IMAGE / VIDEO LAYER SEPARATION

By

Umair Rafiq

MSEE-19

Submitted to the faculty of the Department of Electrical Engineering, Military College of Signals, National University Of Science and Technology, Islamabad in partial fulfillment of the requirement of MS Degree in Electrical (Telecommunication) Engineering

March 2016

Abstract

Reflection due to the shiny surfaces like water or glass being one of the common artifacts which degrade the image quality significantly. Reflection removal sometimes also referred as layer separation is a challenging task in the field of image processing and has practical applications. Different techniques are already proposed for layer separation, but there is still a room for improvement to remove reflections from degraded images/videos to get better results.

In this thesis an algorithm is derived that uses single image to remove reflection from degraded colour image. Proposed scheme is also is also extended for layer separation of degraded videos.

The proposed scheme decompose the source image into different levels for better estimation of horizontal and vertical gradients. Noise and blurring artifacts are incorporated by passing the gradients of the subject image through filters, before passing into the objective function. The coherence between the different frames are utilized to preserve the color consistency of the output video. Visual and quantitative analysis verifies the significance of proposed scheme.

DEDICATION

This thesis is dedicated to

MY FAMILY, FRIENDS AND TEACHERS

for their love, encouragement and endless support

Acknowledgements

All praises and thanks to Almighty Allah who gave me strength and determination to complete this research work.

MS thesis is a demanding task. I am deeply indebted to many people for their support and guidance during this thesis. I first wish to thank and acknowledge the efforts of my thesis supervisor Lt Col Dr. Abdul Ghafoor and my co-supervisor Dr Muhammad Mohsin Riaz, who was always available with a smile, and who encouraged me to think and understand the topic and provided guidance for timely completion of this project.

I am also thankful to my committee members Dr Naima Iltaf and Dr Muhammad Imran for their support.

I would like to thank all colleagues of MSEE-19 who always offered helping hand whenever I needed them.

Finally no words are sufficient to express my gratitude for the love, prayers and encouragement I got from my parents, and family. Their help throughout my MS has been extremely valuable to me.

Umair Rafiq

Contents

List of Figures

List of Tables

List of Algorithms

Acronyms

FAST FOURIER TRANSFORM	FFT
INVERSE FAST FOURIER TRANSFORM	$IFFT$
SUPPORT VECTOR MACHINE	SVM
Peak signal-to-noise ratio	$PSNR$
RED GREEN BLUE	RGB
LEAST MEAN SQUARE ERROR	$LMSE$

Chapter 1

Introduction

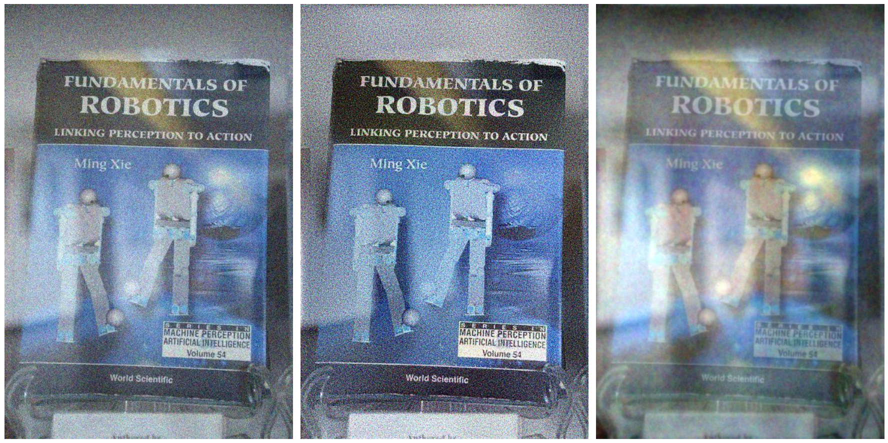
1.1 Introduction

Reflection due to the shiny surfaces like water or glass being one of the common artifacts which degrade the image quality significantly. Reflection removal sometimes also referred as layer separation is a challenging task due to unavailability of scene parameters (like noise and blur level). A lot of work has been done to solve this problem. Many computer vision algorithms can be formulated to decompose the input image into different layers.

In most cases reflection removal problem occurs when an image is captured behind the glass or window. Background layer of such images is mostly desired.

Most of the natural images are combination of original scene and reflection of surrounding from shinny surfaces or glass. Original scene is also called albedo, background and reflectance. Reflection is also known as illumination. Desired background layer is denoted as B and R is the reflection layer that is desired to be removed.Mathematically almost all the layer separation problems take the form

$$A = B + R \tag{1.1}$$



(a) (b) (c)

Figure 1.1: Layer separation problem. (a) Image with reflection and noise (b) Background (c) Reflection. Layers are separated by proposed scheme.

where A is the subject image and is a combination of background B and Reflection R. Figure 1.1 shows a layer separation of a degraded image. Separation is done by proposed scheme that is discussed in chapter 3.

Layer separation is an ill-posed problem because two unknown layers ie. background and reflection layer have to be solved but there is one known input image. So infinite number of solutions are possible. Some additional information is needed to solve the problem. This ill-posed problem can be solved if there is some additional information given as constraint hence two layers can be separated. There are many algorithms that are derived which use additional information to separate two layers e.g. user assisted methods take information of one layer by user indication, multiple images as an input can also reduce the complexity of problem and some techniques learn statistics. Some of the representative methods will be discussed briefly in chapter 2. From the review of previous schemes it can be seen that that reflection removal or layer separation for degraded images and videos is still a challenging task and there is a need to derive more robust and efficient scheme that can be used for practical layer separation.

In this thesis, an improved image/video reflection removal algorithm is developed. The proposed scheme decompose the source image into different levels for better estimation of horizontal and vertical gradients. Noise and blurring artifacts are incorporated by passing the gradients of the subject image through filters, before passing into the objective function. The coherence between the different frames are utilized to preserve the color consistency of the output video. Visual and quantitative analysis verifies the significance of proposed scheme.

1.2 Contribution

In this thesis, an improved algorithm is derived to separate the unwanted reflection layer from the degraded images and videos. Moreover the simulation time of the algorithm is reduced as compared to some state of the art existing schemes.High level overview of the proposed scheme is stated below. Detailed overview will be given in the chapters to follow.

1.2.1 Layer Separation For Degraded Images

Whenever a picture is captured, most of them are a mixture of original scenery and a reflection. Reflection of nearby objects are may be due to the shiny surfaces, water or glass and is not desirable. This is a well known problem of image processing and is known as layer separation problem. Many techniques have been already proposed. In real life noise may be added to input image due to many reasons such as communication channel noise. Most of the pre-existing techniques do not work well in the the presence of noise. In chapter 3 an algorithm is derived which can separate two layers (reflection and background) of degraded image. Image is decomposed into different levels and gradients are calculated.Filters are applied to remove the effects of noise. Results in chapter 3 shows that the proposed scheme works better than some state of the art existing schemes.

1.2.2 Layer Separation For Degraded Videos

The method proposed in chapter 3 for reflection removal of degraded images is extended for reflection removal of degraded videos. Different frames of a video are treated as separate images. Noise and blurring artifacts are incorporated by passing the gradients of the subject frame through filters, before passing into the objective function. The coherence between the different frames are utilized to preserve the color consistency of the output video. Results in Chapter 4 shows the significance of the proposed scheme.

1.3 Thesis Outline

This thesis proposal is organized as five chapters.

- Chapter 1: Introduction and contributions are stated in this chapter.
- Chapter 2: Preliminaries are given in this chapter. Some existing scheme relevant to our topic are discussed
- Chapter 3: This chapter provides complete derivation of the proposed scheme for degraded image layer separation. Experimental results of proposed scheme and its comparison with existing schemes are also given.
- Chapter 4: This chapter describes the proposed scheme for degraded video layer separation. The evaluation based on qualitative and quantitative comparisons with existing schemes are also provided.
- Chapter 5: This chapter concludes the report with some future work directions.

1.4 Conclusion

Basic introduction and contributions are stated in this chapter. Brief review of the approach that is used to solve the problem is provided in this chapter. The organization of this thesis is also provided in this chapter. Chapter 2 provides the literature review related to this thesis.

Chapter 2

Preliminaries

2.1 Introduction

Reflection due to shiny surfaces like water or glass being one of the common artifacts which degrade the image quality significantly. Reflection removal sometimes also referred as layer separation is a challenging task due to unavailability of scene parameters (like noise and blur level). A lot of work has been done to solve this problem. In this chapter some state of the art layer separation techniques for images and videos are described. In the second part different quantitative measures are briefly described that are used to check image quality in this thesis.

2.2 Literature Review

As described in chapter 1 ,There are two main classification of layer separation algorithms. Most of the layer separation techniques use multiple images as an input to separate layers to ease the ill-posed problem. Some techniques use single image to separate layers but this is much harder and complex.

One of the foremost method for estimation of reflection and reflectance is retinex [1], which utilizes log of derivative of target image for reflectance estimation. In this technique reflection and reflectance are characterized by large and small gradients respectively. Smoothness prior was used for classification of image as completely created by shading or reflectance changes. Main assumption in retinex based techniques are smoothly varying reflection layer and abruptly varying reflectance layer. The classical reflection removal techniques [2, 3, 4, 5, 6] are based on Retinex which utilizes image gradients for reflectance estimation.

A classical method that estimate reflection layer by classifying the derivatives of image [6] gives good resuts. It is difficult to correctly classify the derivatives that whether the derivatives are from reflectance layer or illumination layer. The classifiers of derivatives are found by training on some random example images. These classifiers exploit the information from colour images as well as gray scale patterns. When the derivatives are separated, the background and reflection layers are separated automatically.

Some other methods that are proposed to address layer separation problem include user markup and multiple images methods. User markup based techniques [7, 8, 9] utilize empirical information provided by the user (i.e. marking points from background and reflection).

Information of reflected scene is used by[10] and converts the user assisted approach of [7] to computer base approach to automatically calculate gradients without user markup that produces good results by automatically removing the reflection.

Global sparsity prior [11, 12, 5] based techniques, unlike gradient histogram are directly applicable on reflectance values (by assuming the spareness of reflectance coefficients). Intrinsic and spatio-temporal properties of feature points based reflection removal[13, 14] requires multiple images of the same scene. Multiscale parallelized solver and gradients classification based reflectance and illumination [24] severation produces degraded results under high frequency effects of lightning.

A method proposed by [15] utilizes total variation method, measure of blur level and segmentation of a region with the help of fuzzy integral method to classify edge pixels that whether they belong to reflection or reflectance. Multiple images are acquired by rotating a camera with polarizing filter at different angles [16, 17, 18] . Blind source separation method [16], independent components analysis [17], and polarization-based decorrelation [18] are applied to polarization images to separate background and reflection image. In [19, 20, 21, 22, 23], video sequences were used as input. Contrary to polarization images, video frames are temporally correlated. The methods of temporal integration [19], layer information exchange [20], global-to-local time-space alignmen [21], and stereo matching [22] have successfully separated reflection and background images from video sequences.

Temporal and spatial coherence based reflection removal [26] provides limited performance in case of variable or dense reflection. This algorithm exploits the temporal and spatial coherence of reflection which means the reflection remains static and the background keeps on changing as in vehicular black box videos. Heavy-tail distribution is imposed as an image prior to remove reflection. This algorithm works good with the real time black box videos but is not suitable for the problem where reflection layer is changing with time. Moreover videos with saturated reflections do not give good results.

A physically-based approach to separate reflection [25] use multiple polarized images captured behind glass. Three polarized images are taken as input, each captured from different polarizer angle separated by 45 degrees but from the same view point. A pair of orthogonal images are extracted from input images and reflection layer is separated by estimating the spatially-varying incidence angle.

Review shows that most of the reflection removal techniques use multiple images as input. Some schemes takes empirical information from the user to solve the layer separation problem. These types of algorithms may give good quality reflection and background images but are not feasible to use in most practical cases. These type of algorithms are not suitable for reflection removal of videos as well.

Reflection removal from a single image automatically is very difficult because of the ill-posed problem. There are some techniques already proposed that use single image to solve the problem but to our best knowledge there is no such technique that gives significant results for degraded images and videos.

An algorithm is proposed in the chapters to follow that gives high quality results in less computational time using single image for degraded images and videos.

2.3 Quantitative Measures

Output images/Videos are are checked by quantitative measures to get an idea that how much accurate the results are. There are many quantitative measures that are used. Peak Signal to Noise Ratio (PSNR), Least Mean Square Error (LMSE) and Structural Similarity Index (SSIM) are mostly used. Brief review of these quantitative measures is given below.

2.3.1 Least Mean Square Error

Least Mean Square Error, often abbreviated as LMSE is quantitative measure to calculate the difference or error between two images.

Let A and B are two m×n monochrome images where one of the images is a noisy approximation of the other image. LMSE can be mathematically written as:

$$LMSE = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [A(i,j) - B(i,j)]^2 \tag{2.1}$$

LMSE is the sum over all squared value differences divided by size of image and by three. LMSE will be zero when two images are identical.

2.3.2 Peak Signal to Noise Ratio

peak signal-to-noise ratio, often called PSNR, is the ratio between the maximum power of a signal and the power of corrupting noise that affects the accuracy of its representation. PSNR is often expressed in terms of the logarithmic decibel scale because most of the signals have a very wide dynamic range. The PSNR is commonly used as qualitative measure of reconstruction of lossy compression codecs e.g. image compression. In this case the original data is signal and noise is the error due to compression.
PSNR is easily defined in terms of LMSE.

$$PSNR = 10.log(\frac{MAX_I^2}{LMSE}) \tag{2.2}$$

Where MAX_I is the defined as the maximum pixel value of the image.

2.4 summary

In this chapter some existing layer separation techniques are discussed. Some quantitative measures used to check the significance of results are also provided. A lot of work has been done on this problem but still there is a room for improvement. An improved algorithm for the layer separation of degraded images and videos should be derived. Next chapter provide the details of the proposed scheme to separate two layers of degraded image.

Chapter 3

An Improved Reflection Removal Technique For Degraded Images

3.1 Introduction

In this chapter an improved method is proposed to remove reflection from a degraded image. Layer separation is a challenging task as it is an ill posed problem and cannot be solved without assuming any priors. The classical reflection removal techniques [1, 3, 4] are based on Retinex which utilizes image gradients for reflectance estimation. In [1], the reflection and reflectance are characterized by large and small gradients under the assumption of smooth and abrupt variation respectively. User markup based techniques [7, 8, 9] utilize empirical information provided by the user (i.e. marking points from background and reflection). Information of reflected scene is used by[10] to automatically calculate gradients without user markup. Global sparsity prior [11, 12, 5] based techniques, unlike gradient histogram are directly applicable on reflectance values (by assuming the spareness of reflectance coefficients). Temporal and spatial coherence based reflection removal [26] provides limited performance in case of variable or dense reflection. Intrinsic and spatio-temporal properties of feature points based reflection removal [13, 14] requires multiple images of the same scene. Multiscale parallelized solver and gradients classification based reflectance and illumination [24] severation produces degraded results under high frequency effects of lightning. It is assumed that one layer is smoother than the other to remove reflection using one image. Proposed scheme and results are given in the sections to follow.

3.2 Proposed Methodology

Let A be the input image (of size $P \times Q \times \beta$ where $p = 1, 2, \ldots, P$, $q = 1, 2, \ldots, Q$ and $\beta \in \{\text{Red, Green, Blue}\}$ containing a background (albedo or reflectance) image B and a reflection image R i.e.,

$$A = B + R * \phi \tag{3.1}$$

where ϕ is a blurring kernel/filter. Note that the input image A also contains different types of system and environmental noises. To estimate the reflectance image B, the image A is downsampled into different levels i.e.,

$$A_{k+1} = A_k \downarrow \eta \tag{3.2}$$

where η is downsampling factor, $k = 1, 2, \ldots, K$ are levels and $A_1 = A$ is first level. The horizontal and vertical gradients are computed as,

$$\begin{aligned} \tilde{G}_1^k &= A_k * \psi \\ \tilde{G}_2^k &= A_k * \psi^T \end{aligned} \tag{3.3}$$

where $\psi = [1, -1]$ is filter kernel and $*$ is circular convolution operator. Note that when the input image contains noise, the horizontal and vertical edges concentration are relatively high. In such cases, a filter is applied on the horizontal and vertical gradients, i.e.,

$$G_i^k = \begin{cases} \xi\big(\tilde{G}_i^k\big) & \text{if} \quad \alpha > 0.8 \\ \tilde{G}_i^k & \quad \text{otherwise} \end{cases} \tag{3.4}$$

where α is non-zero value concentration of input image and $\xi(.)$ is Wiener filter followed by average and median filters. To separate reflection R, the objective function defined in [4] is utilized, i.e.,

$$\tilde{R}_k = \mathcal{F}^{-1}\left(\frac{\kappa\left(\mathcal{F}(\psi) * \mathcal{F}(G_1^k) + \mathcal{F}(\psi^T) * \mathcal{F}(G_2^k)\right) + \lambda\mathcal{F}(\vartheta) * \mathcal{F}(\vartheta)\mathcal{F}(A)}{\kappa\left(\mathcal{F}(\psi) * \mathcal{F}(\psi) + \mathcal{F}(\psi^T) * \mathcal{F}(\psi^T)\right) + \lambda\mathcal{F}(\vartheta) * \mathcal{F}(\vartheta) + \sigma}\right) \tag{3.5}$$

where $\mathcal{F}$ and $\mathcal{F}^{-1}$ are Fourier and inverse Fourier transforms respectively, κ and λ are weighting constants, $\sigma = 10^{-16}$ is a stability constant and ϑ is a second order Laplacian filter [4]. The reflection layer obtained at k^{th} level $\tilde{R}_k$ is upsampled (for matching dimensions with B image) to obtain R_k. The final background estimated image $\tilde{B}$ is,

$$\tilde{B} = A - \sum_{k=1}^{K} W_k R_k \tag{3.6}$$

where W_k is weighting factor. The whole process is summarized in Algorithm 1.

3.3 Simulation Results

Various simulations are performed on state of art existing (*Li and Brown* [4] and Retinex [3]) and proposed techniques. The specifications of system include: Intel i3 1.7GHz processor, 4 GB RAM and Matlab 2014a. The comparisons are performed visually and quan-

Algorithm 1 Image Layer Separation

Input $\leftarrow$ Input Image A, Pyramid Size k , Smoothness Factor λ, Maximum Iteration Number K, Sampling Rate η_k, β_o
Output $\leftarrow$ Estimation of B and R
Initialization : $B_K \leftarrow A$, $\beta \leftarrow \beta_o$, $K \leftarrow 0$,$A \leftarrow 0$,$\eta_K \leftarrow 1$
while $K \leq k$ **do**

$A_K \downarrow \eta_K$

Calculate $\hat{G_1^K}$ and $\hat{G_2^K}$ using equation-3.3
if Non zero value density $\alpha \geq 0.8$ **then**
Apply filters using equation 3.4 to get G_1^K and G_2^K
else
$\hat{G_1^K} = G_1^K$ and $\hat{G_2^K} = G_2^K$
end if

calculate R_k using 3.5

$\beta = 2 * \beta$, k++
end while

$R = \sum_{K=1 \to k} R_k$

$B = A - R$

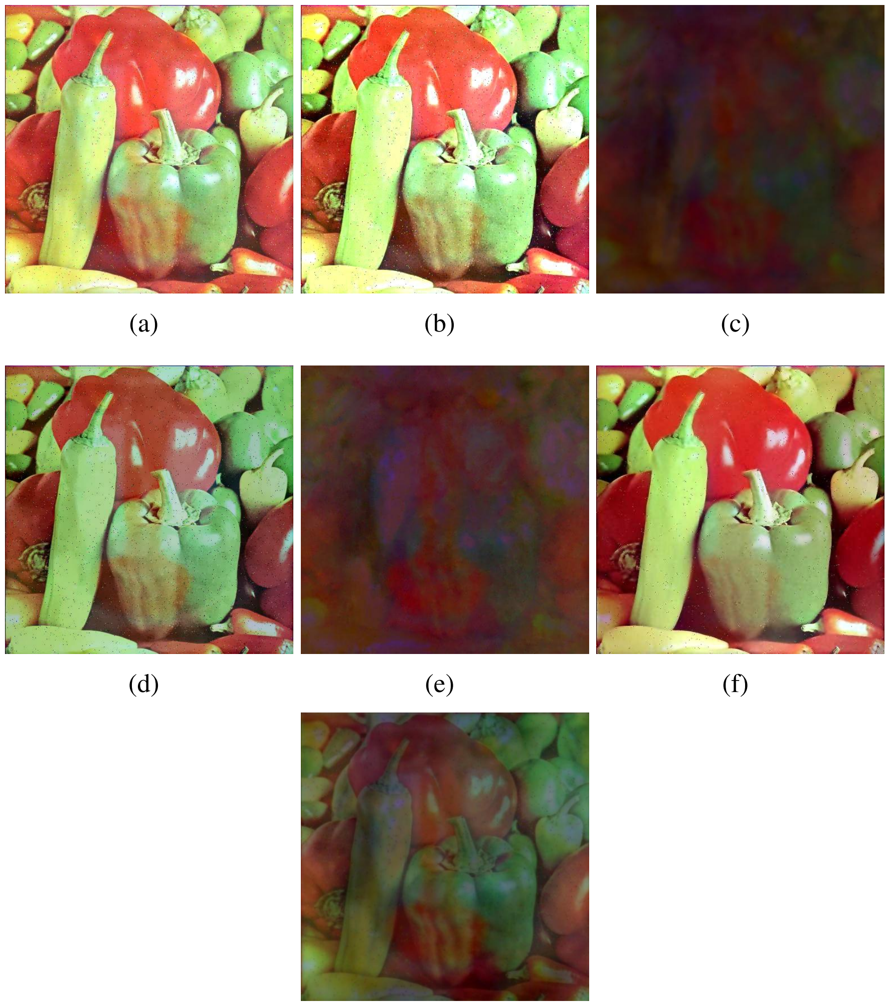
titatively using least mean square error (LMSE) and simulation time.

Figure 3.1 (a) shows the input image containing reflection and system noise. Figure 3.1 (b) and 3.1 (c) show the reflectance and reflection images obtained by *Li and Brown* [4] respectively. The reflectance image obtained using proposed technique (Figure 3.1(d)) provides better visual quality interms of sharp edges and details preservation. Figure 3.1 (e) shows the reflection image extracted by proposed technique.

Table 3.1 shows the quantitative comparison of existing and proposed techniques in terms of LMSE and computational time for example 1.

Table 3.1: Quantitative comparison:Image Example 1

Techniques	Time (sec)	LMSE
Li and Brown [4]	17.007	3.04 e^{-2}
Retinex [3]	17.212	3.11 e^{-2}
Proposed	14.31	2.93 e^{-2}



(a) (b) (c)

(d) (e) (f)

(g)

Figure 3.1: Example 1 (a) original image (b) reflectance obtained using *Li and Brown* [4] (c) reflection obtained using [4] (d) reflectance obtained using *Retinex* [3] (e) reflection obtained using [3] (f) reflectance obtained using proposed scheme (g) reflection obtained using proposed scheme

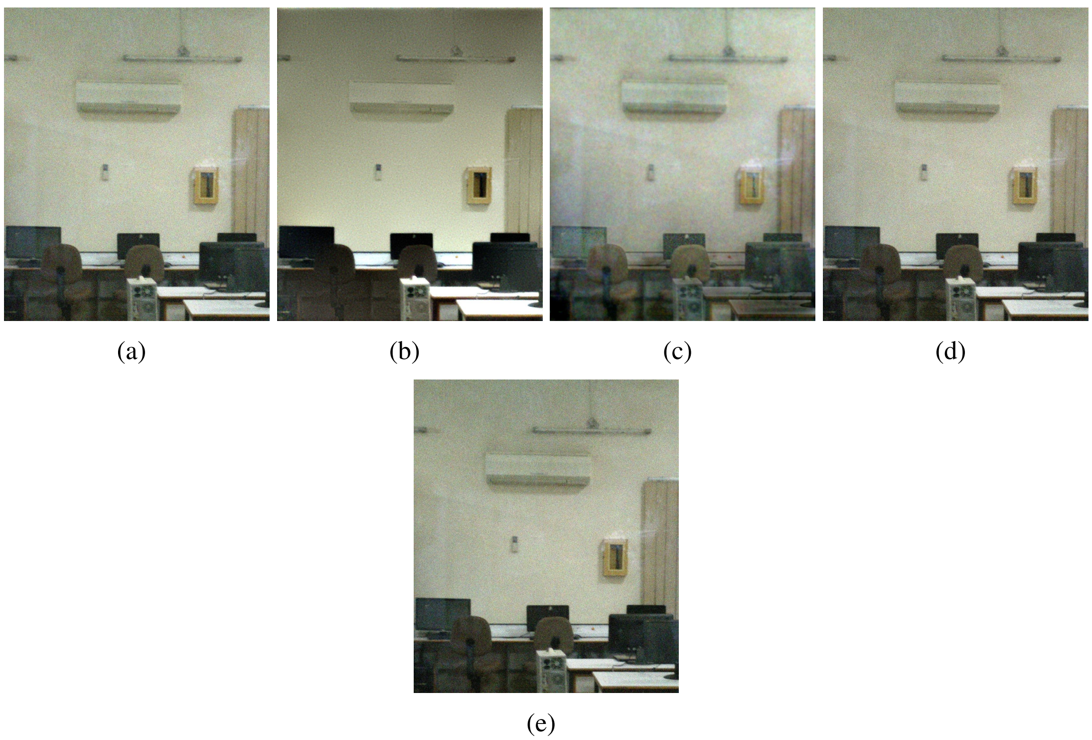


Figure 3.2: Example 2 (a) original image (b) reflectance obtained using proposed scheme (c) reflection obtained using proposed scheme (d) reflectance obtained using *Li and Brown* [4] (e) reflectance obtained using *Retinex* [3]

Figure 3.2 (a) shows another source image corrupted by reflection and system noise. Figure 3.2 (b) and 3.2 (c) show the reflectance (recovered) images obtained by *Li and Brown* [4] and proposed technique respectively. Note that the proposed technique more efficiently extracts the reflection image (Figure 3.2(d)).

Table 3.2 shows the quantitative comparison of existing and proposed techniques in terms of LMSE and computational time for example 2.

Table 3.2: Quantitative comparison:Image Example 2

Method	Time (sec)	LMSE
Li and Brown [4]	80.10	2.09 e^{-2}
Retinex [3]	82.21	2.19 e^{-2}
Proposed	48.44	1.24 e^{-2}

Figure 3.3 (a) shows the image of a book captured behind the showcase glass and contain reflection of the surroundings and system noise. Figure 3.3 (b) and 3.3 (c) show the reflectance and reflection images obtained by *Li and Brown* [4] respectively. The reflectance image obtained using proposed technique (Figure 3.3(d)) provides better visual quality in terms of sharp edges and details preservation. Figure 3.3 (e) shows the reflection image extracted by proposed technique.

Table 3.3 shows the quantitative comparison of existing and proposed techniques in terms of LMSE and computational time for example 3.

Table 3.3: Quantitative comparison:Image Example 3

Techniques	Time (sec)	LMSE
Li and Brown [4]	15	2.73 e^{-2}
Retinex [3]	15.7	2.85 e^{-2}
Proposed	10	2.54 e^{-2}

(a) (b) (c)

(d) (e) (f)

(g)

Figure 3.3: Example 3 (a) original image (b) reflectance obtained using *Li and Brown* [4] (c) reflection obtained using [4] (d) reflectance obtained using *Retinex* [3] (e) reflection obtained using [3] (f) reflectance obtained using proposed scheme (g) reflection obtained using proposed scheme

3.4 summary

In this chapter, an improved layer separation technique is proposed for color images. The proposed scheme decompose the source image into different levels for better estimation of horizontal and vertical gradients. To incorporate the noise and blurring artifacts, the gradients are filtered before passing into the objective function. Visual and quantitative analysis verifies the significance of proposed scheme as compared to state-of-the-art existing techniques.

Chapter 4

An Improved Reflection Removal Technique For Degraded Videos

4.1 Introduction

In this chapter, the scheme proposed in chapter 3 is extended for reflection removal of degraded colour videos. There is a lot of work being done to get videos of better quality. Most of the research focus on the resolution of video but there is another important aspect of video quality that is the readability. Many problems must be tackled to address the issue of readability. Sometimes reflection of the surroundings and noise are added to video. For example the videos that are taken by the camera behind the windscreen are often degraded by the windscreen reflection of objects inside the vehicle. Moreover noise may be added to it. This unwanted noise and reflection causes poor visibility of the videos. Hence it is important to remove the background layer and reflection to get a clear video.

Although the schemes discussed in the previous chapters have given significant results but for the fast moving frames of videos it is very complex to apply these techniques that are mostly used for images to apply directly to video frames. Therefore an improved method for the reflection removal of degraded videos is proposed in the sections to follow.

4.2 Proposed Method

Let $Frm(t)$ are the frames of the degraded video (of size $P \times Q \times \beta$ where $p = 1, 2, \dots, P$, $q = 1, 2, \dots, Q$ and $\beta \in$ {Red, Green, Blue} containing a background (albedo or reflectance) image B and a reflection image as shown in equation 3.1.

To estimate the reflectance each frame is downsampled to different levels using equation 3.2. Then horizontal and vertical gradients $\tilde{G}_1^k$ and $\tilde{G}_2^k$ of a frame are calculated using equation 3.3.

To incorporate the noise artifacts, the gradients are passed through filters using equation 3.4 to get G_i^k.

Frame coherence is exploited to get better results and colour consistency.

Let $G_i^k(t), G_i^k(t+1), \dots, G_i^k(t+\tau)$ be the gradient images (at k^{th} level) obtained at time instants $t, t+1, \dots, t+\tau$, the final gradient $\dot{G}_i^k(t)$ at time t is estimated as,

$$\dot{G}_i^k(t) = \sum_{t_1=t}^{t+\tau} \zeta\big(t_1\big) G_i^k(t_1) \tag{4.1}$$

where $\zeta\big(t_1\big)$ are normalizing constants. Note that the weighting average of gradients not only provide better gradients but also preserves the color consistency in the video.

To separate reflection R, gradients G_i^k are passed to the objective function defined in equation 3.5. Background B of a $frm(t)$ is then calculated using equation 6.

The whole process is described in Algorithm 2.

4.3 Simulation and Results

Various simulations are performed on state of art existing (*Li and Brown* [4] and Retinex [3]) and proposed technique. The specifications of system include: Intel i3 1.7GHz pro-

Algorithm 2 Video Layer Separation

Input $\leftarrow$ Input Video Frames Frm(t),Window Size τ, Pyramid Size k , Smoothness Factor λ, Sampling Rate η_k, β_o, α, Number Of Frames NOF
Output $\leftarrow$ Estimation of $B(t)$ and $R(t)$
Initialization :t $\leftarrow$0, $B_K(t) \leftarrow Frm(t)$, $\beta \leftarrow \beta_o$, $K \leftarrow 0$, ,$\eta_K \leftarrow 1$, $\alpha \leftarrow 0.8$
while $t \leq NOF$ **do**
  calculate $\hat{G_1^K}(t)$ and $\hat{G_2^K}(t)$ using equation-3.3
  while $K \leq k$ **do**
    $Frm_K(t) \downarrow \eta_K$
    if Non zero value density $\geq \alpha$ **then**
      Apply filter using equation 3.4 to get $G_1^K(t)$ and $G_2^K(t)$
    else
      $\hat{G_1^K}(t) = G_1^K(t)$ and $\hat{G_2^K}(t) = G_2^K(t)$
    end if
    Update $G_1^K(t)$ and $G_2^K(t)$ using equation 4.1
    calculate $R_k(t)$ using 3.5
    $\beta = 2 * \beta$, k++
  end while
  $R(t) = \sum_{K=1 \to k} R_k(t)$
  $B(t) = Frm(t) - R(t)$
  t=t+1
end while

Figure 4.1: Example 1 (a)-(d) original video frames (e)-(h) reflectance obtained using *Li and Brown* [4] (i)-(l) reflectance obtained using *Retinex* [3] (m)-(p) reflectance obtained using proposed scheme

cessor, 4 GB RAM and Matlab 2014a. The comparisons are performed visually and quantitatively using least mean square error (LMSE) and simulation time. Results shows the significance of proposed scheme.

Figure 4.1 (a)-(d) shows original video frames that are degraded with the salt and pepper noise of density 0.01. Figure 4.1 (e)-(h) shows reflectance obtained using *Li and Brown* [4], (i)-(l) shows reflectance obtained using *Retinex* [3] and (m)-(p) shows reflectance obtained using proposed scheme.

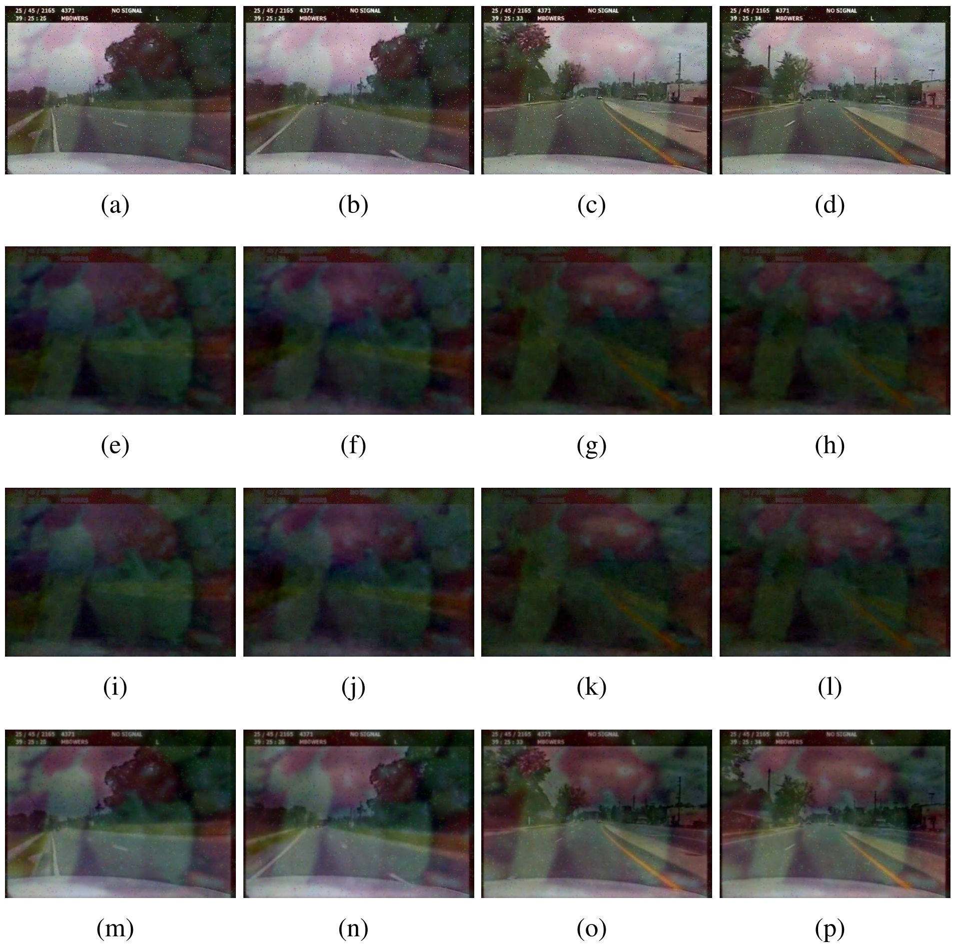


Figure 4.2: Example 1 (a)-(d) original video frames (e)-(h) reflection obtained using *Li and Brown* [4] (i)-(l) reflection obtained using *Retinex* [3] (m)-(p) reflection obtained using proposed scheme

Figure 4.2 (a)-(d) shows original video frames that are degraded with the salt and pepper noise of density 0.01. Figure 4.1 (e)-(h) shows reflection obtained using *Li and Brown* [4], (i)-(l) shows reflection obtained using *Retinex* [3] and (m)-(p) shows reflection obtained using proposed scheme.

Table 4.1 shows the quantitative comparison of existing and proposed techniques in terms of LMSE and computational time for example 1.

Table 4.1: Quantitative comparison:Video Example 1

Method	Time (sec)	LMSE
Li and Brown [4]	500.2	3.96 e^{-2}
Retinex [3]	480.0	4.17 e^{-2}
Proposed	450.3	2.71 e^{-2}

Figuure 4.3 (a)-(d) show some input frames of video that are degraded with the salt and pepper noise of density 0.01, (e)-(h) show the reflectance obtained using proposed scheme, (i)-(l) show reflectance obtained using *Li and Brown* [4], (m)-(p) gives reflectance obtained using *Retinex* [3].

Figuure 4.4 (a)-(d) show some input frames of video that are degraded with the salt and pepper noise of density 0.01, (e)-(h) show the reflection obtained using proposed scheme, (i)-(l) show reflection obtained using *Li and Brown* [4], (m)-(p) gives reflection obtained using *Retinex* [3]. It is interesting to note that the the proposed scheme exploits frame consistency which helps in better reflection removal and preservation of color consistency.

Table 4.2 shows the quantitative comparison of existing and proposed techniques in terms of LMSE and computational time for example 2.

Figure 4.3: Example 2 (a)-(d) original video frames (e)-(h) reflectance obtained using proposed scheme (i)-(l) reflectance obtained using *Li and Brown* [4] (m)-(p) reflectance obtained using *Retinex* [3]

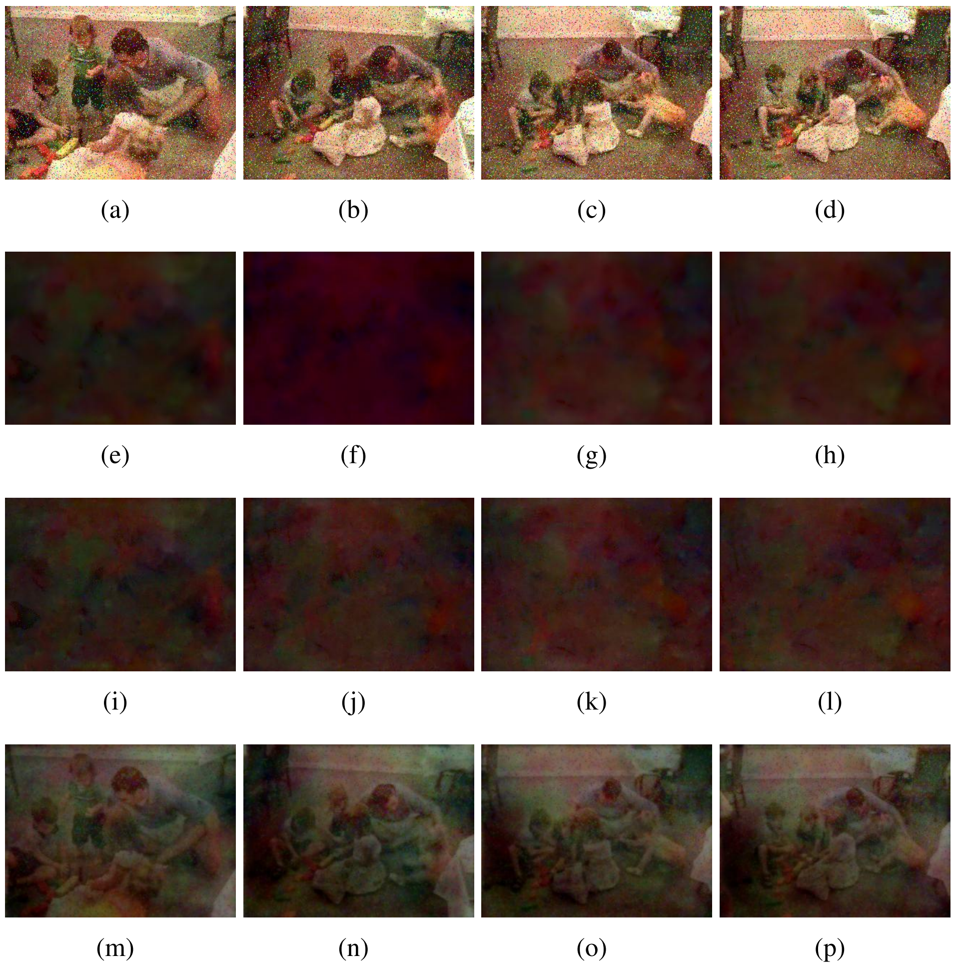


Figure 4.4: Example 2 (a)-(d) original video frames (e)-(h) reflection obtained using proposed scheme (i)-(l) reflection obtained using *Li and Brown* [4] (m)-(p) reflection obtained using *Retinex* [3] (q)-(t) reflection obtained using proposed scheme

Table 4.2: Quantitative comparison:Video Example 2

Method	Time (sec)	LMSE
Li and Brown [4]	603.65	8.8 e^{-2}
Retinex [3]	610.3	8.9 e^{-2}
Proposed	434.32	7.7 e^{-2}

4.4 summary

In this chapter image layer separation technique is extended for videos. Noise and blurring artifacts are incorporated by pre-processing the gradients of the source image through filters. The coherence between the different frames are utilized to preserve the color consistency of the output video. Simulation results evaluated visually and quantitatively verify the significance of proposed scheme.

Chapter 5

Conclusion and Future Work

In this chapter summary of the work that is presented in this thesis is given. Direction to future research that can be carried is also provided.

5.1 Conclusion

In this thesis a method is proposed to extract two layers from a degraded image/video automatically assuming that one layer is smoother than the other. Proposed scheme works by decomposing the noisy image into different levels for better estimation of horizontal and vertical gradients. Filtering is applied on the gradients of subject image before passing them to objective function to reduce the effect of noise and blurring artifacts. For videos spatial as well as temporal correlations of frames are taken into account for color prese rvance and to get better results. Results demonstrates the superiority of proposed scheme when compared with state of the art layer separation schemes.

5.2 Future Work

This work can be extended to following direction.

- Colour consistency in videos can further be improved by using different colour spaces and temporal-spatial characteristics.
- Vertical and horizontal gradients can be calculate with the help of novel techniques.
- Reflection in case of video is static. Research can be carried on to remove moving reflection in videos.
- Improved pyramid decomposition techniques can be explored to increase accuracy and efficiency.
- The algorithms can be suggested for mono-colour (gray scale) videos for different security applications (IR vision etc).
- More accurate filters can be explored to estimate correct noise free gradients.
- Image depth can also be incorporated for more accurate reflection removal.

Bibliography

[1] E. H. Land, and J. McCann, "Lightness and retinex theory," *Journal of Optical Society of America*, vol. 61, no. 1, pp. 1-11, 1971.

[2] Y. Y. Schechner, N. Kiryati, and R. Basri, "Separation of transparent layers using focus," *IJCV,* pp. 25-39, 2000.

[3] R. Grosse, M. K. Johnson, E. H. Adelson, and W. T. Freeman, "Ground truth dataset and baseline evaluations for intrinsic image algorithms," *IEEE International Conference on Computer Vision*, pp. 2335-2342, 2009.

[4] Y. Li, and M. S. Brown, "Single image layer separation using relative smoothness," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2752-2759, 2014

[5] L. Shen, and C. Yeo, "Intrinsic images decomposition using a local and global sparse representation of reflectance," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 697-704, 2011.

[6] M. F. Tappen,W. T. Freeman, and E. H. Adelson, "Recovering intrinsic images from a single image," *TPAMI*, 27(9):pp. 1459-1472, 2005.

[7] A. Levin, and Y. Weiss, "User assisted separation of reflections from a single image using a sparsity prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 9, pp. 1647-1654, 2007.

[8] A. Bousseau, S. Paris, and F. Durand, "User-assisted intrinsic images," *ACM Transactions on Graphics*, vol. 28, no. 5, pp. 130, 2009.

[9] A. Levin and Y. Weiss, "User Assisted Separation of Reflections from a Single Image Using a Sparsity Prior, *European Conf. Computer Vision*,2004

[10] D. Prakash, P. Kalwad, V. Peddigari, and P. Srinivasa, "Automatic reflection removal using reflective layer image information," *IEEE International Conference on Consumer Electronics*, pp. 548-551, 2015

[11] M. Serra, O. Penacchio, R. Benavente, and M. Vanrell, "Names and shades of color for intrinsic image estimation," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 278-285, 2012.

[12] C. Rother, M. Kiefel, L. Zhang, B. Schlkopf, and P. V. Gehler, "Recovering intrinsic images with a global sparsity prior on reflectance," *Advances in Neural Information Processing Systems*, pp. 765-773, 2011.

[13] D. Yang, S. Jayawardena, S. Gould, and H. Marcus, "Reflective features detection and hierarchical reflections separation in image sequences," *IEEE Intenational Conference on Digital lmage Computing: Techniques and Applications*, pp. 1-7, 2014.

[14] Y. Li, and M. S. Brown, "Exploiting reflection change for automatic reflection removal," *IEEE International Conference on Computer Vision*, pp. 2432-2439, 2013.

[15] Y. Chung, S. Chang, J. Wang and S. Chen, "Interference Reflection Separation from a Single Image,"*IEEE International Conference on Applications of Computer Vision*, pp. 1-6. 2009.

[16] A.M. Bronstein, M.M. Bronstein, M. Zibulevsky, and Y.Y. Zeevi, "Blind Separation of Reflections Using Sparse ICA, *4th Intl Symp. On ICA and Blind Signal Separation, Nara, Japan*, pp. 227-232, 2003.

[17] H. Farid and E.H. Adelson, Separating Reflections from Images by Use of Independent Components Analysis,*J. Optical Soc. Am.*, vol. 16, no. 9, pp. 2136-2145, 1999.

[18] Y. Shechner, J. Shamir, and N. Kiryati, Polarization-Based Decorrelation of Transparent Layers: The Inclination Angle of an Invisible Surface, *IEEE Intl Conf. on Computer Vision*, pp. 814-819, 1999.

[19] M. Irani and S. Peleg, Image Sequence Enhancement Using Multiple Motions Analysis, *IEEE Conf. on CVPR*, pp. 216-221, June 1992.

[20] B. Sarel and M. Irani, Separating Transparent Layers through Layer Information Exchange,*ECCV*, 2004.

[21] B. Sarel and M. Irani, Separating Transparent Layers of Repetitive Dynamic Behaviors, *IEEE ICCV*, 2005.

[22] Y. Tsin, S.B. Kang, and R. Szeliski, Stereo Matching with Reflections and Translucency, *IEEE Proc. Conf. CVPR*, pp. 702- 709, 2003.

[23] M. Zibulevsky, P. Kisilev, Y. Zeevi, B. Pearlmutter, Blind Source Separation via Multinode Sparse Representation, *Advances in Neural Information Processing Systems*, vol. 14, 2001.

[24] N. Bonneel, K. Sunkavalli, J. Tompkin, D. Sun, S. Paris and H. Pfister, "Interactive intrinsic video editing," *ACM Transactions on Graphics (TOG)*, 33(6), 197, 2014

[25] N. Kong, Y. W. Tai, and J. S. Shin, "A physically-based approach to reflection separation: from physical modeling to constrained optimization," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 2, pp. 209-221, 2014.

[26] S. Christian, and I. K. Park, "Reflection removal for in-vehicle black box videos," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4231-4239, 2015.