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ONLINERAINORSNOWREMOVALFROMSURVEILLANCE VIDEOS

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ABSTRACT

Video rain/snow removal from surveillance videos is an important task in the computer vision community since rain/snow existed in videos can severely degenerate the performance of many surveillance system. Various methods have been investigated extensively, but most only consider consistent rain/snow under stable background scenes. Rain/snow captured from practical surveillance camera, however, is always highly dynamic in time, and those videos also include occasionally transformed background scenes and background motions caused by waving leaves or water surfaces. To this issue, this paper proposes a novel rain/snow removal approach, which fully considers dynamic statistics of both rain/snow and background scenes taken from a video sequence. Specifically, the rain/snow is encoded as an online multi-scale convolutional sparse coding (OMS-CSC) model, which not only finely delivers the sparse scattering and multi-scale shapes of real rain/snow, but also well distinguish the components of background motion from rain/snow layer. The real-time ameliorated parameters in the model well encodes their temporally dynamic configurations. Furthermore, a transformation operator imposed on the background scenes is further embedded into the proposed model, which finely conveys the background transformations, such as rotations, scalings and distortions, inevitably existed in a real video sequence. The approach so constructed can naturally better adapt to the dynamic rain/snow as well as background changes, and also suitable to deal with the streaming video attributed its online learning mode. The proposed model is formulated in a concise maximum a posterior (MAP) framework and is readily solved by the alternating direction method of multipliers (ADMM). Compared with the state-of-the-art online and offline video rain/snow removal methods, the proposed method achieves best performance on synthetic and real videos datasets both visually and quantitatively. Specifically, our method can be implemented in relatively high efficiency, showing its potential to real-time video rain/snow removal. The code page is at: https://github.com/MinghanLi/OTMSCSC_matlab_2020.

INTRODUCTION

VIDEOS captured from outdoor surveillance system are often contaminated by rain or snow, which has a negative effect on the perceptual quality and tends to degrade the performance of subsequent video processing tasks, such as human detection, person re-identification, object tracking and scene analysis. Thus, removing rain and snow from surveillance videos is an important video pre-processing step and has attracted much attention in the computer vision community. In recent decades, various methods have been proposed for removing rain from a video [1].

The earliest video rain removal approach was proposed based on the photometry property of rain. After that, more methods taking advantage of the essential physical characteristics of rain, such as photometric appearance, chromatic consistency, shape and brightness, and spatial-temporal

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configurations, were introduced to better separate rain streaks from the background of videos [2]. However, these methods do not utilize the prior knowledge of video structure, such as spatial smoothness of foreground objects and temporal similarity of background scenes, and thus cannot always obtain satisfactory performance especially in complex scenes [3]. In recent years, low-rank models show a great potential for this task and always achieve state-of-the-art performance due to their better consideration of video structure prior knowledge both in foreground and background. Specifically, these methods not only use the low rank structure for the background, but also fully facilitate the prior knowledge of the rain, such as sparsity and spatial smoothness . Very recently, deep learning based methods have also been proposed for this task [4].

These methods address the problem of video rain removal by constructing deep recurrent convolutional networks or deep convolutional network and implement the task in a popular end-to-end learning manner. Albeit achieving good progress, most of current methods are implemented on a pre-fixed length of videos and assume consistent rain/snow shapes under static background scenes. This, however, is evidently deviated from the real scenarios. On onehand, the rain/snow contained in a video sequence is generally with configurations changed constantly along time [5].

On the other hand, the background scene in the video is also always dynamic, inevitably containing background motion, such as swing leaves and water waves as typically shown in Fig. 1, and timely transformations such as translation, rotation, scaling and distortion, due to camera jitters. Lacking considerations to such dynamic characteristics inclines to degenerate the performance of current methods in such real cases [6]. Besides, as the dramatically increasing surveillance cameras installed all over the world, the real video is always coming online as a streaming format. Most current methods, however, are implemented/trained on a pre-fixed video sequence, and thus cannot finely and efficiently adapt to such kinds of streaming videos continually and endlessly coming in time. These issues have hampered the availability of existing methods in real applications and thus is worthy to be specifically investigated [7].

Against the aforementioned issues, this paper proposes a new online rain/snow removal method from surveillance videos by fully encoding the dynamic statistics of both rain/snow and background scenes in a video along time into the model, and realizing it with an online mode to make it potentially available to handle constantly coming streaming video sequence. Specifically, inspired by the multi-scale convolutional sparse coding (MS-CSC) model designed for video rain removal (still for static rain) previously proposed in [8], which finely delivers the sparse scattering and multi-scale shapes of real rain, this work encodes the dynamic temporal changing tendency of rain/snow and background motions as a dynamic MS-CSC framework by timely parameter ameIioration for the model in an online implementation manner. Besides, a transformation operator capable of being adaptively updated along time is imposed on the background scenes to finely fit the background transformations existed in a video sequence. All these knowledge are formulated into a concise maximum a posterior (MAP) framework, which can be easily solved by alternative optimization technique.

LITERATURE SURVEY

Westudy the question offeaturesets forrobust visual objectrecognition; adoptinglinear SVMbased humandetection asa test case.After reviewingexistingedge and gradient based descriptors, we show experimentally that grids of histograms of oriented gradient (HOG) descriptors significantly outperform existing feature sets for humandetection.Westudytheinfluenceofeachstageofthecomputationonperformance, concluding that fine-scale gradients, fine orientation binning, relatively coarse spatial binning,andhigh-qualitylocalcontrastnormalizationinoverlappingdescriptorblocksare all important for good results. The new approach gives near-perfect separation on the original MIT pedestrian database, so we introduce a more challenging dataset containing over1800annotatedhumanimageswithalargerangeofposevariationsandbackgrounds.

In this paper, we present an appearance-based method for person re- identification. It consists in the extraction of features that model three complementary aspects of the human appearance: the overall chromatic content, the spatial arrangement ofcolorsintostableregions,andthepresenceofrecurrentlocalmotifswithhighentropy. All this information is derived from different body parts, and weighted opportunely by exploitingsymmetryandasymmetryperceptualprinciples.Inthisway,robustnessagainst verylowresolution,occlusionsandpose,viewpointandilluminationchangesisachieved. The approach applies to situations where the number of candidates varies continuously, considering single images or bunch of frames for each individual. It has been tested on several public benchmark datasets (ViPER, iLIDS, ETHZ), gaining new state-of-the-art performances.

Current vision systems are designed to perform in normal weather condition. However, no one can escape from severe weather conditions. Bad weather reduces scene contrast and visibility, which results in degradation in the performance of variouscomputervisionalgorithmssuchasobjecttracking,segmentationandrecognition. Thus,currentvisionsystemsmustincludesomemechanismsthatenablethemtoperform uptothemarkinbadweatherconditionssuchasrainandfog.Raincausesthespatialand temporal intensity variations in images or video frames. These intensity changes are due to the random distribution and high velocities of the raindrops. Fog causes low contrast andwhitenessintheimageandleadstoashiftinthecolor.Thisbookhasstudiedrainand fogfromtheperspectiveofvision.Thebookhastwomaingoals:1)removalofrainfrom videos captured by a moving and static camera, 2) removal of the fog from images and videos captured by a moving single uncalibrated camera system.The book begins witha literature survey. Pros and cons of the selected prior art algorithms are described, and a generalframeworkforthedevelopmentofanefficientrainremovalalgorithmisexplored. Temporal and spatiotemporal properties of rain pixels are analyzed and using these properties, two rain removal algorithms for the videos captured by a static camera are developed.Fortheremovalofrain,temporalandspatiotemporalalgorithmsrequirefewer numbersofconsecutive frameswhichreducesbuffersizeanddelay.These algorithmsdo notassumetheshape,sizeandvelocityofraindropswhichmakeitrobusttodifferentrain conditions (i.e., heavy rain, light rain and moderate rain). In a practical situation, there is no ground truth available for rain video. Thus, no reference quality metric is very useful in measuring the efficacy of the rain removal algorithms. Temporal variance and spatiotemporal variance are presented in this book as no reference quality metrics. An efficientrainremovalalgorithmusingmeteorologicalpropertiesofrainisdeveloped.The relation among the orientation of the raindrops, wind velocity and terminal velocity is established.Thisrelationisusedintheestimationofshape-basedfeaturesoftheraindrop. Meteorological property-based features helped to discriminate the rain and non-rain pixels. Most of the prior art algorithms are designed for the videos captured by a static camera [9].

A visual attention system, inspired by the behavior and the neuronal architectureoftheearlyprimatevisualsystem,ispresented.Multiscaleimagefeaturesare combined into a single topographical saliency map. A dynamical neural network then selects attended locations in order of decreasing saliency. The system breaks down the complex problem of scene understanding by rapidly selecting, in a computationally efficient manner, conspicuous locations to be analyzed in detaileffectsofrainarecomplex.Rainconsistsofspatiallydistributed dropsfallingathighvelocities [10].Eachdroprefractsandreflectstheenvironment,producing sharpintensitychangesinanimage.Agroupofsuchfallingdropscreatesacomplextime varying signal in images and videos [11]. In addition, due to the finite exposure time of the camera, intensities due to rain are motion blurred and hence depend on the background intensities.Thus,thevisualmanifestationsofrainareacombinationofboththedynamics of rain and the photometry of the environment. In this paper, we present the first comprehensive analysis of the visual effects of rain onanimaging system [12].We develop a correlation model that captures the dynamics of rain and a physics-based motion blur model that explains the photometry of rain. Based on these models, we develop efficient algorithms for detecting and removing rain from videos [13]. The effectiveness of our algorithms is demonstrated using experiments on videos of complex scenes with moving objectsandtime-varyingtextures.Thetechniquesdescribedinthispapercanbeusedina wide range of applications including video surveillance, vision based navigation, video/movie editing and video indexing/retrieval [14].

Rain produces sharp intensity fluctuations in images and videos, which degrade the performance of outdoor vision systems [15]. These intensity fluctuations depend onvariousfactors,suchasthecameraparameters,thepropertiesofrain,andthebrightness of the scene. We show that the properties of rain - its small drop size, high velocity, and lowdensity-makeitsvisibilitystronglydependentoncameraparameterssuchasexposure timeand depth of field [16].Weshowthat these parameterscan beselected so astoreduce or even remove the effectsof rain without altering theappearance of the scene. Conversely, the parameters of a camera can also be set to enhance the visual effects of rain. This can be used to develop an inexpensive and portable camera-based rain gauge that provides instantaneous rain rate measurements. The proposed methods serve to make vision algorithmsmorerobusttorainwithoutanynecessityforpost-processing.Inaddition,they can be used to control the visual effects of rain during the filming of movies [17].

Removal of rain streaks in video is a challenging problem due to the randomspatialdistributionandfastmotionofrain.Thispaperpresentsanewrainremoval algorithm that incorporates both temporal and chromatic properties of rain in video. The temporal property states that an image pixel is never always covered by rain throughout the entire video.The chromatic property states that the changes of R, G, and B values of rainaffected pixels are approximately the same. By using both properties, the algorithm can detect and remove rain streaks in both stationary and dynamic scenes taken by stationarycameras.Tohandlevideostakenbymovingcameras,thevideocanbestabilized for rain removal, and destabilized to restore camera motion after rain removal. It can handle both light rain and heavy rain conditions. Experimental results show that the algorithm performs better than existing algorithms.

Capturing good videos outdoors can be challenging due to harsh lighting, unpredictablescenechanges,andmostrelevanttothiswork,dynamicweather.Particulate weather, such as rain and snow, creates complex flickering effects that are irritating to people and confusing to vision algorithms. Although each raindrop or snowflake only affects a small number of pixels, collections of them have predictable global spatio-temporalproperties.Inthispaper,weformulateamodeloftheseglobaldynamicweather frequencies.Tobegin,wederiveaphysicalmodelofraindropsandsnowflakesthatisused to determine the general shape and brightness of a single streak. This streak model is combinedwiththestatisticalpropertiesofrainandsnow,todeterminehowtheyeffectthe spatio-temporal frequencies of an image sequence. Once detected, these frequencies can then be suppressed.At a small scale, many things appear the same as rain and snow, but by treating them as global phenomena, we achieve better performance than with just a local analysis. We show the effectiveness of removal on a variety of complex video sequences.

Thevisualeffectsofrainarecomplex.Rainconsistsofspatiallydistributed dropsfallingathighvelocities.Eachdroprefractsandreflectstheenvironment,producing sharpintensitychangesinanimage.Agroupofsuchfallingdropscreatesacomplextime varying signal in images and videos. In addition, due to the finite exposure time of the camera, intensities due to rain are motion blurred and hence depend on the background intensities.Thus,thevisualmanifestationsofrainareacombinationofboththedynamics of rain and the photometry of the environment. In this paper, we present the first comprehensive analysis of the

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PROBLEM STATEMENT

In this section, we give a brief review on the methods of video rain and snow removal. The related developments on single image rain and snow removal, multi-scale modeling and video alignment are also introduced for literature comprehensiveness. It should be indicated that albeit different in physical generation mechanisms, in visual imaging perspectives, both rainfall and snowfall on a digital image or a video frame have very similar geometric characteristics, which makes multiple methods, as well as ours, proposed to treat both scenarios simultaneously [19].

Video Rain and Snow Removal Methods

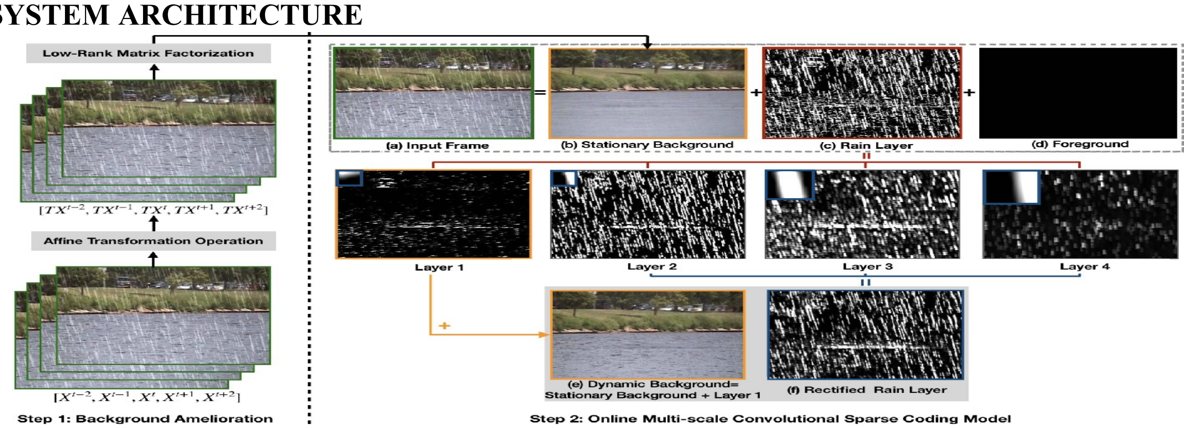
Garg and Nayar madethe earliest study on the photometric appearance of rain drops and developed a rain detection method by utilizing a linear space-time correlation model. To better reduce the effects of rain before camera shots in images/videos, Garg and Nayarfurther proposed a method by adjusting the camera parameters such as field depth and exposure time.

In the past years, more physical intrinsic properties of rain streaks have been explored and formulated in algorithm designing. For example, Zhang et al. incorporated both chromatic and temporal properties and utilized K-means clustering for distinguishing background and rain streaks from videos. Later, Barnum et al. first considered the impact of snow on videos. They derived a physical model for representing raindrops and snowflakes and used them to determine the general shape and brightness of a single streak. The streak model combined with the statistical properties of rain and snow can then conduct how they affect the spatial-temporal frequencies of an image sequence. To enhance the robustness of rain removal, Barnum et al. employed the regular visual effects of rain and snow in global frequency information to approximate rain streaks as a motion-blurred Gaussian. Afterwards, to integrate more prior knowledge of the task, Jiang et al. proposed a tensor-based video rain streak removal approach by considering the sparsity of rain streaks, smoothness along the raindrops and the rain-perpendicular direction, and global and local correlation along time direction.

PROPOSED SYSTEM

In recent decades, various methods have been proposed for removing rain from a video. The earliest video rain removal approach was proposed based on the photometry property of rain. After that, more methods taking advantage of the essential physical characteristics of rain, such as photometric appearance , chromatic consistency , shape and brightness , and spatial-temporal configurations , were introduced to better separate rain streaks from the background of videos. However, these methods do not utilize the prior knowledge of video structure, such as spatial smoothness of foreground objects and temporal similarity of background scenes, and thus cannot always obtain satisfactory performance especially in complex scenes. In recent years, low-rank models show a great potential for this task and always achieve state-of-the-art performance due to their better consideration of video structure prior knowledge both in foreground and background. Specifically, these methods not only use the low rank structure for the background, but also fully facilitate the prior knowledge of the rain, such as sparsity and spatial smoothness . Very recently, deep learning based methods have also been proposed for this task. These methods address the problem of video rain removal by constructing deep recurrent convolutional networks or deep convolutional network and implement the task in a popular end-to-end learning manner [20].

SYSTEM ARCHITECTURE



MODULES

1. **Register:**
   - Thismoduleallowsusersto createanewaccountontheplatform.
   - Userstypicallyprovidetheiremailaddressand choose apassword.
   - You can implementemailverification to ensurethevalidity of theprovided email address.
   - Optionally,youcanincludeadditionalfieldsforuserinformation,suchasname, organization, etc.
2. **Login:**
   - Registereduserscanlogintotheplatformusingtheiremailaddressand password.
   - Implementauthenticationmechanismstosecurely verify user credentials.
   - Upon successful login, users are granted access to the platform's features and functionalities.
3. **UploadMedia:**
   - Thismoduleenablesuserstouploadsurveillancevideostotheplatformfor processing.
   - Implementfile uploadfunctionalitywithsupport forvariousvideo formats.
   - Provideprogressindicatorstoinformusersabout the uploadstatus.

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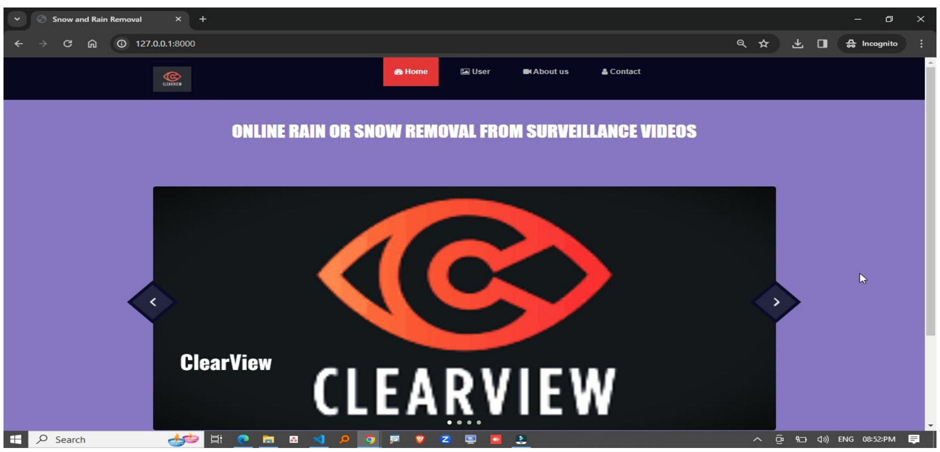
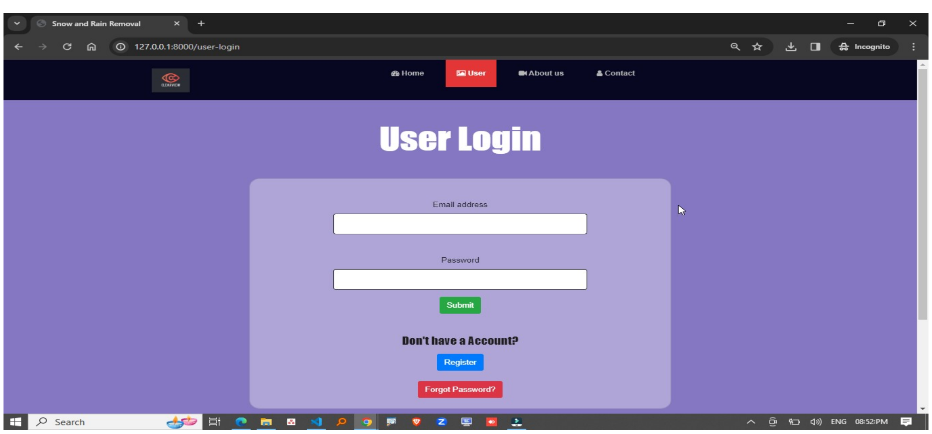
4. **ExtractedImagefromCCTVFootage:**
   - Once a video is uploaded, the platform processes it to remove snow and rainartifacts.
   - Implementimageextractionalgorithmstoextractclearimagesfromthe processed video frames.
   - Userscanviewanddownloadthe extractedimagesforfurther analysisor use.
5. **My Profile:**
   - Thismoduleallowsusersto viewandmanagetheir profileinformation.
   - Userscanupdate theiremail address,password,andotherprofile details.
   - Implementvalidationcheckstoensuretheintegrityofuser-provided information.
6. **Logout:**
   - Userscanlogout ofthe platform tosecurelyendtheir session.
   - Implementsessionmanagementtoinvalidate theuser'ssessionuponlogout.
   - Provideaconfirmationmessagetoconfirmthelogout action.

Eachmoduleplaysacrucialroleintheoverallfunctionalityofyouronlinesnow/rainremoval application, providing users with a seamless and efficient experience.

7.RESULTS





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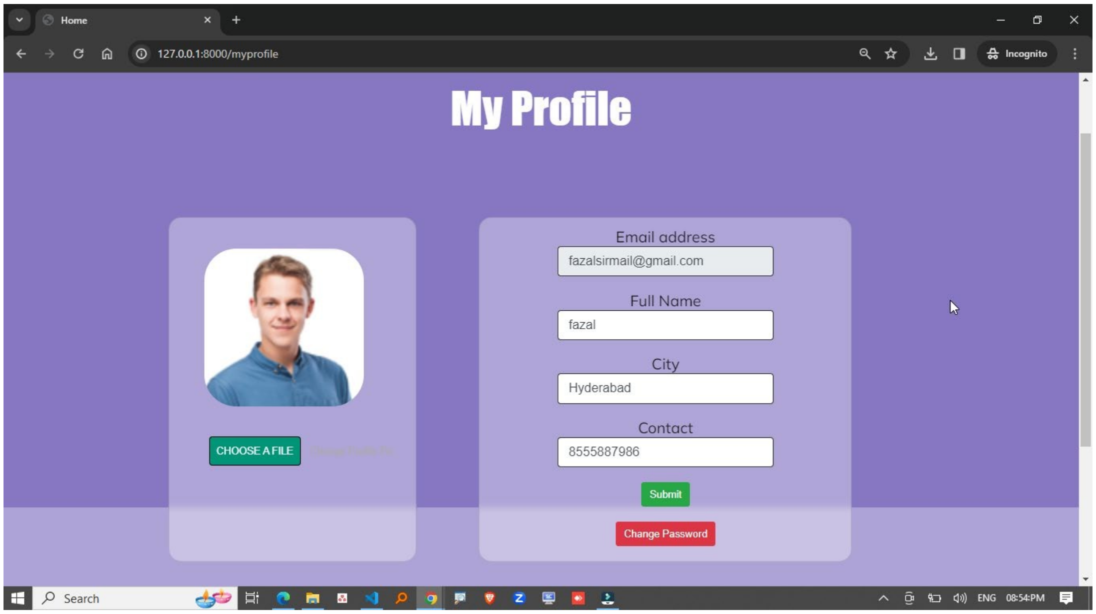

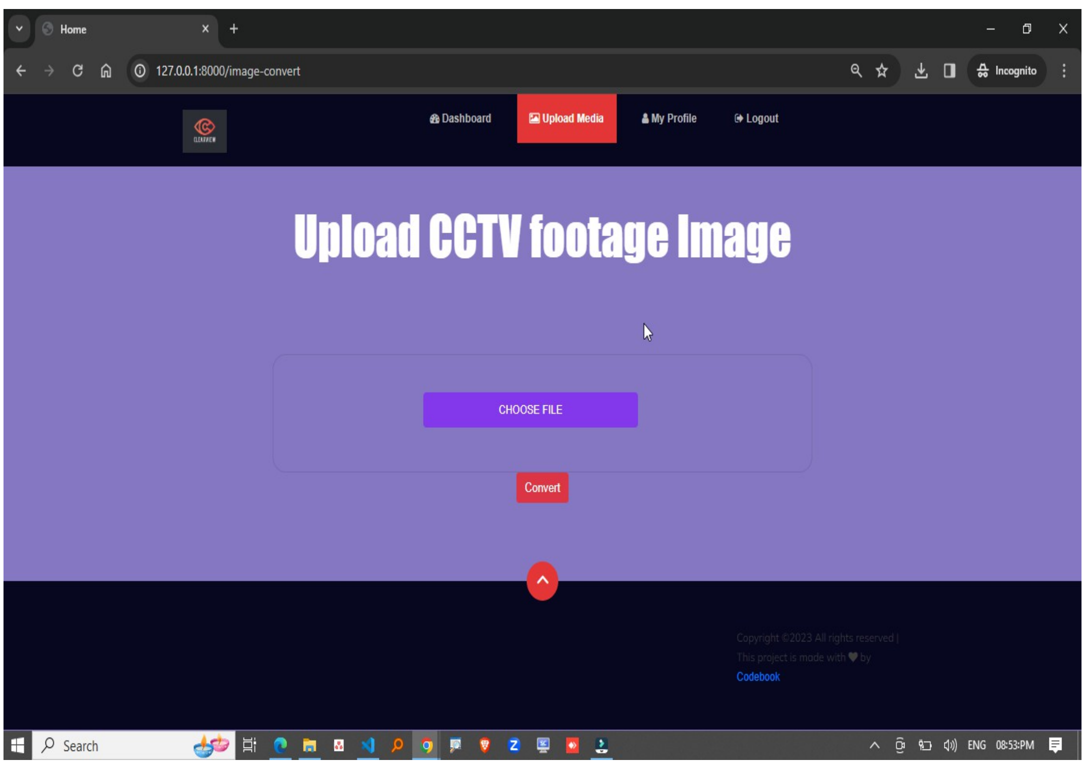

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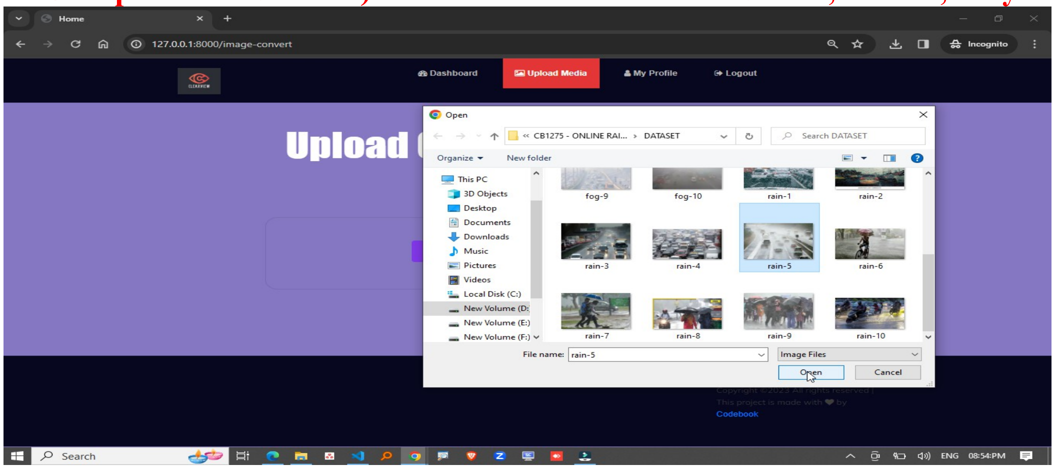
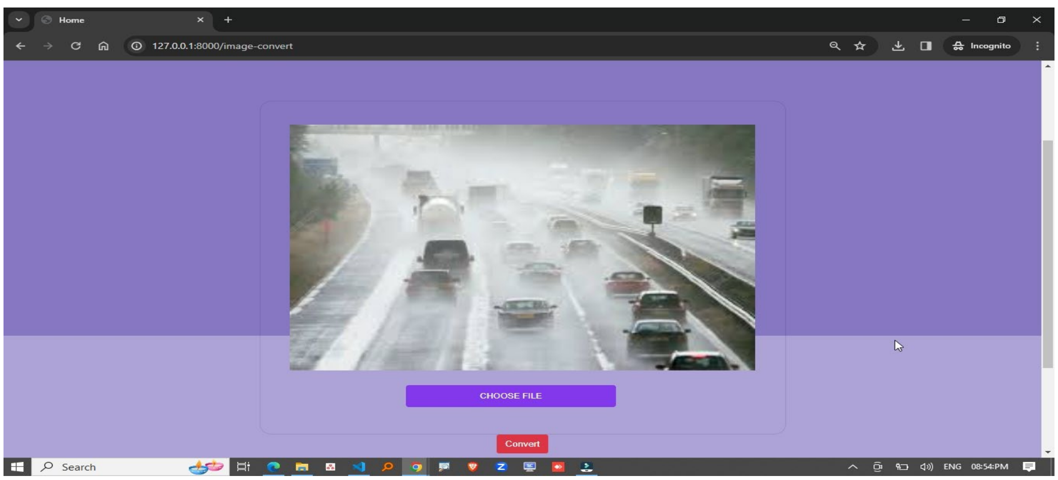
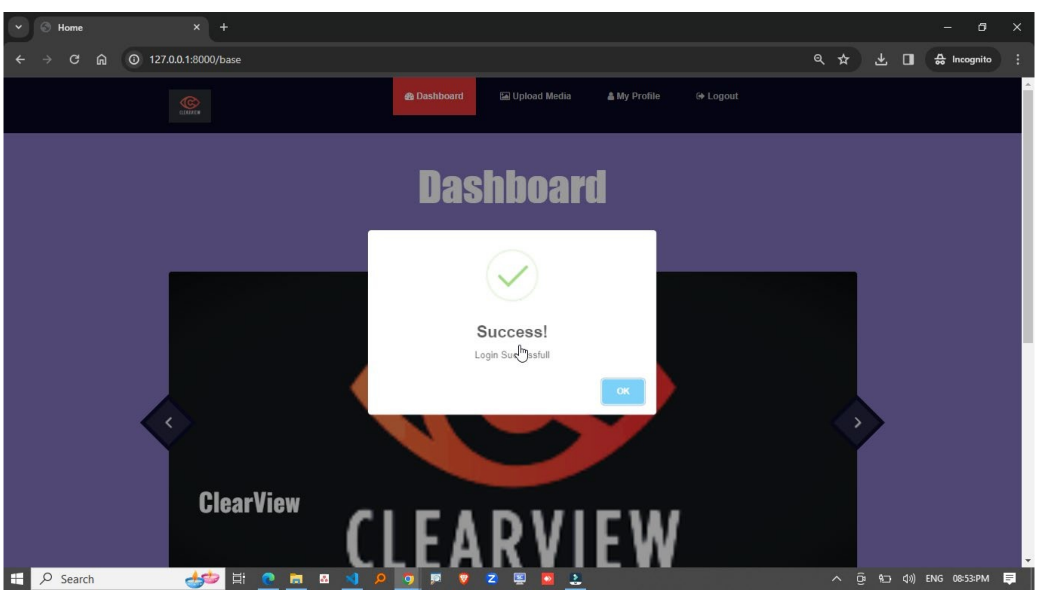
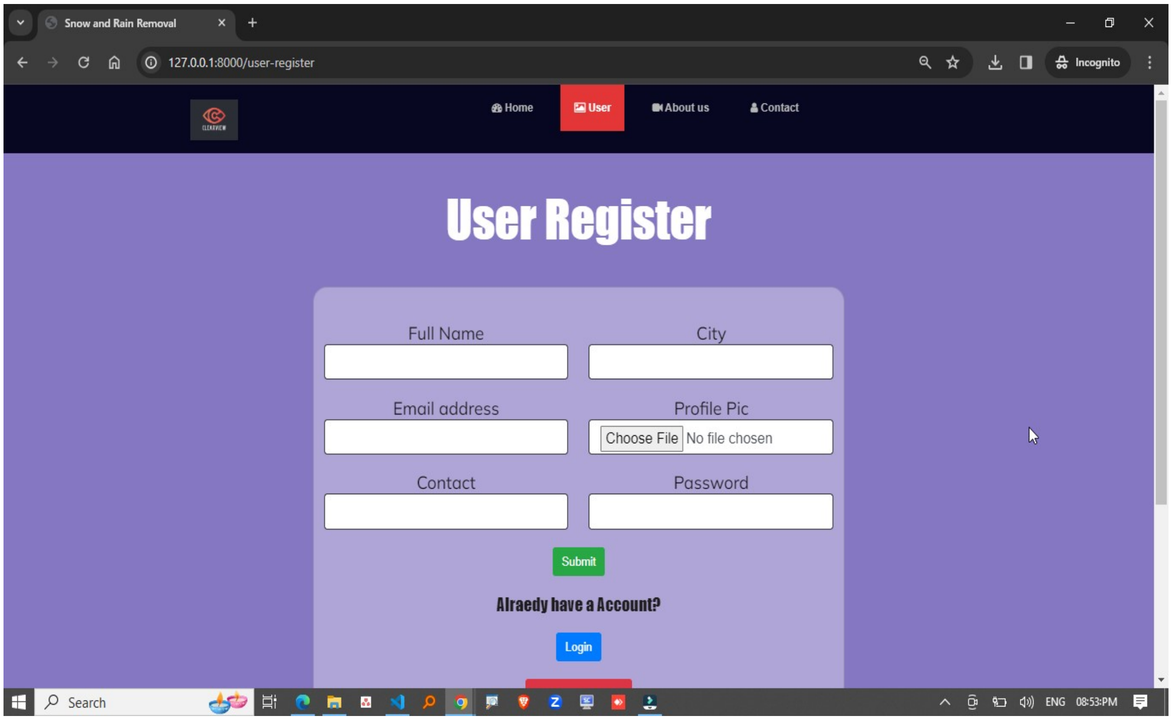
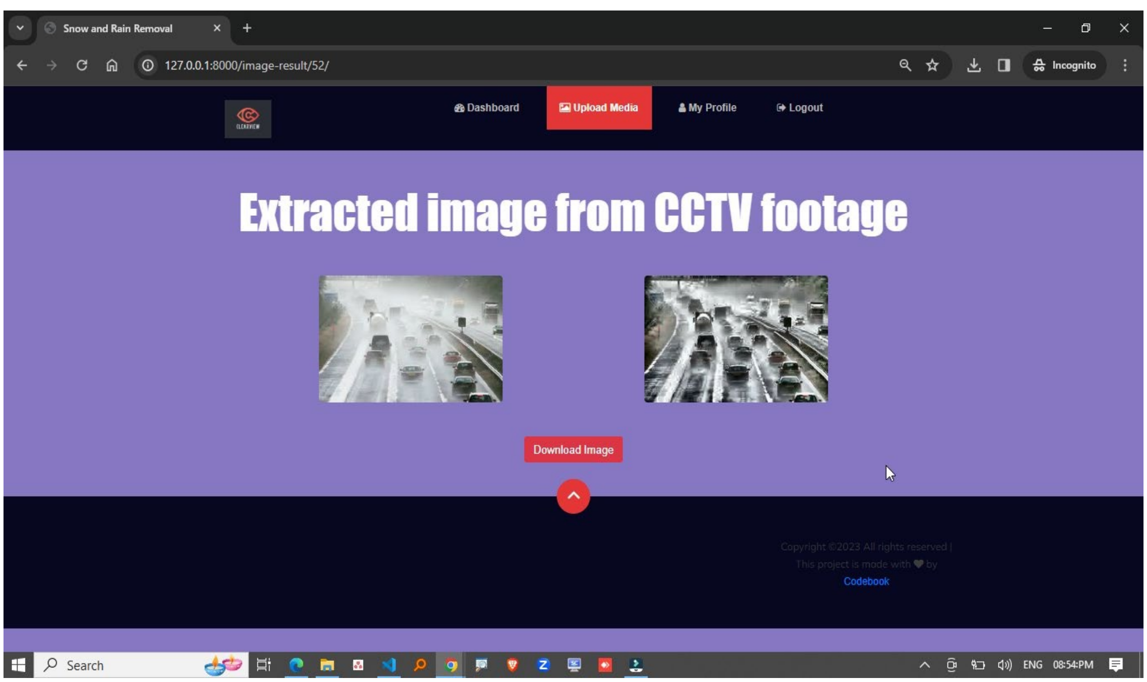







Snow and Rain Removal
127.0.0.1:8000/user-register
Home
User
About us
Contact
User Register
Full Name
City
Email address
Profile Pic
Choose File No file chosen
Contact
Password
Submit
Alraedy have a Account?
Login


Snow and Rain Removal
127.0.0.1:8000/image-result/52/
Dashboard
Upload Media
My Profile
Logout
Extracted image from CCTV footage
Download Image
Codebook

CONCLUSION

In thispaper, we have proposed a newrain/snowremovalmethod forsurveillance videos containing dynamic rain/snow captured with camera jitter. Both dynamic characteristics of rain/snow variations and background scenes along time inevitably encountered in real cases, have been fully considered in ourmethod. Especially, the method is with a natural online implementation manner, with fixed space and time complexity for handling each frame of continuously coming videos, making it potentially useful for dealing with practicalstreamingvideosequences.Inthefuture,wewillfurtheramelioratethecapability of the proposed method in more challenging video cases, like those captured under fast movingcamerasorthoseunderbackgroundwithstrongcolorcontrastandrain/snowwith largestreakshapes,andtrytodesignrationaltechniquesorusesomeadvancedcomputing equipmentstofurtherspeedupthemethodforeachuniqueframetomakeitmeetwiththe real-time requirements on practical streaming videos. Furthermore, we will consider the spatialheteroscedasticitypropertyofnoisesinourfuturework.Wewillalsotrytoconsider howtobetterexpressraindropnumbersintherainremovaltaskstomorefaithfullyencode the feature maps of our model in our future investigations.

FUTURE SCOPE

The future of online rain or snow removal from surveillance videos is promising, with advancements in AI and computer vision. Improved algorithms will enhance accuracy and efficiency, making the process more reliable. Real-time processing capabilities will allow for immediate action in critical situations. Integration with IoT devices will enable automated responses based on weather conditions. Enhanced user interfaces will make the technology more accessible to a broader audience. Collaboration with weather forecasting services will enable proactive measures. Continuous learning and adaptation will ensure effectiveness in varying environments. Adoption in smart cities will lead to safer and more efficient urban environments. Ethical considerations and privacy safeguards will be crucial for responsible implementation.

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