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Automated Real-Time Removal of Mist or Snow Artifacts from Surveillance Video Footage

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ABSTRACT

The removal of mist and snow from surveillance recordings is a crucial topic in the field of computer vision since these elements can seriously impair the functionality of many surveillance systems. Many techniques have been well studied, although most only assess continuous snowfall or mist against stable backgrounds. On the other hand, real surveillance camera footage of mist or snow is always quite dynamic in time, and these videos can feature altered background scenes in addition to background motions produced by shifting water or vegetation surfaces. This research offers a unique method for removing snow and mist that fully incorporates dynamic statistics of the backdrop scenes and snow and mist from a video series in order to solve this issue. An online multi-scale convolutional sparse coding (OMS-CSC) model is used to encode the mist/snow. It is able to separate the elements of background motion from the mist/snow layer and accurately provide the sparse scattering and multi-scale forms of real mist/snow. Their temporally changing configurations are accurately represented by the model's real-time enhanced parameters. Moreover, the proposed model incorporates a transformation operator applied to the backdrop scenes, effectively expressing the background transformations (rotations, scaling, and distortions) that were a necessary part of an actual video sequence. The method as conceived may adapt to changing background conditions including dynamic mist or snow, additionally, because of its online learning mode, it is perfect for handling streaming video. Written in a compact maximal a posterior (MAP) framework, the proposed model can be solved with ease by applying the alternating direction method of multipliers (ADMM). Visually and statistically, the proposed method beats existing offline and online algorithms for video mist/snow removal on both synthetic and real datasets. In particular, our method may be applied quite effectively, showing its potential for real-time video mist/snow removal.

Keywords- multi-scale, convolutional sparse coding, rain/snow removal, dynamic background, online learning, alignment method

1. INTRODUCTION

Snow or rain commonly contaminates recordings captured by outside surveillance equipment, diminishing perceived quality and impeding subsequent processing of footage tasks such as human recognition [1], identity recovery [2], object tracking [3], and scene analysis [4]. Thus, eliminating mist and snow from surveillance film is an important video pre-processing step that has sparked attention in the computer vision field. In recent decades, numerous ways have been developed to remove mist from a video.

In the last few years, low-rank models have exhibited tremendous potential for this task, routinely reaching the highest levels of accuracy because to its superior treatment of video structure [5] previous information in both the foreground and background. These approaches use the low rank structure for the backdrop while also fully enabling preexisting knowledge about the mist [9], such as sparsity and spatial smoothness. Recently, deep learning-based techniques have been proposed for this aim.

These systems solve the challenge of video mist removal by applying deep recurrent convolutional networks or deep convolutional networks and performing the task using a popular end-to-end learning methodology. Despite substantial advancements, the majority of existing systems rely on predefined movie lengths and assume continual mist/snow forms against static backdrops. This, however, is clearly different from the real occurrences. On the one hand, the mist/snow in a film sequence is frequently with patterns that vary continuously over time.

However, as seen in Fig. 1, the movie's backdrop picture is always dynamic, integrating temporal changes caused by camera jitters with background motion such as swinging leaves and ocean waves. In real-world conditions, the performance of present approaches tends to worsen when such dynamic aspects are disregarded. Because of the increasing number of surveillance cameras deployed throughout the world, real footage is constantly being transmitted online. However, because most existing approaches are taught and applied to pre-determined video sequences, they are unable to adapt efficiently and accurately to streaming movies that are released on a regular and continuous basis. These concerns have limited the number of available options in real-world applications, and hence ought to be particularly explored.

2. LITERATURE SURVEY

This section provides a brief overview of the methods for video mist and snow removal. This article also covers improvements in single image mist and snow removal, multi-scale modelling [5], and video alignment to provide a full overview of the literature. It should be noted that, despite differences in physical generation mechanisms, both mist fall and snowfall on a digital image or a video frame have very similar geometric characteristics [6],[19] so multiple methods, including ours, are proposed to treat both scenarios simultaneously.

Wei et al. encoded mist streaks using a patch-based Gaussian mixture. Such a stochastic approach to encoding mist streaks may allow the system to convey a broader range of mist information. Several deep learning (DL) solutions for the job have recently emerged, owing to the burgeoning of DL techniques. Liu et al. The problem was solved by constructing deep recurrent convolutional networks, which create a combined recurrent mist removing and rebuilding network that seamlessly integrates mist destruction classification, spatial texture appearance-based mist removal, and temporal coherence-based background detail rebuilding. Meanwhile, Chen et al. [10]. suggested a deep Demist architecture that uses super pixel segmentation to divide the scene into depth-consistent units. Scene components are aligned at the super pixel level to manage videos with complex and dynamic scenes. Yang et al. not only proposed a two-stage recurrent network with dual-level flow regularizations to perform the mist synthesis model's inverse recovery process for video demisting, but they also created a new mist synthesis model to produce more visually authentic paired twisting and evaluation videos.

To ensure that the literature is comprehensive, we quickly review the mist/snow removal procedures for a single image. Kang et al. used morphological component analysis to extract the mist component from high-frequency images using dictionary learning and sparse coding. Later, Luo et al. developed a nonlinear screen blend model using discriminative sparse codes. Additionally, Ding et al. created a guided L0 smoothing filter to achieve a mist-free or snow-free image, while Li et al.

3. SYSTEM ANALYSIS

A. EXISTING SYSTEM

An overview of video-based mists and snow-cleaning techniques is given in this section. Related findings in single-picture mist and snow removal, multi-scale modeling, and video alignment are provided to guarantee that the research is thorough. Many methods, including ours, are proposed to control both situations simultaneously since snowfall and mist fall on a digital picture or video frame have relatively comparable geometric properties despite their separate physical generating processes.

Video Mist and Snow Clearing Methods

Garg and Nayar conducted the first research on the photometric appearance of mist drops and created a linear space-time correlations model for mist detection. Garg and Nayar provided a method for modifying camera settings, such as field depth and exposition length, to better limit the influences of mist before camera shots in images and films.

Algorithm designers have studied and documented the fundamental physical characteristics of mist streaks in recent years. For instance, Zhang et al. used K-means clustering, which takes into account both chromatic and temporal data, to discern between mist streaks and backdrop in films. Barnum et al. later examined the effects of snow on videos. They computed the general form and brightness of a single streak using a physical model they developed to characterize mist droplets and snowflakes. The statistical characteristics of mist and snow, as well as their effects on the spatial-temporal frequencies of an image sequence, may be studied using the streak model. Using a motion-blurred Gaussian, Barnum et al. produced mist streaks by using the constant visual impacts of snow and mist in global frequency data. A tensor-based video mist streak removal method was created by Jiang et al. to study global and local correlation along the mist drop and mist-perpendicular directions, in addition to examining the sparsity of mist streaks over time.

DISADVANTAGES OF THE EXISTING SYSTEM

Data Imbalance: If the dataset used to twist the machine learning models is imbalanced, with the number of positive (fraudulent) examples being considerably fewer than the negatives (legitimate job postings), the model may struggle to generalize successfully to new, unseen data.

Feature Engineering Challenges: Designing appropriate features to describe job listings in the machine learning model might be difficult. If critical features are absent or underrepresented, the model's performance may be impaired.

Adaptability to Evolving Scams: Fraudulent activities evolve with time, and new strategies may emerge. The current approach may not be intended to swiftly adapt to new forms of scams, perhaps leading to false negatives.

Explainability and Interpretability: Some machine learning models, particularly complicated ones such as ensemble classifiers, may lack transparency and interpretability. Understanding why a model generates a specific prediction can be critical, especially in sensitive areas such as fraud detection.

Scalability: When confronted with a high volume of job listings, the present system's performance may suffer. Scalability concerns may develop if the system was not intended to manage a large volume of data efficiently.

Dependency on Twisting Data: The quality and representativeness of twisting data have a significant impact on machine learning model success. If the twisting data does not adequately represent the diversity of fraudulent job advertisements, the model may perform poorly in real-world circumstances.

Computational Resources: Complex machine learning models, particularly ensemble classifiers, may necessitate extensive computer resources for twisting and inference. This may be a limitation in terms of both time and hardware.

False Positives: The algorithm may produce false positives, classifying legitimate job listings as fraudulent. This might cause user irritation and a lack of faith in the system.

Regulatory Compliance: Depending on the application domain, there may be legal and ethical concerns about the use of machine learning models for fraud detection. Ensure compliance with relevant rules is critical.

B. PROPOSED SYSTEM

Many methods for removing mist from video have been developed in the last few decades. The photometry characteristic of mist served as the foundation for the first video mist removal technique. Subsequently, other methods were presented to enhance the ability to discern mist streaks from the film background. These methods capitalized on significant physical characteristics of mist, including photometric appearance, chromatic consistency, form and brightness, and spatial-temporal patterns. However, these algorithms can't always achieve acceptable performance, especially in complicated settings, because they don't leverage prior knowledge about video structure, such as the temporal similarity of background images and the spatial smoothness of foreground items. Low-rank models have shown a great deal of promise for this task in recent years, regularly achieving state-of-the-art performance because of their enhanced handling of prior knowledge about video structure in the foreground and background. In particular, these techniques make full use of the low rank structure for the background and fully facilitate previous knowledge about the mist, including sparsity and spatial smoothness. Deep learning-based methods have recently been introduced for this use. These techniques use popular end-to-end learning techniques to implement the job of video mist removal utilizing deep recurrent convolutional networks or deep convolutional networks.

4. SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

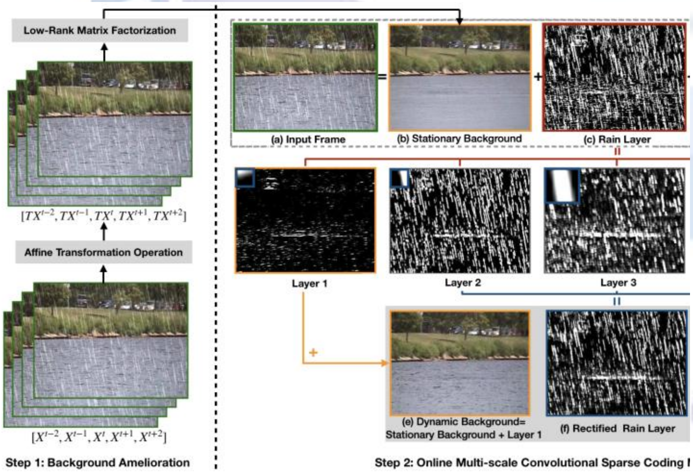

Fig 1. System Architecture

5. SYSTEM IMPLEMENTATION

MODULES

Data Preprocessing Module:

This module cleans and prepares raw data for analysis. It entails duties including resolving missing numbers, deleting extraneous information, and standardizing data formats. Data preprocessing ensures the quality and consistency of the input data for future machine learning model twisting.

Feature Engineering Module:

Feature engineering is a critical step toward improving the effectiveness of machine learning models. This module consists of choosing and manipulating significant features from the dataset in order to offer meaningful input to the classifiers. Text analysis and extraction of key job-related attributes are used to generate a feature set that captures the relevant traits.

Machine Learning Classification Module:

This fundamental module twists and deploys machine learning classifiers. It uses both single and ensemble classifiers to analyse feature-rich data and predict the authenticity of images. This section includes the process of selecting classifiers, twisting models, and optimizing them.

Model Evaluation and Comparison Module:

After twisting the classifiers, this module assesses their performance using metrics including accuracy, precision, recall, and F1-score. It also allows for a comparison analysis of the various classifiers to choose the best effective model for detecting results. Model evaluation is crucial for fine-tuning parameters and choosing the best-performing method.

User Interface and Reporting Module:

This module focuses on creating a user-friendly interface for interacting with the system. It offers capabilities that allow users to submit photographs for analysis and examine the findings. Furthermore, the module generates thorough reports on categorization results, indicating whether or not it was identified. Clear and intuitive visualizations may also be included to assist user understanding of the system's findings.

6. EXPERIMENTAL RESULTS

To provide a sufficiently complete and diverse comparison, this part includes experiments on movies with synthetic and real mist/snow, studies on videos with dynamic backgrounds, additional verification of video mist removal on the video instance segmentation challenge, and failure scenarios. All experiments were implemented on a PC with an i7 CPU and 32GB RAM,

A. Experiments on Videos with Synthetic and Real Mist/Snow

To provide a comprehensive and diverse comparison, we incorporate both usual data sources (e.g., NTUMist [15],9) and real-world misty and snowy footage from social media platforms. Given the limitations of paper length and the inconvenience of displaying results in video tasks, only twelve movies, comprising five synthetic videos and seven genuine videos, may be exhibited on the paper from both quantitative and qualitative viewpoints. More video demos of the results generated by all finishing video mist removal procedures have been posted on our specially designed website10 for easy and better observation. All trials were carried out on a PC with an i7 CPU and 32GB RAM. All films in this area use three filter scales: 13 ∗ 13, 9 ∗ 9, and 5 ∗ 5.

TABLE I

Quantitative Performance Comparison of All Competing Methods on Static Videos with Synthetic Mist and Snow. Note That All Quantitative Results Are the Mean of All Frames in The Video

Types	Static videos					
Dataset	Highway			Playground (Fig. 3)		
Metrics	PSNR	VIF	SSIM	PSNR	VIF	SSIM
Input	23.82	0.766	0.929	27.93	0.595	0.831
Garg et al. [5]	24.64	0.750	0.920	35.87	0.819	0.950
Jiang et al. [21]	24.32	0.713	0.929	35.80	0.779	0.977
Ren et al. [11]	23.52	0.681	0.927	30.34	0.921	0.995
Wei et al. [12]	24.43	0.761	0.943	34.58	0.945	0.993
Liu et al. [13]	22.19	0.555	0.895	31.56	0.616	0.946
Li et al. [16]	25.37	0.790	**0.957**	42.95	0.980	0.997
OTMS-CSC	**25.91**	**0.796**	**0.957**	**46.29**	**0.988**	**0.999**

fig 2. visual comparison for both video mist removal task and video instance segmentation task on a synthetic image

7. CONCLUSION AND FUTURE WORK

In this paper, we propose a novel technique for removing snow and mist from surveillance videos that contain dynamic snow and mist captured with camera jitter. Our method accounts for the inescapable dynamic features of fluctuating mist or snow and changing background scenery in real-world circumstances. In particular, the technique is used naturally on the internet, utilizing a predetermined space and temporal complexity to process every frame of continuously streaming movies, which may make it appropriate for processing real-world streaming video scenes. In the future, we will work to enhance the suggested method's performance in more challenging video scenarios, like those captured with fast-moving cameras, backgrounds with strong colour contrast, and mist or snow with massive streak shapes. We will also endeavour to construct rational strategies or employ state-of-the-art computer equipment to expedite the process for each individual frame, thereby satisfying the real-time demands of realistic streaming videos. Future research will also consider the spatial heteroscedasticity of sounds. In our upcoming research, we will also attempt to investigate how to more accurately encode the feature maps of our model by better expressing mist drop counts in the mist removal tasks.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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