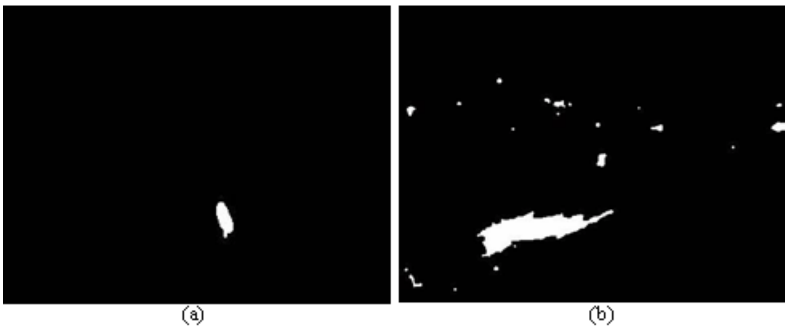

FIGURE 3. the moving objects extraction results using the method proposed in [14]. (a) Campus, and (b) Highway.

2.2. **An improved framework for nighttime video enhancement.** In order to improve the results in the moving objects regions, the moving objects can be extracted from the nighttime video and handled differently. In [15], the moving objects extraction produces region masks M, where pixels in the moving objects regions have a pixel value of 1, and pixels outside the regions have a pixel value of 0. Denote the normalized illumination in the nighttime video as $L_n(x, y)$.

$$L_n(x,y) = \frac{L_{night}(x,y) - L_{min}(x,y)}{L_{max}(x,y) - L_{min}(x,y)} \tag{11}$$

where $L_{min}(x,y)$ and $L_{max}(x,y)$ are the minimum and maximum illumination value in the nighttime video, respectively. $L_n(x,y)$ has a range between 0 and 1. $L_{night}(x,y)$ is input nighttime video. The enhanced video is obtained by setting different weightings for the moving objects and the background regions:

$$W(x,y) = \begin{cases} 1, if M(x,y) = 1 \\ L_n(x,y), if M(x,y) = 0 \end{cases} \tag{12}$$

Here, the weights of the moving objects are set to 1 to prevent the mixing of the daytime background. The effect is to extract the moving objects and paste onto the enhanced images to prevent the ghost pattern.

This approach can effectively prevent the ghost pattern. However, the algorithm has some limitations as follows: (1) it is well known that moving objects extraction is a challenging problem. The moving objects extraction results usually are far from perfect. (2) Moving objects region cannot be enhanced. (3)Due to the low contrast, noisy, and dark image background, enhanced results will fail if the color of the moving objects and that of the background are similar. Therefore, in this paper, we improve this algorithm by the following way. To prevent ghost patterns and prevent boundary variations, the weight in the boundary of moving objects should change smoothly. We perform 10x3 Gaussian low-pass filtering on the enhancement inside the moving objects masks $M(x,y)$. Results show that this simple but effective improved method can address the illumination lost problem. An example result is shown in Figure 4. In Figure 4, the moving person and cars don't severely distort after the enhancement using this approach due to the perfection of the Gaussian low-pass filtering and morphological opening, closing, and connected component to get rid of small and random noises, and to fill the holes. Enhanced results of nighttime video keep on the nighttime lights.

FIGURE 4. the using improved framework for nighttime video enhancement, (a) Campus, and (b) Highway.

2.3. **Final fusion and enhancement using contourlet-transform-based scheme.** In section 2.2, we propose using Gaussian low-pass filtering on the enhancement inside the moving objects masks to change smoothly of moving objects. However, we can not full resolve some limitations in [15]. In this section, we propose video enhancement using contourlet-transform-based scheme to fuse daytime image and nighttime video. This fusion processes are described in detail as follows.

In [16] propose contourlet transform (CT) to represent two dimensional singularities, which is composed of Laplacian pyramid (LP) and directional filter bank (DFB). The transform can represent curve more sparsely due to its directionality and anisotropy. However, there exists frequency aliasing in the process of contourlet transform. In order to eliminate the frequency aliasing, enhance directional selectivity and shift-invariance, and in [17] propose nonsubsampled contourlet transform (NSCT) based on nonsubsampled pyramid decomposition and nonsubsampled filter banks (NSFB). Figure 5 gives nonsubsampled contourlet transform. An overview of NSCT is shown in Figure 5(a). The structure composed of a bank of filters splitting the 2-D frequency plane in the sub bands is illustrated in Figure 5(b).

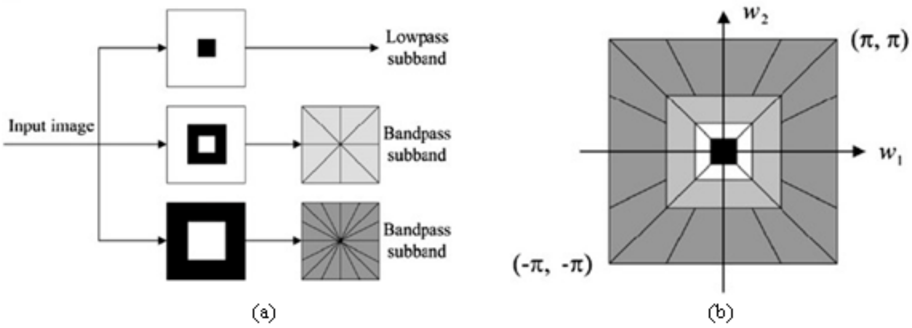

Figure 5. Nonsubsampled contourlet transform: (a) NSFB structure that implements the NSCT and (b) idealized frequency partitioning obtained with the proposed structure.

NSCT is more efficient than other multiresolution analysis in image denoising and image enhancement due to its multiscale, multidirection, anisotropy and shift-invariance. Therefore, we perform multiscale decomposition on daytime background and nighttime video by NSCT in the proposed method. The basic steps of our algorithm are described in Algorithm 2.

Algorithm 2 Final fusion and enhancement using contourlet-transform-based

---

Input: nighttime video and daytime background with the same scene;
Procedure:
Step 1 Get daytime background from input video;
Step 2 Get nighttime video frames from the result using improved framework for nighttime video enhancement;
Step 3 Convert RGB color space into YCbCr and extract Y component as intensity;
Step 4 Multi-resolution decomposition using NSCT from extraction Y component, CT generates approximate and detail coefficients;
Step 5 Using averaging, match, and activity to fuse daytime background and the results of step 2;
Step 6 Inverse multi-resolutions;
Step 7 Inverse color using daytime background colors (CbCr);
Step 8 Fused frames.

If nighttime video is very dark and with noise, using NSCT to directly fuse daytime background, the fused results produce ghost pattern and lost illumination of nighttime video or daytime background. Example results of this case are shown in Figure 6 (a). In this paper, to resolve some limitations in [15], our fusion enhancement combing daytime background and nighttime video frames from the result using improved framework for nighttime video enhancement. Figure 6 (b) shows the experimental results of our proposed algorithm. We can see that our algorithm is robust and effective and the enhancement result of our algorithm maintains the fidelity of important information of both daytime and nighttime frames.

Figure 6. Nonsubsampled contourlet transform. (a) Using NSCT to directly fuse daytime background and nighttime frame. (b) Using NSCT to fuse daytime background and nighttime video frames from the result using improved framework for nighttime video enhancement, the algorithm can efficiently recover the unreasonable enhancement results due to imperfect moving objects extraction and to resolve some limitations of in [15].

3. **Experimental results.** The part data (such as Figure 1(a) and (b), Figure 9 (c) and (d)) for video enhancement is from Canon FS306 which camera is used in our experiment. The part data (such as Figure 1(c) and (d), Figure 8 (a) and (b), Figure 9(a) and (b)) for video enhancement is from the Washington State Department of Transportation website (used by permission). While traffic video is usually enough for a trained traffic controller, if one is not familiar with location, showing a nighttime traffic image makes it very difficult to understand where the lanes and exits on the highway are. The proposed algorithm is to more clearly understand the lanes, exits on the highway or surveillance security on the highway. Experimental results are shown in Figure 8(b) and Figure 9(b).

We also have performed extensive nighttime video enhancement experiments on various real outdoor/ traffic surveillance scenes, with image size of 320X240 pixels and it is very difficult to get an idea of the enhanced image, especially at nighttime. Some traditional video enhancement algorithms include gamma transform, histogram equalization, tone mapping, and de-haze algorithm [18] on the inverted input. However, as mentioned, since these self-enhancement-based algorithms enhance videos without any external information, they often fail to work well when enhancing nighttime videos. Some example results of the self-enhancement-based algorithms are shown in Figure 7.

We also give comparative results of the proposed algorithm. Figure 8 shows experimental results using method in [11] and the proposed algorithm. As we can see from Figure 8 (a), there is obvious lost lighting in highway and inside of the buildings. Figure 8(b) shows the results of using the proposed contourlet-transform-based algorithm, where the enhanced results has enough illumination and obviously more pleasant result than using method in [11].

Figure 9 show the results of our algorithm under different datasets and nighttime videos. We can see that the proposed algorithm is robust and effective on various scenarios and the enhancement results of our method maintains the fidelity of important information of both daytime and nighttime images.

In order to show a measure of the performance to demonstrate that the proposed method perform well the previous method, table 1 shows the results of a user study test where the users are asked to view the original video and the enhanced video side by side

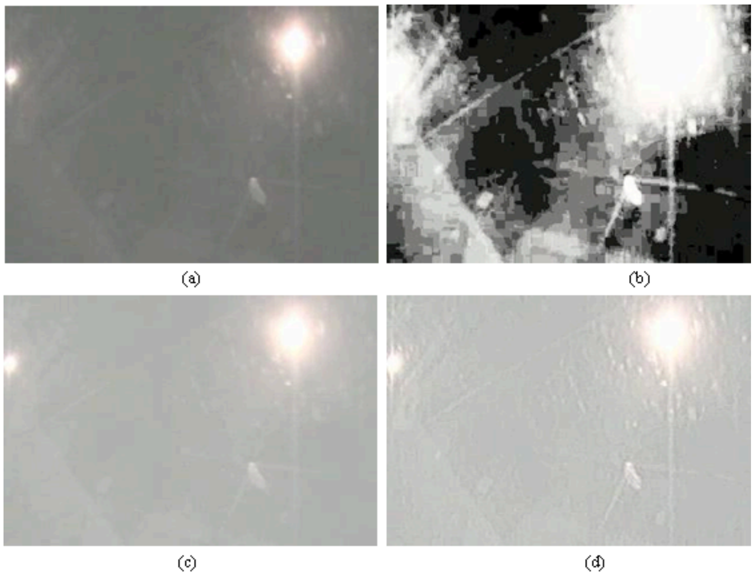

FIGURE 7. Enhancing the nighttime video itself no embeds high-quality background information. (a) Gamma enhancement ($r = 0.4$)using the method in [3], (b) Histogram equalization using the method in [3], (c) Tone mapping method using the method in [13], (d) De-haze algorithm using the method in [18].

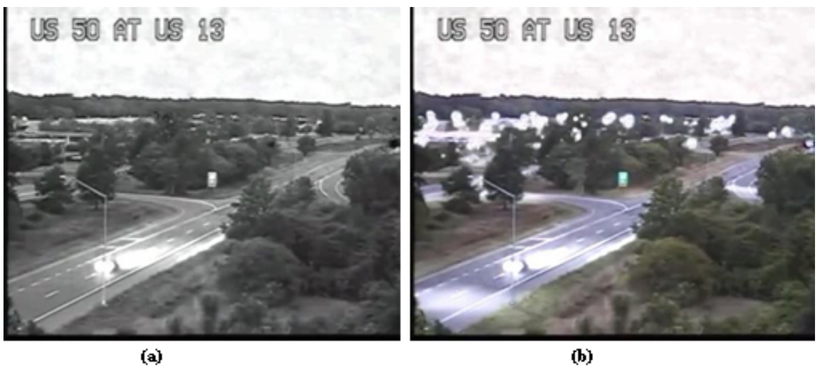

FIGURE 8. Nighttime video enhancement, (a) using the method in [11], (b) using the proposed algorithm.

(as shown in Fig.7 and Fig.8). After viewing the video, the users shall give a score to each video, within the range of 1-5 where 1 indicates very poor quality, 5 indicates very good quality, and a score of 3 is considered acceptable. A total of 12 users responded in our test. Table 1 shows the average scores of the 12 users for the 10 video sequences. Methods including: gamma enhancement, histogram equalization, tone mapping, De-haze algorithm, "denighting" method, and the proposed algorithm. The average score of the original videos is 1.70, the average score of the proposed algorithm is 3.83. Compared to these methods, the proposed algorithm has obviously the highest score. It can be seen that the enhanced videos outperform the original video and other methods in all sequences.

Furthermore, in order to demonstrate that the proposed method perform well the method in [11], we use peak signal-to-noise ratio (PSNR) method. PSNR is most commonly used as a measure of quality of reconstruction in image compression and image

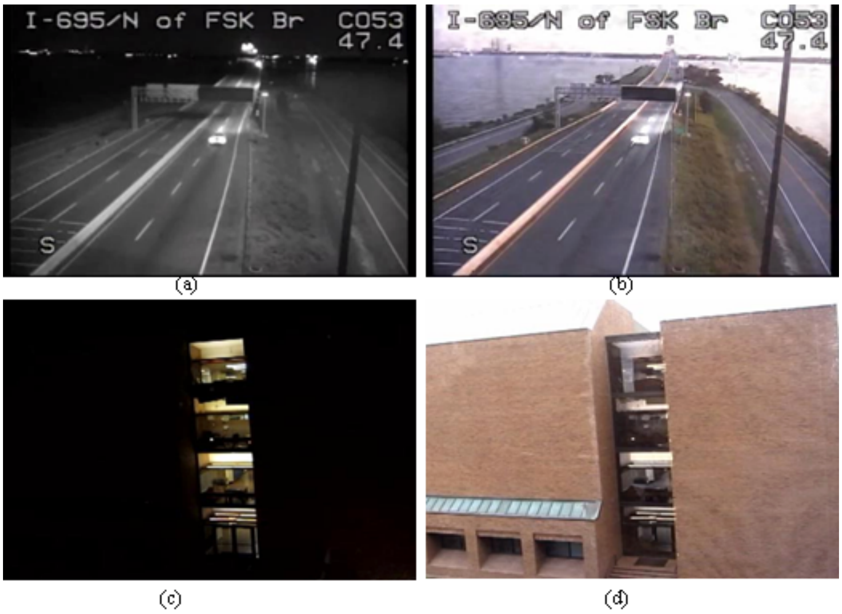

FIGURE 9. Various scenes of video enhancement((a)bridge and (c)building). (a) and (c)original nighttime video, (b) and (d) the enhanced results using the proposed algorithm.

TABLE 1. User study results

Sequence ID	Original Video	Gamma enhancement[3]	Histogram equalization[3]	Tone mapping[13]	De-haze algorithm[18]	Denighting method[11]	The proposed algorithm
1	1.89	2.80	2.67	2.81	3.10	3.50	4.04
2	1.47	2.51	2.48	2.48	2.87	3.31	3.44
3	1.56	2.57	2.51	2.52	2.67	3.45	3.71
4	1.61	2.72	2.70	2.71	2.88	3.56	3.78
5	2.11	3.01	3.11	3.10	3.13	3.80	4.11
6	2.50	3.11	3.14	3.21	3.23	4.01	4.23
7	1.70	2.81	2.70	2.75	2.91	3.48	3.83
8	1.10	2.30	2.10	2.23	2.12	3.03	3.61
9	1.00	2.12	2.08	2.08	2.01	3.00	3.41
10	2.10	3.02	2.89	3.11	3.10	3.87	4.19
Average	1.70	2.69	2.63	2.70	2.80	3.50	3.83

enhancement [19]. It is most easily defined via the mean squared error (MSE) which for $m \times n$ nighttime images f and enhanced image f' in this paper. MSE is defined as follow:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \| f(i,j) - f'(i,j) \| \tag{13}$$

The PSNR is defined as:

$$PSNR = 10 * log_{10}(\frac{MAX_{f'}^2}{MSE}) \tag{14}$$

Where $MAXf'$ is the maximum pixel value of the image. The best data value for each image is highlighted in gray. As Table 2 shows the proposed method outperforms method in [11].

TABLE 2. PSNR of enhanced frames

Sequence ID	Proposed method	Denighting method in [11]
campus	32.37	28.98
highway	33.18	29.13
bridge	31.16	27.26
bulding	30.11	28.71

4. **Conclusions.** In this paper, we show several problems of existing techniques for night video enhancement. We present contourlet-transform-based scheme to enhance nighttime video. To improve the perception quality of the moving objects, we further propose an improved framework for nighttime video enhancement which can efficiently recover the unreasonable enhancement results due to imperfect moving objects extraction and colors shift. The algorithm is suitable for processing low-contrast and noisy inputs while avoiding artifacts present in conventional combining methods such as aliasing, ghosting or haloing. We conduct extensive simulations using various scenes and show the effectiveness and robustness of the proposed algorithm. The enhanced videos are much easier to interpret compared to the original dark videos.

Acknowledgment. The authors would like to thank the anonymous reviewers for their helpful comments. This work is partly supported by National High-Tech Program 863 of China (Grant No. 2007AA010407 and 2009GZ0017) and China Scholarships Council.

REFERENCES

[1] W. Lin, M.-T. Sun, R. Poovendran, and Z. Zhang, Group event detection with a varying number of group members for video surveillance, *IEEE Trans. Circuits and Systems for Video Technology*, vol. 20, no. 8, pp. 1057-1067, 2010.

[2] T. Arici, S. Dikbas, and Y. Altunbasak, A histogram modification framework and its application for image contrast enhancement, *IEEE Trans. Image Processing*, vol. 18, no. 9, pp. 1921-1935, 2009.

[3] R. C. Gonzalez, and R. E. Woods, Person Prentice Hall, *Digital image processing*, New Jersey, 2008.

[4] F. Sadjadi, Comparative image fusion analysis, *Proc. of IEEE Computer Vision and Pattern Recognition*, vol. 8, pp. 1029-1051, 2005.

[5] A. Ardeshir Goshtasby, and S Nikolov, Image fusion: advances in the state of the art, *Science Direct*, 2007.

[6] A. Ilie, R. Raskar, and J. Yu, Gradient domain context enhancement for fixed cameras, *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 19, no. 4, pp. 533-549, 2005.

[7] J. Li, Y. Tao, P. Quan, and Y. Cheng, Combining scene model and fusion for night video enhancement, *Journal of Electronics*, vol. 26, no. 1, pp. 88-93, 2009.

[8] G. Mittal, S. Locharam, S. Sasi, G. R. Shaffer, and AK. Kumar, An efficient video enhancement method using LA*B* analysis, *Proc. of IEEE International Conference on Video and Signal based Surveillance*, Sydney, Australia, pp. 66-71, 2006.

[9] H. A. Melkamu, V.-S. Asirvadam, and L. Iznita, Multi-sensor image enhancement and fusion for vision clarity using contourlet transform, *Proc. of International Conference on Information Management and Engineering*, pp. 352-356, 2009.

[10] Y. B. Rao, W. Lin, and L.-T. Chen, Image-based fusion for video enhancement of nighttime surveillance, *Optical Engineering Letters*, no. 12, 2010.

[11] A. Yamasaki, H. Takauji, S. Kaneko, T. Kanade, and H. Ohki1, Denighting: enhancement of nighttime image for a surveillance camera, *Proc. of International Conference on Production Research*, 2008.

[12] E. H. Land, and J. J. McCann, Lightness and Retinex theory, *Journal of the Optical Society of America*, pp. 61, 1971.

[13] E.-P. Bennett, and L. McMillan, Video enhancement using per-pixel virtual exposures, *ACM Trans. Graphics*, vol. 24, no. 3, pp. 845-852, 2005.

[14] D.-R. Magee, Tracking multiple vehicles using foreground, background and motion models, *Image and Vision Computing*, vol. 22, no. 2, pp. 143-155, 2004.

[15] Y. Cai, K. Huang, T. Tan, and Y. Wang, Context enhancement of nighttime surveillance by image fusion, *Proc. of International Conference on Production Research* , pp. 980-983, 2006.

[16] M. N. Do, and M. Vetterli, The Contourlet transform: an efficient directional multiresolution image representation, *IEEE Trans. Image Process*, vol. 14, no. 12, pp. 2091-2106, 2005.

[17] A. L. da Cunha, J. P. Zhou, and M. N. Do, The nonsubsampled contourlet transform: theory, design,and applications, *IEEE Trans. Image Process*, vol. 15, no. 10, pp. 3089-3101, 2006.

[18] X. Dong, Y. Pang, and J.-T Wen, Fast efficient algorithm for enhancement of low lighting video, *Proc. of SIGGRAPH*, Los Angeles, California, 2010.

[19] V.Caselles, J.-L Lisani, J.-M Morel, and G. Sapiro, Preserving local histogram modification, *IEEE Trans. Image Processing*, vol. 8, no. 2, pp. 220-230, 1999.