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A Novel Method To Reduce Flickering Effects In Degraded Video

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Abstract

Enhancement technique for degraded video that relies on examples, i.e. based on codebookscontaining examples of "how non-degraded images should looklike".Real-time systems using Median filter based standards of still image or video. Median filter based video enhancement produced results but with lesserclarity, less PSNR value and more Mean square error. Therefore the overall objective is to improve the results by combiningwith PCA and non-linear enhancement. The proposed algorithm is designed and implemented in MATLAB using imageprocessing toolbox. The comparison has shown that the proposed algorithm provides a significant improvement over theexisting techniques.

Introduction

Image and video processing has been developed rapidly as an important research fieldat present, since demanded by various and numerous areas of applications such as inbiology, archaeology, medicine, spaceflight, and display industry. Images and videoenhancement is one of the most important and interesting area of video processing. We already have numerous processing algorithms and modules to enhance images. Forall that, these algorithms or modules are usually imperfect. Exceptionable results couldbe produced, if they didn't tune appropriately. In practical, the processing module oftenhas been fixed or work as an integrated algorithm. We need to repair them on theground of the exits processing modules.Video enhancement drawback will be developed as follows given associate input inferiority video and also the outputprime quality video for specific applications. This work triesto boost the standard of video.

Digital video has become associate integral a part oflifestyle. It's well-known that video enhancement as avigorous topic in pc vision has received abundant attentionin recent years. The aim is to boost the visual look of thevideo, or to supply a "better" remodel illustration for futureautomatic video process, like analysis, detection,segmentation, and recognition [1-5]. Moreover, it helpsanalyses background data that's essential to grasp objectbehavior while not requiring pricy human visual review [6].

A specific application of the super-resolution drawback is inmixed-resolution video, i.e., in video with whole completelydifferent resolutions on time. The solutions given inprevious works [2], [8] avoid associate ill-posed draw backby pattern key-frames as example. In those, dictionaries unitcreated as samples of high-resolution photos. Patches oflow-resolution photos unit then matched to the lowresolutionversion of the lexicon entries. Once a match isfound, the low-resolution image is super-resolved with theassistance of the full-resolution entry. Such a method is hereextended and tailored to general repeatable kinds of imagedegradation.

An important difference between the enhancement andrestoration of 2-D images and of video is the amount of datato be processed. Whereas for the quality improvement ofimportant images elaborate processing is still feasible, this isno longer true for the absolutely huge amounts of pictorialinformation encountered in medical sequences and film/videoarchives. Consequently, enhancement and restoration methodsfor image sequences should have a manageable complexity,and should be semi-automatic. The term semi-automaticindicates that in the end professional operators control thevisual quality of the restored image sequences by selectingvalues for some of the critical restoration parameters.

The most common artifact encountered in the abovementionedapplications is noise. Over the last two decades anenormous amount of research has focused on the problem ofenhancing and restoring 2-D images. Clearly, the resultingspatial methods are also applicable to image sequences, butsuch an approach implicitly assumes that the individualpictures of the image sequence, or frames, are temporallyindependent. By ignoring the temporal correlation that exists,suboptimal results may be obtained and the spatial intra-framefilters tend to introduce temporal artifacts in the restoredimage sequences. In this paper we focus our attentionspecifically on exploiting temporal dependencies, yieldinginter-frame methods.

Literature Survey

In the literature [15]–[17], several approaches for superresolutionare often found and square measure sometimesclassified as frequency- and spatial-based-domain. In someworks on frequency-domain super-resolution, the authorsadditionally extend the super-resolution downside by addingnoise and blur into low-resolution pictures [18], [19].

Aselected application of the super-resolution downside is inmixed-resolution video, i.e., in video with totally differentresolutions on time. The solutions bestowed in previousworks [20], [21] avoid AN ill-posed downside byvictimization key-frames as example. In those, dictionariessquare measure created as samples of high-resolutionpictures. In this paper, we tend to target video improvementconsidering each areas of self-enhancement and frame-basedfusion improvement. Research within the field started asearly as within the 70s with the appearance of computersand therefore the development of efficient video processingtechniques.

We tend to conjointly discuss connected imageimprovement techniques, since most video improvement techniques area unit supported frame improvement. We tendto don't aim at covering the complete field of videoimprovement and its applications. it's a broad subject that'sstill evolving. E.g. we tend to don't discuss contributions,that area unit created by ITU and ISO normal during thisspace. There square measure connected works supported videoquality improvement [22], spatiotemporal filtering [23],video debluring [24], or video denoising. Studies concerningaflicker [25] additionally yield video improvementsupported temporal correlation. To the simplest of our data,we tend to square measure the primary to use AN example based approach for video improvement, that square measure appropriate for cloud-based applications [26].

Tomasi projected a bilateral filtering technique for imagefiltering in [9], that exploits the native image structurethroughout filtering. By augmenting the definition of theproximity between pels by incorporating conjointly the pixelvalues, instead of solely the abstraction locations, Bilateralfiltering overcomes the well-known blurring result of aGaussian filter, and exhibits edge-preserving property, thatis fascinating for several image and video process tasks.

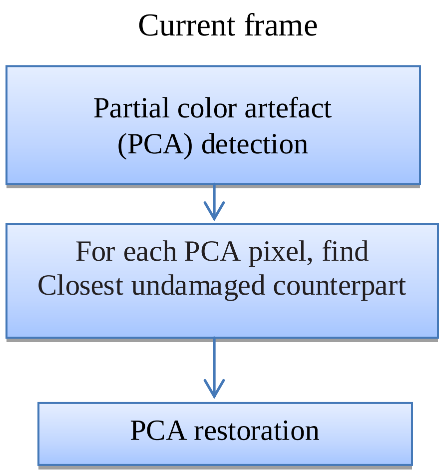
Tschumperl´e et al. [7] projected a typical framework forimage restoration that is predicated on the repetitive nativediffusion within the image plane radio-controlled by thenative structure tensor. Treating image restoration as a regression task on the 2nd image plane, Li [10] and Takeda et al. [8] projectedseverally to boost the regression performance via regressionkernels custom-made to the native structures within theimage.

Li [11] any developed AN implicit mixture motion modelfor video process, that exploits the native spatial-temporalstructures existing in videos. The generalization of 2dimensionalkernel regression to 3- dimensions hasconjointly been studied in [13] for video super resolution. To sum up, one common measure for the success of thesemodels is that the exploration of the native image structuresin pictures and videos.

Proposed System

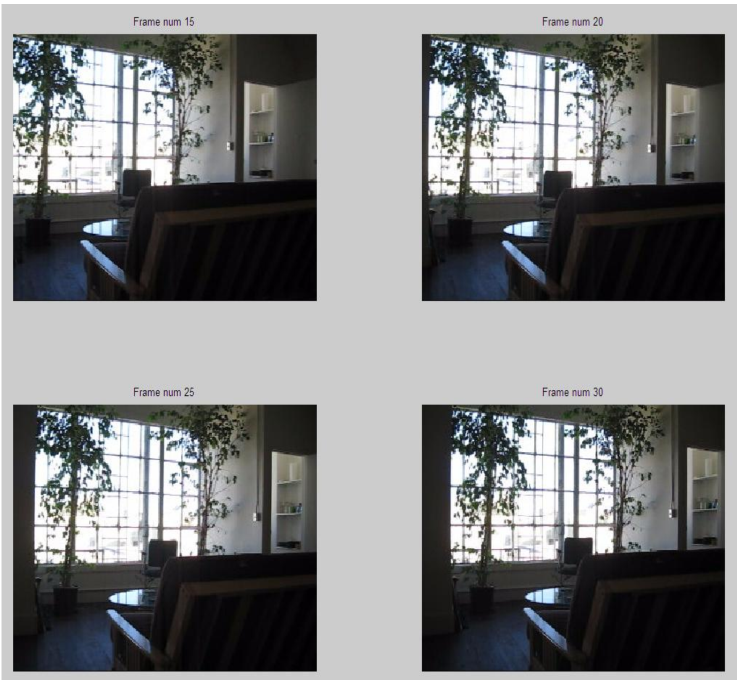
Intensity Flicker Correction

Intensity flicker is defined as unnatural temporal fluctuationsof frame intensities that do not originate from the originalscene. Intensity flicker is a spatially localized effect that occursin regions of substantial size. Figure 19 shows three successiveframes from a sequence containing flicker. The earliest attempts to remove flicker from imagesequences applied intensity histogram equalization or meanequalizationon frames. These methods do not form a generalsolution to the problem of intensity flicker correction becausethey ignore changes in scene contents, and do not appreciatethat intensity flicker is a localized effect. In section we showhow the flicker parameters can be estimated on stationaryimage sequences.



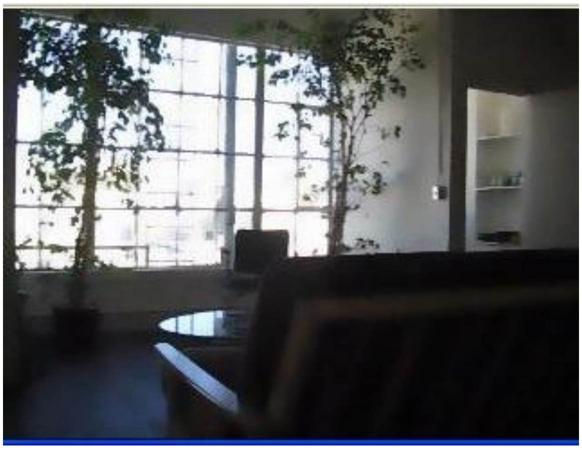
Results and Analysis

We apply the PCA based filtering degraded video sequences algorithm to a low-quality video sequence. The video sequence(320 X240) is compressed using MJPEG codec (each frame is anbmp image) at quality 50. Figure 2a showframe 15,20,25,30 of the degraded video input and the High quality output, respectively



Degraded frames

Flicker noise and Bilateral filter



Proposed PCA Enhanced Video sequence

Mean Square Error = 62.6945
Peak Signal to Noise Ratio = 30.1585dB
Normalized Cross-Correlation = 0.9975
Average Difference = -0.3941
Structural Content = 1.0009
Maximum Difference = 49
Normalized Absolute Error = 0.0658

Performance analysis

This section contains the cross validation between existing andproposed techniques. Some well-known image performanceparameters for digital images have been selected to prove thatthe performance of the proposed algorithm is quite better thanthe existing methods. Table 2 has shown the quantized analysis of the mean squareerror.

As mean square error need to be reduced therefore theproposed algorithm is showing the better results than theavailable methods as mean square error is less in every case.

AverageDifference. As Average Difference needs to be minimized; sothe main objective is to reduce the Average Difference as muchas possible.

NormalizedAbsolute Error. As Normalized Absolute Error needs to bereduced.

MaximumDifference. As Maximum Difference needs to be minimized; so the main objective is to reduce them Maximum Differenceas much as possible.

StructuralContent. As SC need to be close to 1, therefore proposedalgorithm is showing better results than the available methodsas SC is close to 1 in every case.

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