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Total variation regularization low-rank decomposition based tensor model for video rain streaks removal

Xinghan Lu[1], Yuhui Zheng, Jianwei Zhang
Nanjing University of Information Science and Technology, Nanjing-210044, China
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Abstract: With superior real-time and storage performance, outdoor computer vision systems have high application value in traffic, public security, identification detection and other fields, but the captured images are affected by environmental factors such as outdoor rainfall, which have obscuration or missing problems and are not conducive to the processing and application of post-level systems. To this end, this paper proposes a tensor model based on total variation regularization low-rank decomposition for video rain streaks removal. Considering the influence of moving objects in the video image on the low-rank structure of the video background, the rainy video is decomposed into static background, dynamic objects and rain streaks, and their a priori characteristics are analyzed separately, combined with the corresponding low-rank characteristics or sparse characteristics to construct a tensor model, and the targets are extracted through low-rank decomposition, and then the rain removal is completed. The proposed tensor model is solved by the alternating direction multiplier method (ADMM), and extensive experiments are carried out on synthetic and real data sets. The results show that the proposed method can effectively remove rain streaks from video images while retaining more background details under dynamic background conditions. Compared with related advanced methods, the proposed method has advantages in three comprehensive quantifiers, namely, peak signal-to-noise ratio, structural similarity and residuals.

Keywords: Rain removal, tensor model, total variation, low rank, ADMM.

1. Introduction

Outdoor computer vision systems have a wide range of applications in many fields such as road traffic and public safety video surveillance. However, rain can degrade the acquired video images, resulting in image contrast degradation, blurring or detail loss, etc., which adversely affects the subsequent work of computer vision systems (e.g., target detection [1,2], recognition [3], and tracking [4]). Therefore, it is of great research significance to recover such video images to minimize the effect of rain on images and to improve the stability and practicality of outdoor computer vision systems.

In recent years, many methods have been used to de-rain video images. From the perspective of methods, there are three main categories: time-domain-based methods, frequency-domain-based methods and sparse-domain-based methods.

Based on the time-domain perspective, Zhu et al. [5] used a photometric model to obtain the candidate rain streaks and used the inter-frame difference method for motion object detection, deducting the motion objects in the candidate rain streaks to obtain the final rain line detection results. The inter-frame difference method has advantages such as simple computation, but it is susceptible to background illumination changes and extraneous events, resulting in large errors in motion detection. For this reason, Wang et al. [6] used a multi-frame anisotropic filter based on a kernel function that can adaptively change the filter intensity and direction according to the local characteristics of the rain streaks to remove the rain streaks while the rain streaks are detected and improve the robustness in dynamic scenes.

Based on the frequency domain perspective, Barnum et al. [7], abandoned the approach of analyzing pixels and pixel blocks from the time domain and proposed a video de-rain method based on frequency domain spatial analysis. Santhaseelan et al. [8] proposed a video de-rain method based on local phase consistency, which overcomes the error brought by the fixed threshold recovery model and enhances the smoothness of the video. Chen et al. [9] obtained detail edge information based on wavelet transform, filtered after doing difference operation using inter-frame pixel brightness, and used fast bilateral filtering for rain line removal.

Based on the sparse domain perspective, Kang et al. [10] used bilateral filtering to decompose the image with rain into low-frequency and high-frequency components based on morphological component analysis (MCA), and then separated the rain streaks in the high-frequency components by dictionary learning and sparse coding. The sparse decomposition-based rain removal method does not require contextual information and has the advantages of wide applicability, from which a series of improved methods have been derived [11-17]. To improve the convergence speed of the algorithm, Ramya et al. [13] used an enhanced K-SVD (EKSVD) method for dictionary learning and an orthogonal matching tracking method for sparse coding of images with rain. Li et al. [18] used sub-block image a priori information for modeling, and used Gaussian Mixture Model (GMM) for learning the rain line component and the video background, the background part is further constrained. This method can remove rain streaks better. However, when the input image contains many structures similar to the distribution of rain streaks, this method is difficult to effectively distinguish between layers with and without rain. KIM et al. [20] proposed a time-dependent video de-rain method based on obtaining the initial rain map by optical flow estimation, applying a support vector machine classifier refinement, and eliminating rain streaks using a low-rank matrix filling technique [21]. Li et al. [23] learned a multiscale convolution filter from rain data to decompose the rain component into different levels of rain streaks and sparse coding of the different features. The method achieves excellent results in real videos with rain, but the rain removal results may be blurred if there are complex moving objects in the video.

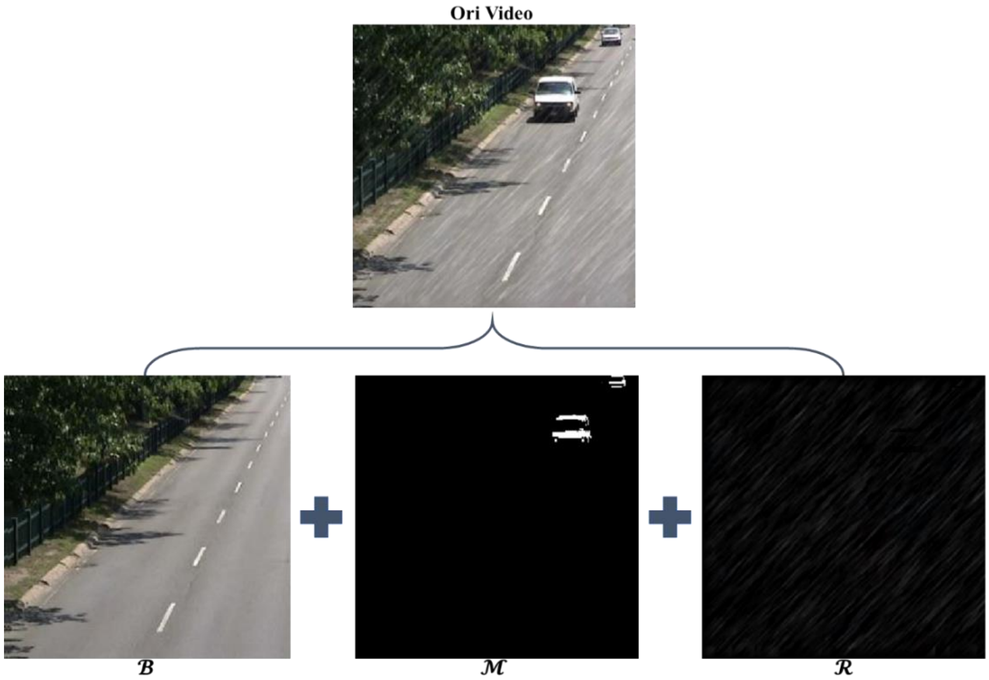

Fig.1 Rainy video $\mathcal{O}$, static background $\mathcal{B}$, moving object $\mathcal{M}$ and rain streaks $\mathcal{R}$

Unlike the methods that require dictionary learning, Chen et al. [19] proposed a tensor low-rank epistemic model to detect spatio-temporal correlated rain streaks using similar patterns of rain streaks in the image scene. The method does not require dictionary learning, but it causes certain rain line misclassification due to the insufficiently strong constraints. Jiang et al. [22] proposed a tensor-based video rain line removal model with great advantages in time consumption by considering the difference between the intrinsic properties of video background and rain marks and enhancing sparsity using the parametric norm. Sun et al. [24] proposed a directional norm-based de- rain tensor model, which simulates the non-vertical landing of real rain streaks with constraints on the rain line direction. The method can effectively remove the rain streaks at different angles, but it is not optimistic in terms of running time. Considering the different prior information in the rainy video, Wang et al. [25] proposed a group sparsity-based rain removal method, which enhances the sparsity of rain streaks using group sparsity while modeling different prior information to facilitate rain line separation.

Recently, deep learning-based methods have also achieved better results [26-30]. It is worth noting that the rain removal effect depends heavily on the number and diversity of training datasets. To make the rain removal method more flexible and stable, inspired by the literature [25], a video rain removal tensor model based on fully variational regular low-rank decomposition is proposed in this paper, considering the irregular motion of dynamic objects in the video background.