



**HAL**  
open science

# Color Correction and Contrast Enhancement for Natural Images and Videos

Qi-Chong Tian

► **To cite this version:**

Qi-Chong Tian. Color Correction and Contrast Enhancement for Natural Images and Videos. Image Processing [eess.IV]. Université Paris sciences et lettres, 2018. English. NNT : 2018PSLED020 . tel-01923658

**HAL Id: tel-01923658**

**<https://theses.hal.science/tel-01923658v1>**

Submitted on 15 Nov 2018

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# THÈSE DE DOCTORAT

de l'Université de recherche Paris Sciences et Lettres  
PSL Research University

Préparée à l'Université Paris-Dauphine

Color Correction and Contrast Enhancement  
for Natural Images and Videos

**École doctorale n°543**

ÉCOLE DOCTORALE DE DAUPHINE

**Spécialité** SCIENCES

Soutenue par **Qi-Chong TIAN**  
le 4 octobre 2018

Dirigée par **Laurent D. COHEN**

## COMPOSITION DU JURY :

M. Laurent D. COHEN  
CEREMADE, Directeur de thèse

M. Edoardo PROVENZI  
Université de Bordeaux, Rapporteur

M. Yann GOUSSEAU  
Télécom ParisTech, Rapporteur

M. Philippe CARRÉ  
Université de Poitiers, Président

Mme Agnès DESOLNEUX  
ENS Cachan, Membre du jury

M. Jamal ATIF  
LAMSADE, Membre du jury



# Color Correction and Contrast Enhancement for Natural Images and Videos



**Qi-Chong Tian**

Supervisor: Prof. Laurent D. Cohen

CEREMADE, CNRS, UMR 7534,

Université Paris Dauphine, PSL Research University, Paris, France

This dissertation is submitted for the degree of

*Doctor of Philosophy*

October 2018



To my loving family.



## Acknowledgements

I would like to take this opportunity to thank everyone involved during my PhD research.

Firstly, I would like to express my deepest sincere gratitude to my supervisor, Prof. Laurent D. Cohen, for his constant guidance and support to my research. Without his professional knowledge, novel ideas, constructive suggests, patient guidance and encouragement, I would not have been able to complete this thesis.

My sincere thanks are also given to all the jury members of my thesis. I would like to warmly thank Prof. Edoardo Provenzi and Prof. Yann Gousseau for their constructive comments after reading this manuscript. Their reports are very helpful to improve the quality of this thesis. Thank Prof. Philippe Carré, Prof. Jamal Atif, and Prof. Agnès Desolneux to evaluate this work during the thesis defense.

I would like to thank Prof. Hao Wen and Prof. Wei Chen for giving helpful suggestions to my work during these years.

During this Ph.D. program, I had the chance to work with many friendly colleagues and friends at CEREMADE. I would like to thank them for the discussions, help, chatting in coffee breaks and lunch breaks.

I would like to thank the China Scholarship Council for the financial support during these four years. I also thank CEREMADE for providing funds to attend international academic conferences in Finland, Iceland, China, and Italy.

Special thanks go to my loving parents for supporting and encouraging me through these years. I would also like to thank my brother and sister for their kindly help. Without the support from my family, this work would not have been possible.





# Abstract

Due to the limitations of imaging devices and environmental illuminations, the captured color images are usually not desirable in terms of color and contrast. Image enhancement aims to improve the image visual quality, and plays a very important role in the domains of image processing and computer vision. Specifically, we consider color correction and contrast enhancement to improve the image quality.

In the first part of this thesis, we focus on color correction for natural images. Firstly, we give a simple review of color correction, including the background of color imaging, some color fundamentals, several kinds of existing color correction methods, and the relevant applications. Secondly, we propose an efficient color correction method for image stitching via histogram specification and global mapping. We use original pixels and the corresponding pixels after histogram specification to compute a global mapping function with an iteration method. Thirdly, We have proposed a color consistency approach for image collections, based on range preserving histogram specification. This method can enforce the same image collection to share the same color style and not to cause gamut problems.

In the second part, we pay attention to contrast enhancement for natural images and videos. Firstly, we introduce the research background, summarize three kinds of contrast enhancement methods, present five metrics for evaluating image quality, and give some applications. Secondly, we propose a naturalness preservation global contrast enhancement method, which is able to avoid over-enhancement problems. Thirdly, we present a variational-based fusion method for non-uniform illumination image enhancement, which can improve the visibility of images without over-enhancement or under-enhancement. Finally, we extend the fusion-based

---

framework to enhance videos with a temporally consistent strategy, which does not result in flickering artifacts.

**Keywords:** Image enhancement, color correction, color transfer, color consistency, contrast enhancement, histogram specification, naturalness preservation, image fusion, variational model, flicker reduction.

# Table of Contents

<b>List of Publications</b>	<b>xv</b>
<b>Notations</b>	<b>xvii</b>
<b>Introduction en Français</b>	<b>xix</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Background and Motivation . . . . .	2
1.2 Contributions of this Thesis . . . . .	6
1.2.1 Histogram-based Color Correction for Image Stitching . . . . .	6
1.2.2 Color Consistency without Gamut Problems . . . . .	7
1.2.3 A Global Naturalness Preservation Contrast Enhancement Method . .	7
1.2.4 A Variational-based Fusion Model for Contrast Enhancement . . . . .	7
1.2.5 Temporally Consistent Video Enhancement . . . . .	8
1.3 Outline of this Thesis . . . . .	8
<b>I Color Correction for Natural Images</b>	<b>13</b>
<b>2 A Simple Review of Color Correction</b>	<b>15</b>
2.1 Introduction . . . . .	16
2.2 Color Fundamentals . . . . .	18
2.3 Color Correction Methods . . . . .	26

## Table of Contents

---

2.4	Performance Criteria . . . . .	30
2.5	Applications of Color Correction . . . . .	31
2.6	Conclusions . . . . .	34
<b>3</b>	<b>Histogram-based Color Correction for Image Stitching</b>	<b>35</b>
3.1	Introduction . . . . .	37
3.2	Related Work . . . . .	39
3.2.1	Motion Models . . . . .	40
3.2.2	Image Alignment . . . . .	41
3.3	The Proposed Approach . . . . .	43
3.3.1	Overview . . . . .	43
3.3.2	The Detailed Description of This Algorithm . . . . .	45
3.4	Experiments . . . . .	49
3.4.1	Test Dataset and Evaluation Metrics . . . . .	49
3.4.2	Experiments on Synthetic Image Pairs . . . . .	50
3.4.3	Experiments on Real Image Pairs . . . . .	54
3.4.4	An Example of Stitching More Than Two Images . . . . .	57
3.5	Discussion . . . . .	57
<b>4</b>	<b>Color Consistency for Photo Collections without Gamut Problems</b>	<b>61</b>
4.1	Introduction . . . . .	63
4.2	Related work . . . . .	65
4.2.1	Color Enhancement for a Single Image . . . . .	65
4.2.2	Color Transfer Between Two Images . . . . .	66
4.2.3	Color Balance for Image Collections . . . . .	66
4.3	Overview . . . . .	67
4.4	Color Consistency without Gamut Problems . . . . .	68
4.4.1	Image Quality Assessment by Non-Reference Measures . . . . .	68

4.4.2	Color Balance without Gamut Problems . . . . .	70
4.4.3	Color Transfer without Gamut Problems . . . . .	72
4.5	Experiments . . . . .	73
4.5.1	Image Datasets . . . . .	73
4.5.2	Results . . . . .	74
4.6	Conclusion . . . . .	77
<b>II Contrast Enhancement for Natural Images and Videos</b>		<b>79</b>
<b>5</b>	<b>A Simple Review of Contrast Enhancement</b>	<b>81</b>
5.1	Introduction . . . . .	82
5.2	Contrast Enhancement Methods . . . . .	83
5.2.1	Histogram-based Methods . . . . .	83
5.2.2	Retinex-based Methods . . . . .	87
5.2.3	Learning-based Methods . . . . .	90
5.3	Quantitative Measures . . . . .	91
5.4	Application of Contrast Enhancement . . . . .	93
5.5	Conclusions . . . . .	95
<b>6</b>	<b>A Global Naturalness Preservation Contrast Enhancement Method</b>	<b>97</b>
6.1	Introduction . . . . .	98
6.2	Proposed Method . . . . .	101
6.2.1	Overview . . . . .	101
6.2.2	A Global Naturalness Preservation Contrast Enhancement Method . .	101
6.3	Results . . . . .	104
6.3.1	Performance Criteria . . . . .	104
6.3.2	Result Analysis . . . . .	105
6.4	Conclusions and Future Work . . . . .	109

## Table of Contents

---

<b>7</b>	<b>A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement</b>	<b>111</b>
7.1	Introduction . . . . .	113
7.2	Related Work . . . . .	116
7.2.1	Global Enhancement Methods . . . . .	116
7.2.2	Local Enhancement Methods . . . . .	116
7.2.3	Image Fusion . . . . .	117
7.3	The Proposed Method . . . . .	118
7.3.1	Global Contrast Adaptive Enhancement . . . . .	118
7.3.2	Local Contrast Adaptive Enhancement . . . . .	122
7.3.3	A Variational Method for Fusion via Contrast Optimization and Color Correction . . . . .	123
7.3.4	Fusion with other Global Enhancement and Local Enhancement Methods . . . . .	128
7.4	Experiments and Comparisons . . . . .	130
7.4.1	Qualitative Comparisons . . . . .	130
7.4.2	Quantitative Comparisons . . . . .	137
7.5	Conclusions . . . . .	138
<b>8</b>	<b>Temporally Consistent Contrast Enhancement for Videos</b>	<b>141</b>
8.1	Introduction . . . . .	143
8.2	Related Work . . . . .	144
8.2.1	Histogram-based Image Enhancement . . . . .	144
8.2.2	Fusion-based Image Enhancement . . . . .	144
8.2.3	Temporally Consistency Video Enhancement . . . . .	146
8.3	The Proposed Method . . . . .	146
8.3.1	Temporally Consistent Global Contrast Adaptive Enhancement . . . . .	147
8.3.2	Local Contrast Adaptive Enhancement . . . . .	150

## Table of Contents

---

8.3.3	Contrast-Brightness-based Fusion . . . . .	150
8.4	Experiments . . . . .	151
8.4.1	Subjective Comparisons . . . . .	151
8.4.2	Objective Comparisons . . . . .	154
8.4.3	Flickering-artifact Comparisons . . . . .	155
8.5	Conclusion . . . . .	156
<b>9</b>	<b>Conclusion</b>	<b>157</b>
9.1	Summary of the Thesis . . . . .	158
9.2	Future Work . . . . .	160
	<b>References</b>	<b>163</b>





# List of Publications

The work done during this Ph.D. thesis lead to the following conference papers and journal papers.

## Peer-reviewed Conference Papers

1. **Qi-Chong Tian** and Laurent D. Cohen. "Global and Local Contrast Adaptive Enhancement for Non-Uniform Illumination Color Images", *International Conference on Computer Vision Workshops (ICCV'17 Color and Photometry in Computer Vision Workshop)*, IEEE, pp.3023-3030. October 2017, Venice, Italy.

2. **Qi-Chong Tian** and Laurent D. Cohen. "Naturalness Preservation Image Contrast Enhancement via Histogram Modification", *the Ninth International Conference on Graphic and Image Processing (ICGIP'17)*, SPIE, Vol 10615, pp.106152U. October 2017, Qingdao, China.

3. **Qi-Chong Tian** and Laurent D. Cohen. "Color Consistency for Photo Collections without Gamut Problems", *the 23rd International Conference on Multimedia Modeling (MMM'17)*, LNCS, Vol 10132, pp.90-101. January 2017, Reykjavic, Iceland.

4. **Qi-Chong Tian** and Laurent D. Cohen. "Color Correction in Image Stitching Using Histogram Specification and Global Mapping", *the 6th International Conference on Image Processing Theory, Tools and Applications (IPTA'16)*, IEEE, pp.1-6. December 2016, Oulu, Finland.

## Peer-reviewed Journal Papers

5. **Qi-Chong Tian** and Laurent D. Cohen. "A variational-based fusion model for non-uniform illumination image enhancement via contrast optimization and color correction", *Signal Processing*, Vol 153, pp. 210-220, December 2018.

6. **Qi-Chong Tian** and Laurent D. Cohen. "Histogram-based Color Transfer for Image Stitching", *Journal of Imaging*, 3(3), Article 38. September 2017.

## Manuscripts Under Preparation

7. **Qi-Chong Tian** and Laurent D. Cohen. "A Flicker-free Temporally Consistent Enhancement Method for Improving Video Contrast".

# Notations

$\Omega$	image domain, an open subset of $\mathbb{R}^2$ , $\Omega \subset \mathbb{R}^2$
$\mathbf{I}$	a color image, a vector-valued function $\mathbf{I} : \Omega \subset \mathbb{R}^3$
$I$	a gray-scale image, an integrable function $I : \Omega \subset \mathbb{R}$
$I_r$	the red channel of a color image $\mathbf{I}$
$I_g$	the green channel of a color image $\mathbf{I}$
$I_b$	the blue channel of a color image $\mathbf{I}$
$\mathbf{x}$	a position of a pixel in the image domain $\mathbf{x} \subset \Omega$
$k$	a gray-scale value of a pixel, $k \in [0, 1, \dots, 255]$ for 8-bit images
$T$	a transform function between two gray-scale images
$h$	a normalized histogram of a gray-scale image
$g_\sigma$	a Gaussian function, $\sigma$ controls the Gaussian kernel
$\Psi_\varepsilon$	a non-linear function, $\varepsilon$ is a small constant
$\tau$	a time step in a numerical method for variational minimization
$t$	a iteration index in a numerical method for variational minimization
$\mathbf{t}$	a frame index in a video
$\nabla$	gradient operator,



# Introduction en Français

## Contexte et motivation

Avec le développement rapide des dispositifs d'imagerie numérique, il est très commode d'obtenir des images. Parmi ces images, les images en couleurs naturelles sont le type le plus commun. Ce genre d'images est produit avec des appareils photos numériques et est apparu dans beaucoup d'applications, telles que la photographie, les médias sociaux, et les programmes de télévision. Ces images sont théoriquement capables de répliquer des scènes réelles. Cependant, elles sont souvent différentes des scènes réelles à cause des angles de capture variables, des différents dispositifs d'imagerie, des paramètres des caméras ou des conditions d'éclairages différentes. La Fig. 1.1 montre un exemple de différence de couleur entre deux images d'une même scène. Ces deux images sont obtenues avec différents angles de capture et différentes conditions d'éclairage. Puisqu'il y a une différence de couleur entre ces deux images, les applications de ces images sont limitées. Afin de traiter ce problème, la correction de couleur est nécessaire pour traiter ces images et leurs incohérences de couleur. Après correction des couleurs, les images considérées pourraient avoir des styles de couleur similaire. Ensuite, les images corrigées peuvent être utilisées dans certaines applications de vision par ordinateur.

A partir d'albums de photos en ligne ou des réseaux sociaux, nous pouvons facilement obtenir des milliers de photos des mêmes scènes, en particulier pour les monuments célèbres. Et ces types de collections de photos ont été utilisées pour résoudre des problèmes de vision

par ordinateur de haut niveau, y compris pour les photos de scènes touristiques [120], la reconnaissance de monuments [46] et la recherche d'images par le contenu [70]. Toutefois, ces images en ligne sont généralement prises avec des appareils ayant différents paramètres ou avec des éclairages différents, c'est pourquoi il y a différents styles de couleurs dans une même collection de photos. La Fig. 1.2 montre un exemple de différence de couleur entre quatre images d'un même album photo. Afin d'obtenir de meilleurs résultats pour les applications mentionnées ci-dessus de vision par ordinateur, la cohérence de couleur ou la correction de couleur est une procédure de prétraitement essentielle avant la mise en œuvre des algorithmes principaux. La méthode de correction de couleur la plus simple est la technique automatique d'ajustement de couleur [114], qui est mise en application dans la plupart des outils commerciaux d'édition de photo. Toutefois, ce type de méthode effectue la correction de couleur pour chaque image indépendamment et ne considère pas de relation entre les distributions de couleurs de toutes les images dans la même collection. Un autre type de méthode est de régler manuellement toutes les images par des photographes professionnels, ce qui nécessite une quantité importante de temps de traitement pour un grand nombre de photos. Afin de produire une cohérence de couleur parmi ces images et d'éviter les inconvénients des méthodes traditionnelles de correction de couleur, une méthode appropriée de correction de couleur est proposée dans cette thèse.

Pour les images naturelles, la couleur est un indicateur important pour décrire les scènes. En outre, le contraste des images considérées est également très important pour exprimer les informations structurelles de la scène. Certaines images ne sont généralement pas bonnes en termes de contraste parce que ces images sont capturées dans des conditions d'éclairage médiocres, par des caméras de faible qualité ou avec des paramètres incorrects. La Fig. 1.3 montre le faible contraste de certaines images en couleur. L'amélioration du contraste est une sorte de méthode d'amélioration de l'image qui consiste à améliorer le contraste et la visibilité des images considérées. Elle rend les images considérées plus claires et ainsi l'amélioration du contraste de l'image fonctionne comme une technique de prétraitement très importante dans

---

quelques applications de vision d'ordinateur. Il y a beaucoup de genres différents de méthodes [41, 107, 81] ayant été proposées pour l'amélioration de contraste d'image. Une approche basée sur l'histogramme est un type très populaire de méthode d'amélioration. Beaucoup d'algorithmes d'amélioration du contraste basés sur l'histogramme, y compris les méthodes globales et les méthodes locales, nécessitent généralement de sélectionner les paramètres avec soin faute de quoi cela entraîne des problèmes de sur-amélioration. Pour éviter ces problèmes, une méthode d'amélioration du contraste basée sur l'histogramme et préservant l'aspect naturel des images est proposée dans cette thèse.

Les images capturées dans un environnement d'illumination uniforme peuvent être bien améliorées en termes d'amélioration du contraste. Cependant, la plupart des algorithmes d'amélioration ne parviennent pas à traiter des images avec des éclairages non uniformes. Certaines méthodes existantes [151, 122, 10, 54] soit sous-accentuent les régions sombres, soit sur-améliorent les régions lumineuses des images. En général, les méthodes d'amélioration sont classées en deux catégories: les algorithmes d'amélioration globale et les algorithmes d'amélioration locale. Habituellement, les méthodes d'amélioration globale produisent des résultats de sur-amélioration dans les régions lumineuses des images. Les algorithmes d'amélioration locale obtiennent des résultats de sous-amélioration dans les régions sombres des images. Un exemple est montré dans la Fig. 1.4, à partir de laquelle nous pouvons voir que la méthode d'amélioration globale sur-améliore les régions lumineuses et la méthode locale sous-améliore les régions sombres. Afin de faire face à ce problème, nous devons développer une méthode d'amélioration plus appropriée pour ce genre d'images.

L'amélioration de contraste vidéo est une autre question que l'on examinera dans cette thèse. L'incohérence temporelle des couleurs ou l'incohérence lumineuse peuvent apparaître si certains algorithmes d'amélioration de contraste d'image sont appliqués directement pour le traitement des vidéos. Puisque les méthodes d'amélioration de contraste d'image ne tiennent pas compte des relations entre les images dans les vidéos, la consistance de couleur et la consistance lumineuse ne sont pas assurées. Un exemple est illustré à la Fig. 1.5. Nous



pouvons facilement observer que l'incohérence temporelle apparaît dans les résultats améliorés. Pour éviter ces inconvénients, une méthode spécifique d'amélioration de contraste vidéo est considérée dans cette thèse.

## Contributions de cette thèse

Le but de cette thèse est de développer des méthodes de correction de couleurs pour les images naturelles et de concevoir des algorithmes d'amélioration des contrastes pour des images et des vidéos naturelles.

La contribution de cette thèse est résumée ci-dessous.

### Correction de couleur basée sur un histogramme pour la couture d'images

Nous avons proposé une méthode efficace de transfert de couleurs pour la couture d'images, qui combine les idées de la spécification d'histogramme et de transformation globale [125, 128]. La principale contribution de la méthode proposée consiste à utiliser les pixels originaux et les pixels correspondants après la spécification de l'histogramme pour calculer une fonction de transformation globale avec une méthode itérative qui peut réduire efficacement les différences de couleur entre une image référence et une image de test. La fonction de transformation des couleurs peut bien répandre le style de couleur de la région de chevauchement à l'image entière. Les expériences montrent également les avantages de notre algorithme en termes d'évaluation objective et d'évaluation subjective.

### Cohérence des couleurs sans problèmes de gamme

Nous avons proposé une approche de cohérence des couleurs pour les collections d'images, basée sur la spécification d'histogramme, et préservant les gammes de couleurs [126]. Cette méthode peut s'appliquer à toute la collection d'images pour partager le même style de couleur et ne pas provoquer de problèmes de gamme. Les principales contributions de notre travail sont

---

de réduire les effets des images de mauvaises qualités visuelles à l'ensemble de la collection d'images basée sur de la méthode d'évaluation de la qualité des images hors référence et de trouver des histogrammes cibles appropriés pour les spécifications d'histogramme préservant une plage d couleurs. Les expériences démontrent que la méthode proposée surpasse l'algorithme comparé en termes de cohérence des couleurs et évite les problèmes de gamme.

### **Une méthode globale d'amélioration du contraste préservant l'aspect naturel**

Nous avons proposé une méthode d'amélioration automatique de contraste préservant l'aspect naturel des images [129]. Les principales contributions de cette méthode sont : (a). définition de la somme pondérée de l'histogramme d'origine, de l'histogramme uniforme et de l'histogramme en forme de Gaussienne comme histogramme cible optimal pour l'amélioration du contraste. (b). en utilisant la mesure de la structure et la mesure de naturel statistique pour déterminer les paramètres optimaux. La méthode proposée considère le compromis entre l'amélioration du contraste et la préservation du naturel.

### **Méthode variationnelle pour un Modèle de fusion pour l'amélioration du contraste**

Nous avons proposé une méthode variationnelle pour un modèle de fusion pour l'amélioration d'images de luminosité non uniforme par l'optimisation du contraste et la correction des couleurs. Notre méthode a trois principales contributions. Tout d'abord, une méthode d'amélioration adaptative de contraste global est introduite pour améliorer le contraste global. Deuxièmement, un cadre de préservation de la teinte est pris en compte dans l'amélioration globale et l'amélioration locale. Troisièmement, une méthode de fusion d'images basée sur une méthode variationnelle est développée pour obtenir des images finales améliorées. Les expériences montrent que la méthode proposée surpasse les autres méthodes d'amélioration en termes de comparaisons visuelles et d'évaluations objectives d'un critère.

### Amélioration temporellement cohérente de la vidéo

Nous avons proposé une méthode d'amélioration adaptative temporellement cohérente de contraste pour les vidéos. Il y a trois principales contributions de notre méthode. Premièrement, une méthode d'amélioration temporellement cohérente est proposée pour améliorer de manière adaptative le contraste global. Deuxièmement, une méthode de fusion d'images basée sur la luminosité contrastée est développée pour obtenir des images finales améliorées. Les expériences montrent que la méthode proposée surpasse les autres méthodes d'amélioration en termes de comparaisons visuelles, d'évaluations objectives et de problèmes de scintillement.

### Résumé de cette thèse

Cette thèse est divisée en deux parties. La partie I comprend les chapitres 2-4. La partie II couvre les chapitres 5-8. Le chapitre 1 présente les antécédents, les motivations, la contribution et le cadre de cette thèse. Le chapitre 2 donne un bref aperçu des méthodes de correction des couleurs. Le chapitre 3 propose une méthode de correction des couleurs pour la couture d'images en utilisant la spécification d'histogramme et une transformation globale. Le chapitre 4 propose une méthode de cohérence des couleurs pour les collections de photos, basée sur l'évaluation de la qualité de l'image et la spécification de l'histogramme préservant la plage de couleurs. Le chapitre 5 résume les méthodes d'amélioration du contraste d'image. Le chapitre 6 propose une méthode globale d'amélioration du contraste préservant l'aspect naturel des images. Le chapitre 7 propose une méthode variationnelle de fusion pour l'amélioration d'images d'illumination non uniforme par l'optimisation du contraste et la correction des couleurs. Le chapitre 8 propose une méthode temporellement cohérente d'amélioration du contraste vidéo. Le chapitre 9 conclut cette thèse et décrit les travaux futurs.

- **Le chapitre 1** présente les travaux antérieurs, les motivations, la contribution et le cadre de cette thèse.

- 
- **Le chapitre 2** donne un bref aperçu des méthodes de correction des couleurs. La correction des couleurs est l'une des techniques les plus importantes et les plus exigeantes en matière de recherche en traitement d'images et pour les systèmes d'imagerie couleur grand public. Puisque ce type de méthode est capable d'améliorer la qualité visuelle des images en couleur, elle a reçu une attention considérable au cours des dernières décennies. Elle a été largement appliquée à la fois dans les projets de recherche académique et les produits industriels. Dans ce chapitre, nous examinons simplement la correction des couleurs qui permet aux lecteurs de comprendre rapidement le travail pertinent. Tout d'abord, nous introduisons les antécédents de l'imagerie couleur et indiquons l'importance de la correction des couleurs. Deuxièmement, nous résumons quelques fondamentaux à propos des couleurs, y compris le système visuel humain, l'espace colorimétrique RGB, les caractéristiques des couleurs et la correction des couleurs. Ensuite, trois types de méthodes de correction des couleurs sont résumées, tels que des méthodes basées sur la géométrie, des algorithmes basés sur des statistiques et des approches guidées par l'utilisateur. Certaines applications pertinentes de correction des couleurs sont également données pour indiquer l'utilisation de ce type de technique. Enfin, nous concluons ce chapitre.
  - **Le chapitre 3** propose une méthode de correction des couleurs pour la couture d'images. L'incohérence des couleurs existe souvent entre les images à combiner et réduira la qualité visuelle des résultats de cette couture. Le transfert de couleur joue un rôle important dans la couture d'image. Ce type de technique peut produire des images corrigées qui sont de couleur cohérente. Ce chapitre présente une approche de transfert de couleur via la spécification d'histogramme et une transformation globale. L'algorithme proposé peut proposer des images partageant le même style de couleur et obtenir de la cohérence dans les couleurs. Il y a quatre étapes principales dans cet algorithme. Tout d'abord, on cherche les régions qui se chevauchent entre une image de référence et une image test. Deuxièmement, une spécification d'histogramme exacte est effectuée

pour la région qui se chevauche dans l'image de test à l'aide de l'histogramme de la région de chevauchement dans l'image de référence. Troisièmement, une fonction de transformation globale est obtenue en minimisant les différences de couleurs avec une méthode itérative. Enfin, la fonction de transformation globale est appliquée à l'image de test entière pour produire une image corrigée des couleurs. Des données synthétiques et des données réelles sont testées. Les expériences démontrent que l'algorithme proposé surpasse les méthodes comparées quantitativement et qualitativement.

- **Le chapitre 4** présente une technique de cohérence des couleurs afin que des images d'une même collection partagent le même style de couleur et que cela évite les problèmes de gamme. Certaines méthodes plus anciennes définissent des modèles globaux simples basés sur des paramètres et utilisent des algorithmes d'optimisation pour obtenir des paramètres inconnus, ce qui provoque généralement des problèmes de gamme dans les régions claires et sombres. Notre méthode est basée sur la spécification d'histogramme de préservation de la portée et peut appliquer des images pour partager le même style de couleur, sans entraîner de problèmes de gamme. Nous divisons les images d'entrée en deux ensembles ayant respectivement une qualité visuelle élevée et une qualité visuelle faible. Les images de haute qualité visuelle sont utilisées pour faire l'équilibre des couleurs. Ensuite les images de qualité visuelle faible sont transférées en couleur à l'aide des images corrigées précédentes de haute qualité. Nos expériences indiquent que cette méthode de correction des couleurs basée sur l'histogramme est meilleure que l'algorithme comparé.
- **Le chapitre 5** résume les méthodes d'amélioration du contraste d'image. L'amélioration du contraste est une sorte de méthode d'amélioration de l'image pour améliorer le contraste et la visibilité des images considérées. Cette technique est l'une des tâches les plus importantes et les plus stimulantes dans le traitement de l'image et les systèmes d'imagerie grand public. Dans ce chapitre, nous donnons une revue simple de l'amélioration de contraste d'image, qui permet aux lecteurs de comprendre rapide-

---

ment les travaux similaires. Tout d'abord, nous introduisons les travaux antérieurs de l'amélioration de contraste d'image. Deuxièmement, nous résumons trois types d'amélioration du contraste approché, y compris les méthodes basées sur l'histogramme, les méthodes Retinex, et les méthodes basées sur l'apprentissage. Ensuite, cinq mesures d'évaluation de la qualité de l'image sont décrites pour mesurer la performance de différents algorithmes. Certaines applications pertinentes de l'amélioration du contraste sont également données pour indiquer l'utilisation de ce type de technique. Enfin, nous concluons ce chapitre.

- **Le chapitre 6** propose une méthode d'amélioration du contraste préservant l'aspect naturel des images. L'amélioration de contraste est une technique importante dans le traitement d'image. Étant donné que de nombreux algorithmes de renforcement des contrastes produisent généralement des résultats surhaussés, la préservation du naturel est nécessaire pour être considérée dans le cadre de l'amélioration du contraste d'image. Ce chapitre propose une méthode d'amélioration de contraste avec préservation de l'aspect naturel qui adopte l'histogramme correspondant pour améliorer le contraste et utilise l'évaluation de la qualité de l'image pour sélectionner automatiquement l'histogramme cible optimal. L'amélioration du contraste et la préservation de la naturalité sont tous deux considérés dans l'histogramme cible, de sorte que cette méthode peut éviter le problème de sur-amélioration. Dans la méthode proposée, l'histogramme cible optimal est une somme pondérée de l'histogramme d'origine, de l'histogramme uniforme et de l'histogramme en forme de Gauss. Ensuite, la métrique structurale et la métrique de naturalité statistique sont utilisées pour déterminer le poids des histogrammes correspondants. Enfin, l'image améliorée par contraste est obtenue par l'intermédiaire de l'histogramme cible optimal.
- **Le chapitre 7** propose une méthode de fusion à base de variations pour l'amélioration de l'éclairage non uniforme d'une image. Ces images sont de visibilité limitée en raison d'une sous-exposition, d'une surexposition ou d'une combinaison des deux.

L'amélioration de ce type d'images est une tâche très difficile dans le traitement d'images. Bien qu'il y ait beaucoup de méthodes d'amélioration pour améliorer la qualité visuelle des images, beaucoup de ces méthodes produisent des résultats indésirables pour l'amélioration du contraste ou l'amélioration de la saturation. Afin d'améliorer la visibilité des images sans suramplification ou sous-amélioration, une méthode de fusion basée sur des variations est proposée. Tout d'abord, un algorithme d'amélioration adaptative de contraste global de préservation de teinte donne une image globalement améliorée. Deuxièmement, une méthode d'amélioration adaptative de contraste local qui préserve la teinte produit l'image localement améliorée. Enfin, le résultat amélioré est obtenu par un modèle de fusion à base de variations avec optimisation du contraste et correction des couleurs. Le résultat amélioré final représente un compromis entre le contraste global et le contraste local et maintient également l'équilibre des couleurs entre l'image globalement améliorée et l'image localement améliorée. Cette méthode produit la qualité visuelle souhaitable en termes d'amélioration de contraste et d'amélioration de saturation.

- **Le chapitre 8** propose une méthode temporellement cohérente d'amélioration du contraste vidéo. L'amélioration vidéo est un travail très difficile qui est une tâche beaucoup plus difficile que l'amélioration de l'image. L'amélioration vidéo vise non seulement à améliorer la qualité visuelle des vidéos, mais aussi empêcher de produire certains problèmes secondaires. Ce n'est pas une bonne solution d'appliquer directement la méthode d'amélioration d'image existante au traitement des vidéos parce que ce genre d'opération peut se traduire par un scintillement des cadres dans la vidéo considérée. Afin d'obtenir des résultats mieux améliorés pour les vidéos, nous avons proposé une méthode temporellement cohérente d'amélioration du contraste. L'idée est tirée du modèle basé sur la fusion évoqué au chapitre 7. Tout d'abord, les images vidéo sont converties de l'espace colorimétrique RGB à l'espace colorimétrique HSV. Ensuite, le canal de luminance de chaque trame est amélioré par la méthode d'amélioration adaptative globale et la méthode d'amélioration adaptative locale. La technique clé est considérée dans la méthode globale

---

puisque les méthodes d'amélioration globales produisent souvent des scintillements quand elles sont employées pour améliorer chaque armature indépendamment. Après cela, un canal de luminance de fusion amélioré est obtenu avec les résultats globaux et les résultats locaux. Enfin, l'image couleur améliorée est produite via la conversion de l'espace colorimétrique HSV-RGB.

- **Le chapitre 9** conclut cette thèse et décrit les travaux futurs.





# Chapter 1

## Introduction

### Contents

---

- 1.1 Background and Motivation . . . . . 2**
- 1.2 Contributions of this Thesis . . . . . 6**
  - 1.2.1 Histogram-based Color Correction for Image Stitching . . . . . 6
  - 1.2.2 Color Consistency without Gamut Problems . . . . . 7
  - 1.2.3 A Global Naturalness Preservation Contrast Enhancement Method . . . . . 7
  - 1.2.4 A Variational-based Fusion Model for Contrast Enhancement . . . . . 7
  - 1.2.5 Temporally Consistent Video Enhancement . . . . . 8
- 1.3 Outline of this Thesis . . . . . 8**

---

### 1.1 Background and Motivation

With the rapid development of digital imaging devices, it is very convenient to obtain images. Among these images, natural color images are the most common type. This kind of images is produced with digital cameras and appears in lots of applications, such as photography, social media, and television programs. These images are theoretically able to describe the information similar to the real scenes. However, they are often different from the real scenes due to the varying capture angles, various imaging devices, individual camera settings, or different illumination conditions. Fig. 1.1 shows an example of the color difference between two images captured in the same scene. These two images are obtained with different capture angles and different illumination conditions. Since there is color difference between these two images, the applications driven from these images are limited. In order to deal with this problem, color correction is needed to process these color inconsistency images. After color correction, the considered images could have the similar color style. And then, the corrected images are able to be used in some computer vision applications.

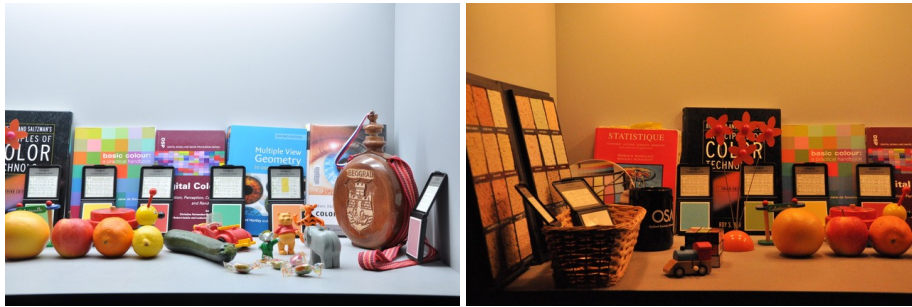


Fig. 1.1 An example of the color difference between two images captured in the same scene.

From online photo albums or social networks, we can easily obtain thousands of photos of the same scenes, especially for the famous landmarks. And these kinds of photo collections have been used in high level computer vision problems, including visual photo tourism [120], scene completion [49], landmark recognition [46], and content-based image retrieval [70]. However, these online images are usually taken with various camera settings or different illuminations,

## 1.1 Background and Motivation

---

which are the reasons for the different color styles in the same photo collection. Fig. 1.2 shows an example of the color difference of four images in the same photo album. In order to obtain better results for the above mentioned interesting computer vision applications, the color consistency or color correction is an essential pre-processing procedure before implementing the main algorithms. The most simple color correction method is the auto color adjustment technique [114], which is implemented in most commercial photo editing tools. However, this kind of method makes the color correction for each image independently, not considering the color distribution relations among all images in the same collection. Another kind of method is manually adjusting all images by professional photographers, which requires a significant amount of processing time for a large number of photos. In order to produce color consistency among these images and avoid the disadvantages of the traditional color correction methods, a suitable color correction method is proposed in this thesis.



Fig. 1.2 An example of the color difference of four images in the same photo album.

For natural images, color is an important indicator for describing the scene information. Besides, the contrast of the considered images is also very important for expressing the structural information of the scene. Some images are usually not good in terms of the contrast

## Introduction

---

information, because these images are captured in poor illumination conditions, by low-quality cameras, or with bad parameter settings. Fig. 1.3 shows the low contrast of some color images. Contrast enhancement is a kind of image enhancement method for improving the contrast and the visibility of the considered images. It makes the considered images more clear, so image contrast enhancement works as a very important pre-processing technique in some computer vision applications. There are many different kinds of methods [41, 107, 81] having been proposed for image contrast enhancement. A histogram-based approach is a very popular kind of enhancement method. Many previous histogram-based contrast enhancement algorithms, including global methods and local methods, usually need to select the parameters carefully or result in over-enhancement problems. To avoid these issues, a naturalness preservation histogram-based contrast enhancement approach is proposed in this thesis.



Fig. 1.3 Low contrast color images.

Images captured in uniform illumination environment can be enhanced well in terms of contrast improvement. However, most of the enhancement algorithms fail to process non-uniform illumination images. Some existing methods [151, 122, 10, 54] either under-enhance dark regions or over-enhance bright regions of images. Generally speaking, enhancement

## 1.1 Background and Motivation

---

methods are categorized into two kinds: global enhancement algorithms and local enhancement algorithms. Usually, global enhancement methods produce over-enhancement results in the bright regions of images. Local enhancement algorithms obtain under-enhancement results in the dark regions of images. An example is shown in Fig. 1.4, from which we can see that the global enhancement method over-enhanced the bright regions and the local method under-enhanced the dark regions. In order to deal with this problem, we need to develop more suitable enhancement method for this kind of images.



Fig. 1.4 Contrast enhancement with a global method and a local method, respectively.

Video contrast enhancement is another issue considered in this thesis. The temporally color inconsistency or bright inconsistency may appear if some image contrast enhancement algorithms are applied directly for processing videos. Since image contrast enhancement methods do not consider the relations among the frames in videos, the color consistency and bright consistency are not ensured. An example is shown in Fig. 1.5. We can easily observe that the temporal inconsistency appears in the enhanced results. To avoid these disadvantages, a specific video contrast enhancement method is considered in this thesis.

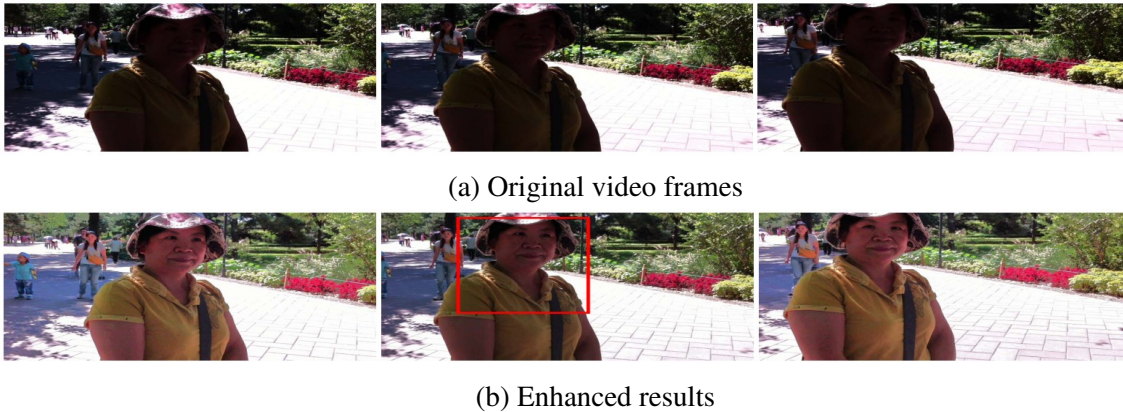


Fig. 1.5 Video enhanced directly by a image contrast enhancement method.

## 1.2 Contributions of this Thesis

The goal of this thesis is to develop color correction methods for natural images, and design contrast enhancement algorithms for natural images and videos.

The contribution of this thesis is summarized below.

### 1.2.1 Histogram-based Color Correction for Image Stitching

We have proposed an efficient color transfer method for image stitching, which combines the ideas of histogram specification and global mapping [125, 128]. The main contribution of the proposed method is using original pixels and the corresponding pixels after histogram specification to compute a global mapping function with an iteration method, which can effectively minimize color differences between a reference image and a test image. The color mapping function can spread well the color style from the overlapping region to the whole image. The experiments also demonstrate the advantages of our algorithm in terms of objective evaluation and subjective evaluation.

### 1.2.2 Color Consistency without Gamut Problems

We have proposed a color consistency approach for image collections, based on range-preserving histogram specification [126]. This method can enforce the same image collection to share the same color style and not to cause gamut problems. The main contributions of our work are reducing the effects of bad visual quality images to the whole image collection based on non-reference image quality assessment method, and finding suitable target histograms for range-preserving histogram specifications. The experiments demonstrate the proposed method outperforms the compared algorithm in terms of color consistency and avoiding gamut problems.

### 1.2.3 A Global Naturalness Preservation Contrast Enhancement Method

We have proposed a naturalness preservation automatic contrast enhancement method [129]. The main contributions of this method are: (a). defining the weighted sum of the original histogram, the uniform histogram and the Gaussian-shaped histogram as the optimal target histogram for contrast enhancement. (b). using the structure measure and the statistical naturalness measure to determine the optimal parameters. The proposed method considers the trade-off between the contrast enhancement and the naturalness preservation.

### 1.2.4 A Variational-based Fusion Model for Contrast Enhancement

We have proposed a variational-based fusion method for non-uniform illumination image enhancement via contrast optimization and color correction [127, 130]. There are three main contributions of our method. Firstly, a global contrast adaptive enhancement method is introduced to improve the global contrast. Secondly, a hue preservation framework is considered in the global enhancement and the local enhancement. Thirdly, a variational-based image fusion method is developed for obtaining final enhanced images. Experiments demonstrate the pro-



posed method outperforms other enhancement methods in terms of subject visual comparisons and objective performance evaluations.

### 1.2.5 Temporally Consistent Video Enhancement

We have proposed a temporally consistent contrast adaptive enhancement method for videos. There are three main contributions of our method. Firstly, a temporally consistent enhancement method is proposed to improve the global contrast adaptively. Secondly, a contrast-brightness-based image fusion method is developed for obtaining final enhanced images. Experiments demonstrate the proposed method outperforms other enhancement methods in terms of subject visual comparisons, objective evaluations, and the flickering problem.

## 1.3 Outline of this Thesis

This thesis is divided into two parts. Part I includes chapters 2-4. Part II covers chapters 5-8. Chapter 1 introduces the backgrounds, motivations, contributes and the outline of this thesis. Chapter 2 gives a brief review of color correction methods. Chapter 3 proposes a color correction method for image stitching using histogram specification and global mapping. Chapter 4 proposes a color consistency method for photo collections, based on image quality assessment and range-preserving histogram specification. Chapter 5 summarizes the methods of improving image contrast. Chapter 6 proposes a naturalness preservation global contrast enhancement method. Chapter 7 proposes a variational-based fusion method for non-uniform illumination image enhancement via contrast optimization and color correction. Chapter 8 proposes a temporally consistent video contrast enhancement method. Chapter 9 concludes this thesis and describes the future work.

- **Chapter 1** introduces the backgrounds, motivations, contributes and the outline of this thesis.

- **Chapter 2** gives a brief review of color correction methods. Color correction is one of the most important and challenging technique in image processing research and consumer color imaging systems. Since this kind of method is able to improve the visual quality of color images, it has received considerable attention in recent decades. It has been widely applied both in academic research projects and industrial products. In this chapter, we give a simple review of color correction, which allows the readers to quickly understand the relevant work. Firstly, we introduce the backgrounds of color imaging and indicate the importance of color correction. Secondly, we summarize some color fundamentals, including the human visual system, the RGB color space, color features, and color correction. Then, three kinds of color correction methods are summarized, such as geometry-based methods, statistical-based algorithms, and user-guided approaches. Some relevant applications of color correction are also given to indicate the use of this kind of technique. Finally, we conclude this chapter.
- **Chapter 3** proposes a color correction method for image stitching. Color inconsistency often exists between the images to be stitched and will reduce the visual quality of the stitching results. Color transfer plays an important role in image stitching. This kind of technique can produce corrected images which are color consistent. This chapter presents a color transfer approach via histogram specification and global mapping. The proposed algorithm can make images share the same color style and obtain color consistency. There are four main steps in this algorithm. Firstly, overlapping regions between a reference image and a test image are obtained. Secondly, an exact histogram specification is conducted for the overlapping region in the test image using the histogram of the overlapping region in the reference image. Thirdly, a global mapping function is obtained by minimizing color differences with an iterative method. Lastly, the global mapping function is applied to the whole test image for producing a color-corrected image. Both the synthetic dataset and real dataset are tested. The experiments demonstrate that

the proposed algorithm outperforms the compared methods both quantitatively and qualitatively.

- **Chapter 4** presents a color consistency technique in order to make images in the same collection share the same color style and to avoid gamut problems. Some previous methods define simple global parameter-based models and use optimizing algorithms to obtain the unknown parameters, which usually cause gamut problems in bright and dark regions. Our method is based on the range-preserving histogram specification and can enforce images to share the same color style, without resulting in gamut problems. We divide the input images into two sets having respectively high visual quality and low visual quality. The high visual quality images are used to make color balance. And then the low visual quality images are color transferred using the previous corrected high-quality images. Our experiments indicate that such histogram-based color correction method is better than the compared algorithm.
- **Chapter 5** summarizes the methods of improving image contrast. Contrast enhancement is a kind of image enhancement method for improving the contrast and the visibility of the considered images. This technique is one of the most important and challenging tasks in image processing research and consumer imaging systems. In this chapter, we give a simple review of image contrast enhancement, which lets the readers to quickly understand the relevant work. Firstly, we introduce the backgrounds of image contrast enhancement. Secondly, we summarize three kinds of contrast enhancement approached, including histogram-based methods, retinex-base methods, and learning-based methods. Then, five image quality assessment metrics are described for measuring the performance of different algorithms. Some relevant applications of contrast enhancement are also given to indicate the use of this kind of technique. Finally, we conclude this chapter.
- **Chapter 6** proposes a naturalness preservation global contrast enhancement method. Contrast enhancement is an important technique in image processing. Since many

existing contrast enhancement algorithms usually produce over-enhanced results, the naturalness preservation is needed to be considered in the framework of image contrast enhancement. This chapter proposes a naturalness preservation contrast enhancement method, which adopts the histogram matching to improve the contrast and uses the image quality assessment to automatically select the optimal target histogram. The contrast improvement and the naturalness preservation are both considered in the target histogram, so this method can avoid the over-enhancement problem. In the proposed method, the optimal target histogram is a weighted sum of the original histogram, the uniform histogram, and the Gaussian-shaped histogram. Then the structural metric and the statistical naturalness metric are used to determine the weights of corresponding histograms. At last, the contrast-enhanced image is obtained via matching the optimal target histogram.

- **Chapter 7** proposes a variational-based fusion method for non-uniform illumination image enhancement. Non-uniform illumination images are limited visibility due to under-exposure, over-exposure, or a combination of them. Enhancement of this kind of images is a very challenging task in image processing. Although there are lots of enhancement methods to improve the visual quality of images, many of these methods produce undesirable results in the aspect of contrast improvement or saturation improvement. In order to improve the visibility of images without over-enhancement or under-enhancement, a variational-based fusion method is proposed for adaptively enhancing the non-uniform illumination images. Firstly, a hue-preserving global contrast adaptive enhancement algorithm obtains the globally enhanced image. Secondly, a hue-preserving local contrast adaptive enhancement method produces the locally enhanced image. Finally, the enhanced result is obtained by a variational-based fusion model with contrast optimization and color correction. The final enhanced result represents a trade-off between global contrast and local contrast, and also maintains the color balance between the globally

enhanced image and the locally enhanced image. This method produces the desirable visual quality in terms of contrast improvement and saturation improvement.

- **Chapter 8** proposes a temporally consistent video contrast enhancement method. Video enhancement is a very challenging work, which is a much more difficult task than image enhancement. Video enhancement is aimed to not only improve the visual quality of videos but also do not produce some side problems. It is not a good solution to directly apply the existing image enhancement method to processing video frames one by one. Because this kind of operation maybe results in flickering among the frames in the considered video. In order to obtain better-enhanced results for videos, we proposed a temporally consistent contrast enhancement method. The idea is driven from the fusion-based model in chapter 7. Firstly, the video frames are converted from the RGB color space to the HSV color space. Then, the luminance channel of each frame is enhanced by both global adaptive enhancement method and local adaptive enhancement method. The key technique is that temporally consistent is considered in the global method since global enhancement methods often produce flickering when they are used to enhance each frame independently. After that, a fusion enhanced luminance channel is obtained with the global results and the local results. Finally, the enhanced color image is produced via HSV-RGB color space conversion.
- **Chapter 9** concludes this thesis and describes the future work.

# **Part I**

## **Color Correction for Natural Images**



# Chapter 2

## A Simple Review of Color Correction

### Contents

---

2.1	Introduction . . . . .	16
2.2	Color Fundamentals . . . . .	18
2.3	Color Correction Methods . . . . .	26
2.4	Performance Criteria . . . . .	30
2.5	Applications of Color Correction . . . . .	31
2.6	Conclusions . . . . .	34

---



### Abstract

Color correction is one of the most important and challenging technique in image processing research and consumer color imaging systems. Since this kind of method is able to improve the visual quality of color images, it has received considerable attention in recent decades. It has been widely applied both in academic research projects and industrial products. In this chapter, we give a simple review of color correction, which allows the readers to quickly understand the relevant work. Firstly, we introduce the backgrounds of color imaging and indicate the importance of color correction. Secondly, we summarize some color fundamentals, including the human visual system, the RGB color space, color features, and color correction. Then, three kinds of color correction methods are presented, such as geometry-based methods, statistical-based algorithms, and user-guided approaches. Some relevant applications of color correction are also given to indicate the use of this kind of technique. Finally, we conclude this chapter.

### 2.1 Introduction

In the last 60 years, digital image processing has been studied by academic researchers. However, most of these work is focused on gray-scale image processing before inventing the color imaging devices. With the development of digital color imaging devices, more and more researchers paid attention to color image processing, which can be regarded as a dimensional extension problem. Color images are considered as three intensity channels. Each of these three channels is a gray-scale image. An example is shown in Fig. 2.1, which gives the three channels of the considered color image.

In recent two decades, the importance of color image processing has received much attention. Since color images provide more information than gray images, color is a very important cue for computer vision and image processing applications, such as image stitching [118], digital photography [149], video display [29], image retrieval [39], human-computer

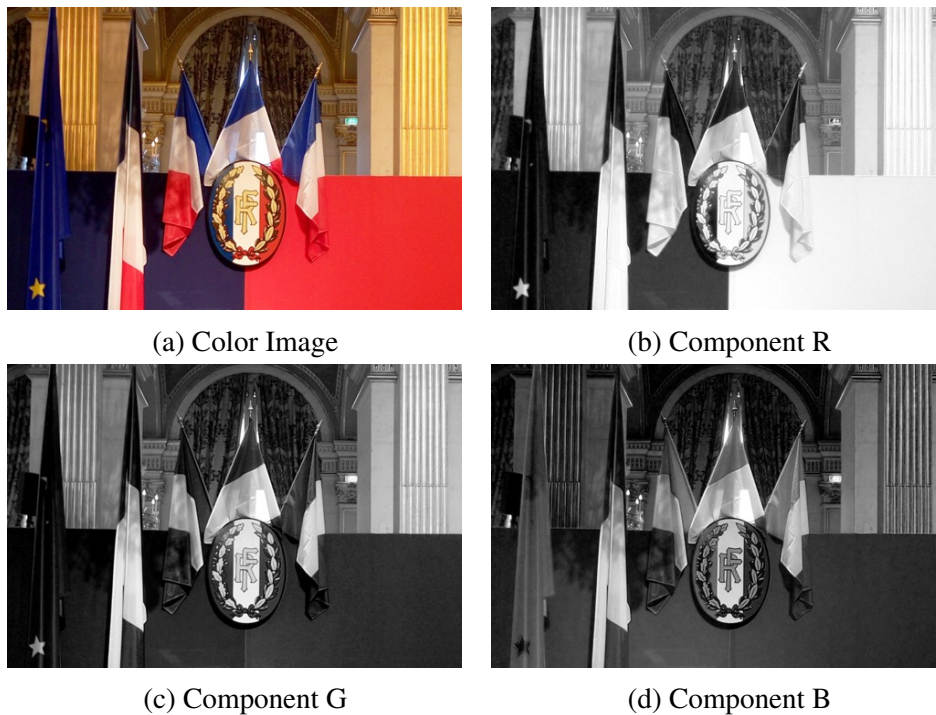


Fig. 2.1 A color image and the corresponding R, G, B component.



Fig. 2.2 An example of image segmentation with color features [109].

interaction [28], landmark recognition [46], image segmentation [109], and time-lapse [78]. The color information is able to provide more help for improving the performance of the above mentioned applications. In Fig. 2.2, we show an example of image segmentation using the RGB color features [109].

Due to the importance of color processing, there are a number of relevant research papers, review papers, or professional technical books address this issue. Trussell et al. [132] gave a basic and special issue overview of color image processing, which helps the signal processing community to better understand the fundamental differences between color image processing

## A Simple Review of Color Correction

---

and gray image processing. Trémeau et al. [131] provided an overview of the recent trends and the future research topics in color image processing. Reinhard et al. [112] published a book focused on the fundamentals and applications of color imaging, which introduces some physical models on color imaging. Recently, Provenzi [105] edited a special issue on the topic of color image processing, which includes color image enhancement, colorization, color transfer, color balancing, color consistency, and so on.

The rest of this chapter is organized as follows. The color fundamentals are given in Section 2.2. The relevant previous work on color correction is summarized in Section 2.3. Some applications with color correction are described in Section 2.4. Finally, we conclude this chapter in Section 2.5.

## 2.2 Color Fundamentals

- **Human Visual System**

The human visual system (HVS) [65, 104] has been considered in lots of computer vision and image processing applications since it helps us to model the way our eyes imaging. Images perceived by human eyes provide more information than images captured by digital devices. There are two components in HVS. The first part is the eye which is similar to the function of a camera. The second component is the brain which is similar to the image processing algorithms. A cross-section of the human eye is shown in Fig. 2.3. The images, perceived by the human eye, depend on the light from the observed objects. When we see an object, the corresponding light firstly passes through the cornea, then subsequently through the aqueous humor, the pupil, the iris, the lens, the vitreous humor, and the retina. In the retina, the light is detected and converted to digital signals by photoreceptors. There are two kinds of photoreceptors, which are rods and cones. Rods perceive gray information. Cones can perceive color information. We can perceive the color difference since there are three kinds of cones which are able to be sensitive to corresponding electromagnetic spectrum. Combining the response of these three

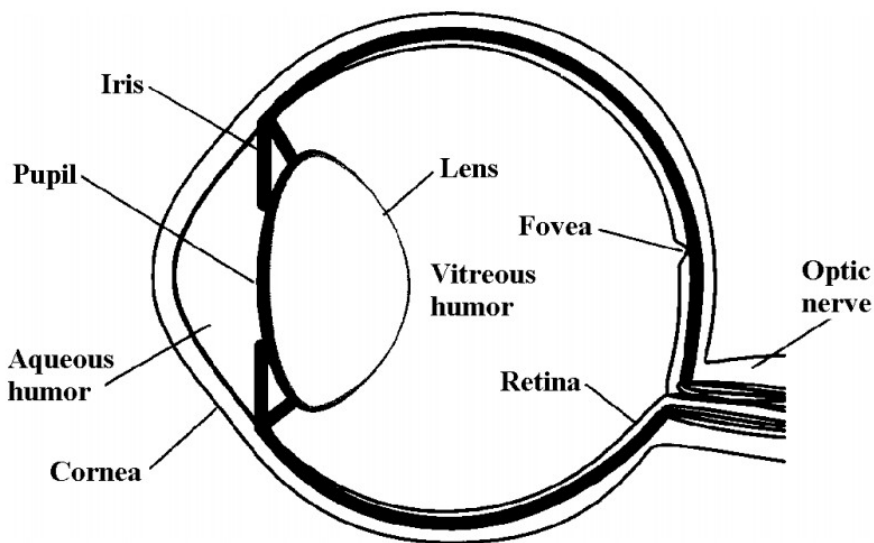


Fig. 2.3 A cross-section of the human eye.

kinds of cones in retina, any type of color is able to distinguished by human eyes. This kind of human visual system is simulated by digital imaging devices, which use three kinds of color (Red, Green, and Blue) to build any other color.

### • RGB Color Space

In digital image processing, RGB color space is the most popular color space for representing color images. Each pixel is represented by the intensities of the red (R), the green (G), and the blue (B) primary. The CIE (French: Commission Internationale de l'Éclairage, English: International Commission on Illumination) defined a reference RGB color space, which is widely used in image processing and computer vision. The defined three primaries are monochromatic. These pure primaries are able to generate a number of color by positive summations. Fig. 2.4 shown an example of the three primaries to generate some new colors. For 24 bits color images, we can generate  $2^8 \times 2^8 \times 2^8 = 16,777,216$  colors based on the three primaries. Fig. 2.5 shown an illustration of RGB color space as a 3D cube. In this cube, there are  $256 \times 256 \times 256 = 16,777,216$  points. Each point represents the corresponding color. These huge number of colors can represent most of the colors the human eyes perceived.

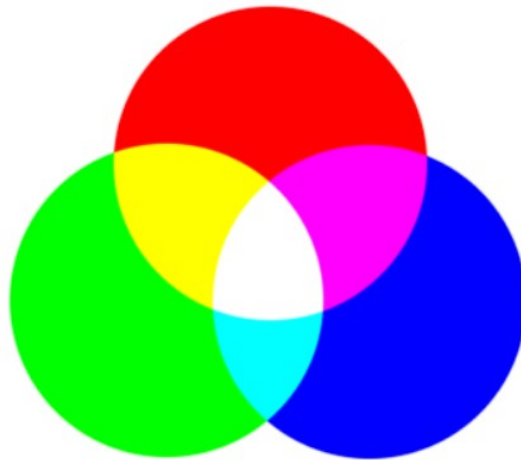


Fig. 2.4 The three primaries of RGB color space.

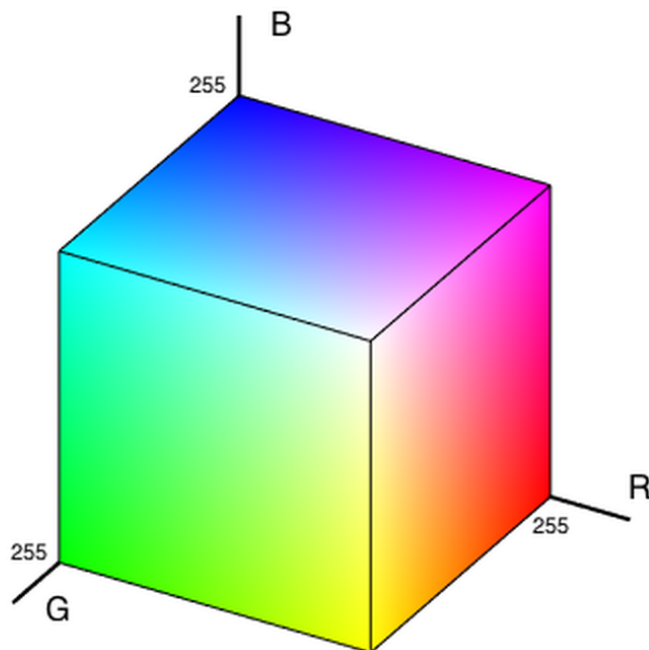


Fig. 2.5 An illustration of RGB color space as a 3D cube.

• HSV Color Space

To make the color representation intuitive, colors may be ordered along the three independent dimensions (hue, saturation, and lightness channels). For the device-dependent color display, there are several kinds of color spaces. When the lightness channel is replaced by value channel, the corresponding color space is HSV color space [55]. This color space is commonly applied in color image processing techniques. Given a RGB color image, (R,G,B) are the values of the three channels. *max* and *min* denote the maximum and minimum of (R,G,B). The conversion between RGB and HSV is given by

$$V = \max, \tag{2.1}$$

$$S = \begin{cases} 0 & \text{if } V = 0, \\ \frac{(V-\min)}{V} & \text{if } V > 0, \end{cases} \tag{2.2}$$

$$H = \begin{cases} 0 & \text{if } S = 0, \\ 60 \frac{(G-B)}{\max-\min} & \text{if } (R = \max \ \& \ G \geq B), \\ 60 \frac{(G-B)}{\max-\min} + 360 & \text{if } (R = \max \ \& \ G < B), \\ 60 \frac{(B-R)}{\max-\min} + 120 & \text{if } G = \max, \\ 60 \frac{(R-G)}{\max-\min} + 240 & \text{if } B = \max, \end{cases} \tag{2.3}$$

An illustration of HSV color space is shown in Fig. 2.6. In the domain of color image enhancement, the original RGB color image are usually converted to HSV color image. After enhancing the V channel, the enhanced HSV color image is then converted back to RGB color image.

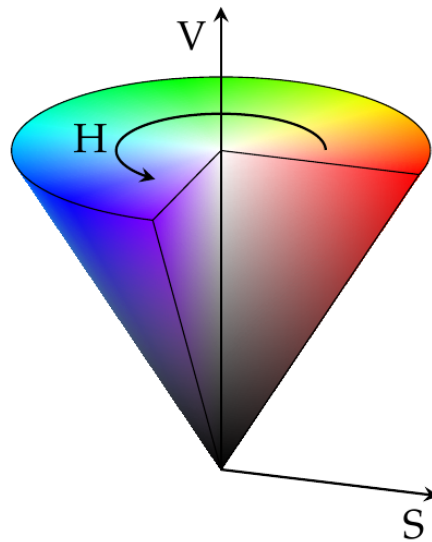


Fig. 2.6 An illustration of HSV color space.

- **Illuminant**

Due to different atmospheric conditions, different time or different light sources, there are also different illumination. The color of an object depends on the spectral power distribution of the light that illuminates the object and the spectral reflectance properties of the considered object. Different kind of illumination could affect the color style of the considered object. Matching the color style of a considered object to a given standard is a problem in academical research and industry applications. The CIE defines a set of specific spectral power distributions (CIE Standard Illuminants) [112]. These standard illuminants can ensure color consistency in measurements. An illuminant is a relative spectral power distribution which may be realizable by a light source. The definition of an illuminant precedes the construction of a light source which is aimed to represent the illuminant. CIE standard illuminants give general types of light sources. CIE Standard Illuminant A is one of these defines. Its spectral power distribution is shown in Fig. 2.7.

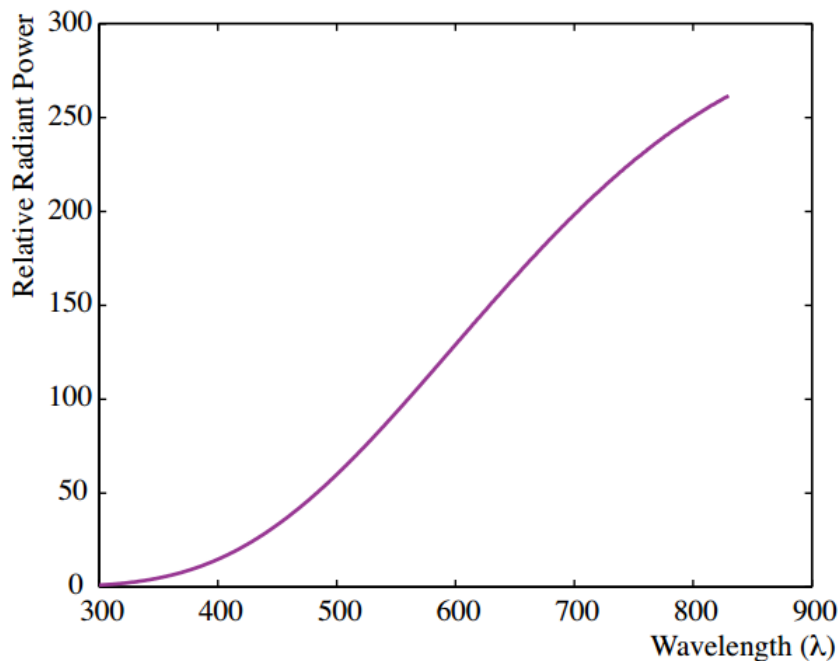


Fig. 2.7 Relative spectral radiant power distribution of CIE standard illuminant A.

- **Color Feature**

Since intensity features provide limited information in image processing and computer vision applications, more and more researchers pay attention to use color features to finish some tasks of image processing. There are some properties of color features: (1). color features are robust to the photometric variation. (2). color features are robust against noises. (3). color features provide more cue than relevant intensity features. There are lots of applications of color features. Fig. 2.8 shown an object detection results by luminance features and color features respectively. We can easily observe the method by color features outperforms the method by luminance features. Gevers and Stokman [40] presented an effective object recognition framework based on histograms derived from photometric color invariants. Hurtu et al. [52] used the spatial organization of colors and the independence relations between pixels to obtain better classification results. Papadakis et al. [92] proposed a variational model for color transfer based on color histograms. Gremontieri and Provenzi [42] presented a computational model to fill lacunae in frescoes based on a variational color perception.



## A Simple Review of Color Correction

---



(a) Results by luminance features



(b) Results by color features

Fig. 2.8 Object detection based on luminance features and color features. [38]

- **Color Correction**

Due to the differences in imaging devices, camera settings or illumination conditions, the captured images usually need to be corrected in term of color. The original captured undesirable color style will affect the performance of other image processing applications. So color correction plays an important role in the domain of image processing and computer vision. Fig. 2.9 gives an example of color correction. We can see that this kind of technique is very helpful to improve the visual results of the considered images.



(a) Image 1



(b) Image 2



(c) Correction for image 2

Fig. 2.9 Color correction



(a) Color cast

(b) Daylight white balance

Fig. 2.10 An example of white balance.

- **White Balance**

White balance is the basic color consistency method [76]. It is aimed to maintain the color style close to an observation under natural light source. Color temperature is a metric for assessing different light sources. It is based on the ratio of the blue light to the red light. Different light sources have corresponding different color temperatures, which will produce different kind of color styles for the same object. White color may be displayed in different color since there are many different color temperatures. Human eye system can easily adjust what is white under different color temperatures. However, the digital camera usually have some difficult to adjust the right white color. In order to remove the unrealistic color casts, white balance algorithms are usually used to finish the task of color consistency. An example of white balance is shown in Fig. 2.10.

- **Histogram Matching**

In image processing, histogram matching is also known as histogram specification or histogram transfer in literature. It is a technique for transferring the original histogram of the considered image to match a specific histogram. Given a test image  $I_1$  and a reference

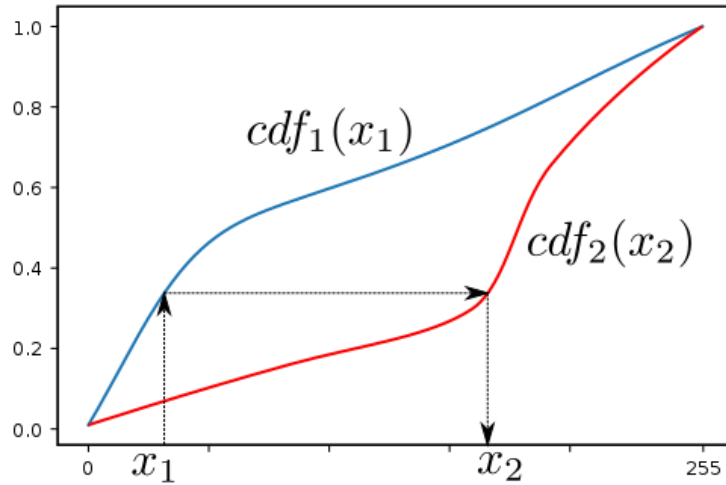


Fig. 2.11 An example of histogram matching.

image  $I_2$ , their histograms are  $h_1$ ) and  $h_2$ . The cumulative distribution of these two histograms are  $cdf_1$  and  $cdf_2$  respectively. We also call  $cdf_1$  and  $cdf_2$  as the cumulative histograms of the image  $I_1$  and  $I_2$ . For each gray level  $x_1 \in [0, 255]$ , we try to find the corresponding gray level  $x_2$ , which meets the condition  $cdf_1(x_1) = cdf_2(x_2)$ . Then, we could obtain the histogram matching function  $T(x_1) = x_2$ . Finally, this matching function  $T$  is applied to the each pixel in the test image  $I_1$ . The result is  $\hat{I}_1$ . The histogram of  $\hat{I}_1$  matches  $h_2$ , which is the histogram of the reference image  $I_2$ . Fig. 2.11 is an example of histogram matching, which shows the cumulative histogram of the test image matches the cumulative histogram of the reference image.

### 2.3 Color Correction Methods

Color correction related methods are called color transfer, color mapping, color balance or color alignment in the literature [145][53][30][31][34]. This kind of technique is aimed to transfer the color style of a reference image to a test image. It can make these images to be color consistent. In this chapter, we focus on the color correction methods for one image using the color style of the other image.

- **Geometry-based methods**

Geometry-based color transfer methods compute the color mapping functions using the corresponding feature points in multiple images. Feature detection algorithms are adopted to obtain the interesting points. Scale-Invariant Feature Transform (SIFT) [74] and Speeded-Up Robust Feature (SURF) [12] are the two most widely used methods for feature point detection. After obtaining the feature points of each image, the correspondences between the considered images are matched using the RANdom SAMple Consensus algorithm (RANSAC), which can remove the outliers efficiently to improve the matching accuracy. Then, the correspondences are used to build a color transfer function via minimizing the color difference between the corresponding feature points. Finally, this transfer function is applied to the target image to produce the color transferred image. An example of a geometry-based color correction method is shown in Fig. 2.12.

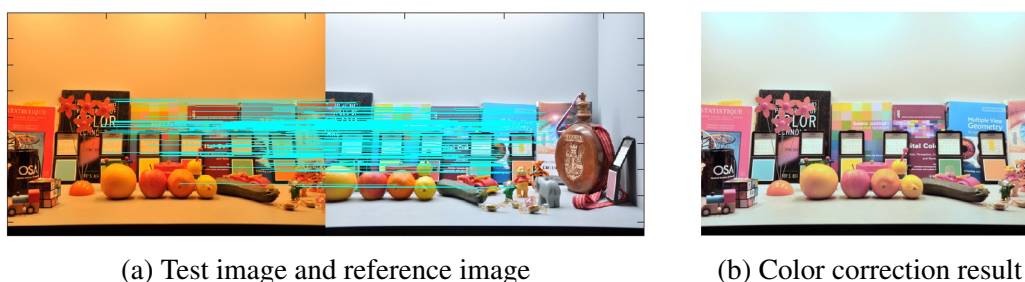


Fig. 2.12 An example of a geometry-based color correction method

Faridul et al. [30] proposed an approximate cross-channel color correction method using sparse color correspondences. This method includes three steps. Firstly, the feature correspondences are obtained by SIFT. They used the colors near to these feature correspondences to generate the color correspondences. Then, a channel-wise and nonlinear color mapping model is robustly computed. Finally, a cross-channel and linear color correction model is estimated. This method is tested on images captured by different cameras, with different parameter settings, and in different illuminations. The experiments demonstrated the efficiency and the robustness of this method.

## A Simple Review of Color Correction

---

HaCohen et al. [44] presented a non-rigid dense correspondence matching method for color correction. This method is designed for pairs of images having similar regions, which are captured by different cameras and under non-rigid transformations. There are four steps of this method. Firstly, for every patch in the test image, the corresponding nearest neighbors in the reference image are searched. Secondly, consistent region aggregation is conducted. Then, A color transformation model is robustly estimated with the reliable consistent regions. Finally, the search range is adjusted, and the above three steps are repeated. This coarse-to-fine framework is able to produce better results than the method via only one iteration. This method is robust to geometric variations and photometric variations, which makes it suitable for color correction in real-world images.

Wang et al. [135] proposed a robust color correction algorithm for stereo images. In this method, firstly, they extract SIFT key-points from the considered two images and obtain the matched pairs with optical flow based SIFT. Secondly, the test image is segmented by mean-shift segmentation method. Then, for each region, they computed its color discrepancy by averaging the color difference between the matched pairs. Instead of applying a global mapping function, this method conducts color correction region by region.

- **Statistical-based methods**

When the feature detection and matching are not available, the geometry-based color transfer cannot work. In this situation, the statistical correlation [103] between the reference image and the test image is used to create the color mapping function, which can transfer the color style of the reference image to the test image and enforce the considered images to share the same color style. An example [50] of a statistical-based color correction method is shown in Fig. 2.13.

Reinhard et al. [110] proposed a simple and traditional statistics-based algorithm to transfer colors between two images, which was also extended by many researchers. This method is able to transfer color styles from one image to the other image in  $l\alpha\beta$  color space. Firstly, they subtract the mean from the data points. Secondly, they scale the data points comprising the synthetic image by factors determined by the respective standard deviations.



Fig. 2.13 An example of a statistical-based color correction method

The resulting data points have standard deviations that conform to the photograph. Then, they add the averages computed for the photograph. Finally, the results are converted to RGB color space.

Papadakis et al. [92] proposed a variational model for color image histogram transfer, which used the energy functional minimization to finish the goal of transferring the image color style and maintaining the image geometry. Hristova et al. [50] presented a style-aware robust color transfer method, which was based on the style feature clustering and the local chromatic adaptation transform. Frigo et al. [35] proposed an example-based color transfer method using optimal transportation. They use an example-based chromatic adaptation transform to obtain illuminant matching and generate a transfer mapping with optimal transportation.

- **User-guided methods**

When the feature matching information and the statistical information of the considered images are both difficult to be obtained, it is essential to adopt user-guided methods to create the correspondences and use them to build the color transfer mapping function. Color swatch based algorithm [140] is related to the construction of the correspondences between the considered images. The color mapping function is obtained from swatched regions in one image and can be applied to the corresponding regions in the other image. The transfer function between images can be also obtained from a set of strokes [141], which are user-defined by painting on the considered images. Then, the transfer function can be computed via different minimization approaches. An example [141] of a user-guided color correction method is shown in Fig. 2.14.



(a) Strokes on the test image    (b) Strokes on the reference image    (c) Color correction result

Fig. 2.14 An example of a user-guided color correction method

## 2.4 Performance Criteria

The quality of the color corrected images can be assessed in many aspects. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [139] are the most popular metrics to assess image quality and compare the performance of different algorithms. In this thesis, we use the metric PSNR to measure the pixel value fidelity, and use the metric SSIM to measure the structure fidelity.

Given a test image  $A$  and a reference image  $B$ , the PSNR is obtained via

$$PSNR(A, B) = 10 \times \log_{10} \left( \frac{L^2}{MSE(A, B)} \right), \quad (2.4)$$

$$MSE(A, B) = \frac{1}{m \times n} \sum_{i=1}^m \sum_{j=1}^n (A(i, j) - B(i, j))^2,$$

where  $L=255$  for 8 bits images,  $m$  and  $n$  are the height and width of the considered images.

The SSIM is computed by

$$SSIM(A, B) = \frac{1}{N} \sum_{i=1}^N SSIM(a_i, b_i), \quad (2.5)$$

where  $N$  is the number of local windows for the considered images, and  $a_i, b_i$  are the image contents at the  $i$  th local window of the image  $A$  and  $B$  respectively. SSIM is defined as a

combination of luminance, contrast and structure components. The detailed computation of  $SSIM(a_i, b_i)$  is described by

$$SSIM(a, b) = [l(a, b)]^\alpha \times [c(a, b)]^\beta \times [s(a, b)]^\gamma, \quad (2.6)$$

where  $l(a, b) = \frac{2\mu_a\mu_b + C_1}{\mu_a^2 + \mu_b^2 + C_1}$ ,  $c(a, b) = \frac{2\sigma_a\sigma_b + C_2}{\sigma_a^2 + \sigma_b^2 + C_2}$ ,  $s(a, b) = \frac{\sigma_{ab} + C_3}{\sigma_a\sigma_b + C_3}$ ,  $\mu_a$  and  $\mu_b$  are the mean luminance values of the windows  $a$  and  $b$ , respectively,  $\sigma_a$  and  $\sigma_b$  are the standard variance of the windows  $a$  and  $b$ , respectively,  $\sigma_{ab}$  is the auto-covariance between the windows  $a$  and  $b$ ,  $C_1, C_2, C_3$  are small constants to avoid divide-by-zero error, and  $\alpha, \beta, \gamma$  are constants controlling the weight among the three components. The default settings recommended in [139] are:  $C_1 = (0.01L)^2, C_2 = (0.03L)^2, C_3 = \frac{C_2}{2}, L = 255, \alpha = \beta = \gamma = 1$ . The higher the value of SSIM the more similar the structure between the test image and the reference image.

## 2.5 Applications of Color Correction

- **Photography**

With the development of digital imaging devices, we are able to easily capture color images. However, these images are usually not satisfying resulting from the limitation of cameras, illuminations, or parameter settings. To deal with this problem, there are lots of color correction methods to improve the image visual quality, which makes the photo to be more colorful. Fig. 2.14 can be regarded as the color correction applied in photography. Another example [23] of color correction applied in photography is shown in Fig. 2.15. From these figures, we can observe that color correction method makes the original image to be more colorful and more similar to the real scene. This makes it widely used in the domain of photography.



## A Simple Review of Color Correction

---



(a) Original image

(b) Color correction result

Fig. 2.15 An example of color correction applied in photography

- **Video Display**

There are lots of kinds of display devices. Different display devices need the corresponding color correction methods to maintain and display the right colors. After color correction techniques, videos can be displayed normally in the relevant devices. Otherwise, the colors in the display results are not consistent to the real-world scenes. An example of color correction applied in video display is shown in Fig. 2.16. We can see that the colors have been displayed in the right way.



Fig. 2.16 An example of color correction applied in video display

- **Image Stitching**

Image stitching is the technique for producing a panorama large-size image from multiple small-size images. Generally speaking, there are four main steps of image stitching algorithms. Firstly, we need to detect key points of the considered images. Usually, we detect Scale-Invariant Feature Transform (SIFT) [74] features and find corresponding key points. Secondly, we extract feature descriptors on each key points and match corresponding key points. Thirdly, we use the RANdom SAMple Consensus algorithm (RANSAC) to exclude the outliers and estimate the homography. Finally, we need to warp images and combine two images.

Due to the differences in imaging devices or illumination conditions, these multiple images are usually color inconsistent. This will affect visual results of image stitching. Thus, color correction plays a very important role in image stitching. It can maintain the color consistency and make the panorama be more natural than the results without color correction. Fig. 2.17 shown an example of color correction for image stitching [125]. We can see that this kind of technique is very helpful to improve the visual results of image stitching.

## A Simple Review of Color Correction

---

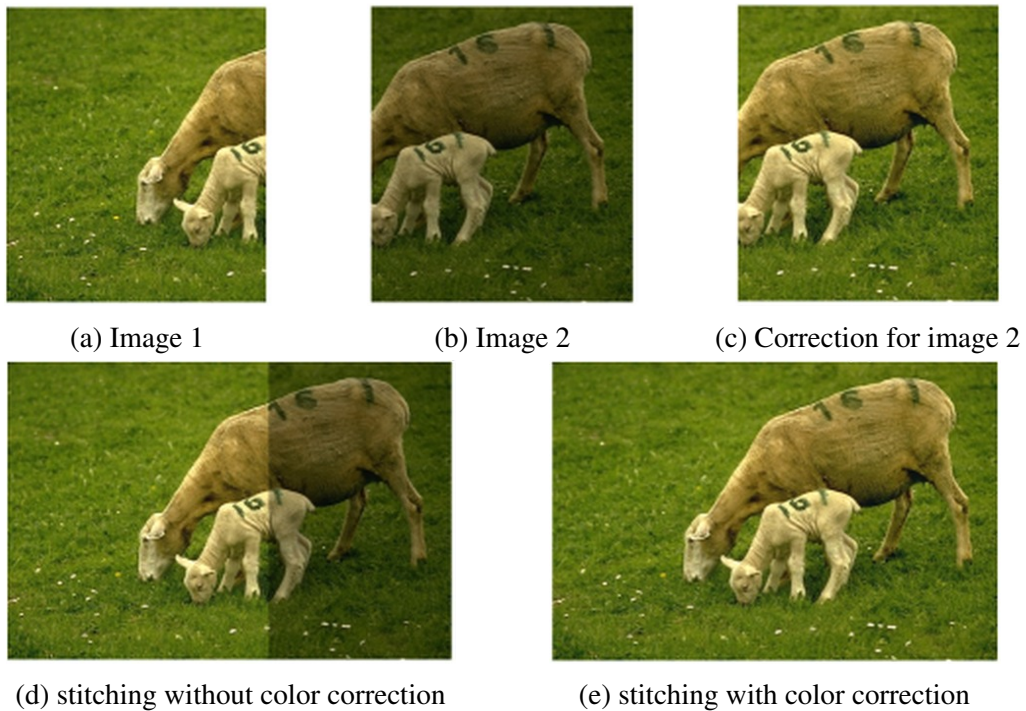


Fig. 2.17 Color correction for image stitching

## 2.6 Conclusions

This chapter simply reviews the relevant work of color correction. We expect that it could make the readers understand the research background easily. From the above sections, readers can quickly know some color fundamentals, several typical color correction methods, and the corresponding applications. This basic knowledge of color correction can be also regarded as a supplementary description of the work in the following chapters.

# Chapter 3

## Histogram-based Color Correction for Image Stitching

### Contents

---

<b>3.1</b>	<b>Introduction</b>	<b>37</b>
<b>3.2</b>	<b>Related Work</b>	<b>39</b>
3.2.1	Motion Models	40
3.2.2	Image Alignment	41
<b>3.3</b>	<b>The Proposed Approach</b>	<b>43</b>
3.3.1	Overview	43
3.3.2	The Detailed Description of This Algorithm	45
<b>3.4</b>	<b>Experiments</b>	<b>49</b>
3.4.1	Test Dataset and Evaluation Metrics	49
3.4.2	Experiments on Synthetic Image Pairs	50
3.4.3	Experiments on Real Image Pairs	54
3.4.4	An Example of Stitching More Than Two Images	57
<b>3.5</b>	<b>Discussion</b>	<b>57</b>

**Histogram-based Color Correction for Image Stitching**

---

---

### Abstract

Color inconsistency often exists between the images to be stitched and will reduce the visual quality of the stitching results. Color correction plays an important role in image stitching. This kind of technique can produce corrected images which are color consistent. This chapter presents a color correction approach via histogram specification and global mapping. This method has been presented in our previous research papers [125, 128]. The proposed algorithm can make images share the same color style and obtain color consistency. There are four main steps in this algorithm. Firstly, overlapping regions between a reference image and a test image are obtained. Secondly, an exact histogram specification is conducted for the overlapping region in the test image using the histogram of the overlapping region in the reference image. Thirdly, a global mapping function is obtained by minimizing color differences with an iterative method. Lastly, the global mapping function is applied to the whole test image for producing a color-corrected image. Both the synthetic dataset and real dataset are tested. The experiments demonstrate that the proposed algorithm outperforms the compared methods both quantitatively and qualitatively.

### 3.1 Introduction

Image stitching [123] is the technique for producing a panorama large-size image from multiple small-size images. Due to the differences in imaging devices, camera parameter settings or illumination conditions, these multiple images are usually color inconsistent. This will affect visual results of image stitching. Thus, color correction plays an important role in image stitching. It can maintain the color consistency and make the panorama be more natural than the results without color correction. In this chapter, we present a color transfer method to achieve the goal of color correction for image stitching.

Color transfer is also known as color correction, color mapping or color alignment in the literature [145, 53, 30, 31, 34, 84]. This kind of technique is aimed to transfer the color style

## Histogram-based Color Correction for Image Stitching

---

of a reference image to a test image. It can make these images to be color consistent. One example is shown in Figure 3.1, from which we can obviously see the effectiveness of color transfer in image stitching.

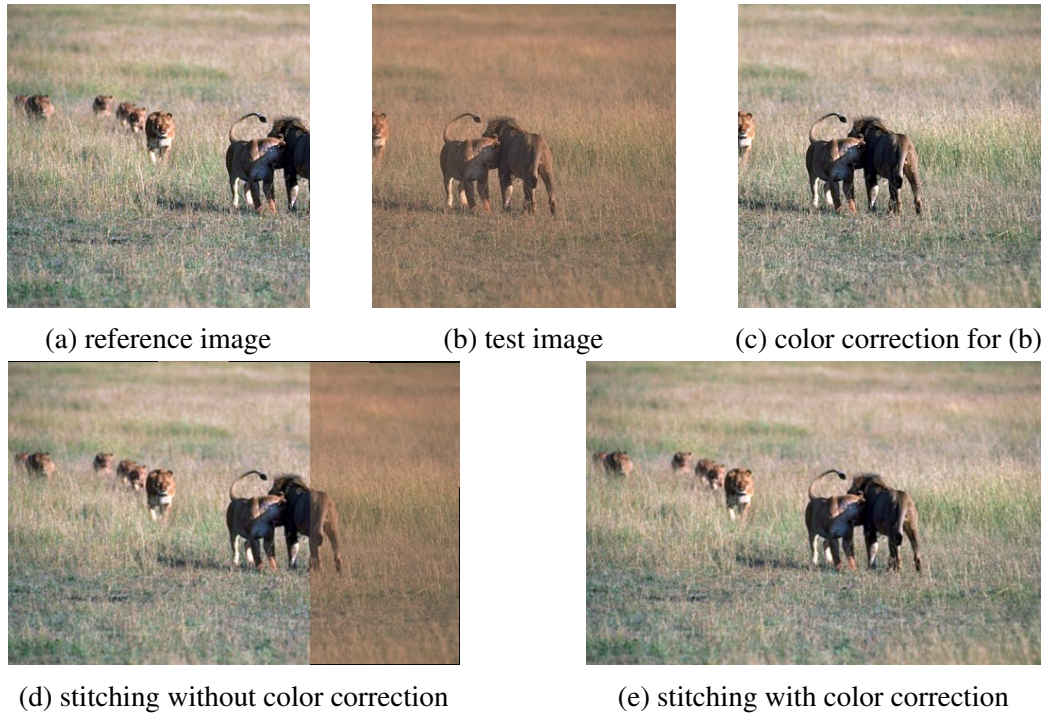


Fig. 3.1 An example of color transfer in image stitching.

Pitie et al. [99, 98] proposed an automated color mapping method using color distribution transfer. There are two parts in their algorithm. The first part is to obtain a one-to-one color mapping using three-dimensional probability density function transfer, which is iterative, nonlinear and convergent. The second part is to reduce grain noise artifacts via a post-processing algorithm, which adjusts the gradient field of the corrected image to match the test image. Fecker et al. [33] proposed a color correction algorithm using cumulative histogram matching. They used basic histogram matching algorithm for the luminance component and chrominance components. Then, the first and last active bin values of cumulative histograms are modified to satisfy the monotonic constraint, which can avoid possible visual artifacts. Nikolova et al. [87, 86] proposed a fast exact histogram specification algorithm, which can be applied to color transfer. This approach relies on an ordering algorithm, which is based on a specialized

variational method [88]. They used a fast fixed-point algorithm to minimize the functions and obtain color corrected images.

Compared to the previous approaches described above, we combine the ideas of histogram specification and global mapping to produce a color transfer function, which can extend well the color mapping from the overlapping region to the entire image. The main advantage of our method is the color transfer ability for two images having small overlapping regions. The experiments also show that the proposed algorithm outperforms other methods in terms of objective evaluation and subjective evaluation.

This chapter has been presented in our previous work [125, 128]. The rest of this chapter is organized as follows. The related work is summarized in Section 3.2. The detailed proposed color transfer algorithm is presented in Section 3.3. The experiments and the result analysis are shown in Section 3.4. The discussion and conclusion are given in Section 3.5.

## 3.2 Related Work

Image stitching approaches can combine multiple small-size images together to produce a large-size panorama image. General steps of image stitching and the role of color correction (color transfer) in image stitching are described in Section 2.5. Generally speaking, motion models, image alignment methods and color transfer methods are the important challenging tasks in image stitching, which has received a lot of attention recently [123, 18, 143, 136, 118, 71]. Different kinds of motion models, image alignment methods or color transfer algorithms can construct different approaches for image stitching. Even though color transfer method is the main topic studied in this chapter, we also introduce motion models and image alignment algorithms to make this research be comprehensive and be understood easily.



### 3.2.1 Motion Models

Before we can stitch images to create panoramas, we need to build the mathematical relationships which map pixel coordinates from one image to another image. Motion models describe this kind of mathematical relationships between two images. There are some kinds of motion models in image stitching, such as 2D motions, 3D transformations, cylindrical and spherical coordinates.

#### 2D Motions

2D motions is the simplest motion model. The basic set of 2D transformations is illustrated in Fig. 3.2. Among these transformations, 2D translation is the most basic one. 2D Euclidean transformation is also known as 2D rigid body motion, which combines 2D translation and rotation. Similarity transform, also known as scaled rotation, can be expressed as a combination of 2D translation and scaled rotation. Affine transformation is based on a  $2 \times 3$  matrix. Projective transformation, also known perspective transform or homography, operates on homogeneous coordinates [123].

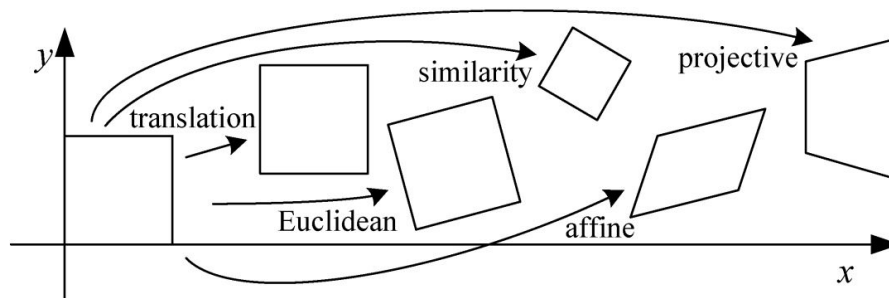


Fig. 3.2 The basic set of 2D transformations.

#### 3D Transformations

For 3D coordinate transformations, there are similar motion models that can be denoted using  $4 \times 4$  transformation matrices, with 3D equivalents to translation, Euclidean, affine, and homography.

### Cylindrical and Spherical Coordinates

In order to adopt 3D motions to align images, we need to first warp the images into cylindrical or spherical coordinates and then use a transformation model to align images [123]. Projections from 3D to cylindrical and spherical coordinates are illustrated in Fig. 3.3.

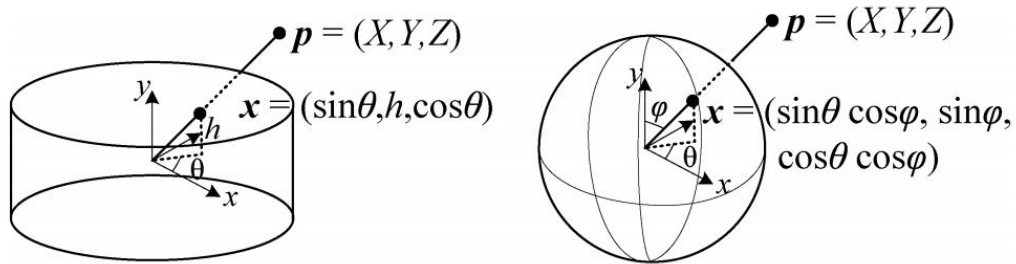


Fig. 3.3 Projections from 3D to cylindrical and spherical coordinates.

### 3.2.2 Image Alignment

Image alignment is also called image registration. It aims to establish the relationship between two images. For a specific application, a corresponding motion model needs to be defined first. Then, the parameters in the motion model can be estimated using corresponding algorithms. At last, the considered images can be aligned rightly to create a panorama image. We summarize two kinds of alignment algorithms, including pixel-based alignment and feature-based alignment.

#### Pixel-Based Alignment

The pixel-based alignment methods are to shift or warp the images relative to other images and to compare the corresponding pixels. Generally speaking, an error metric is firstly defined to compare the difference between the considered images. Then, a suitable search algorithm is applied to obtain the optimal parameters in the motion model. The detailed techniques and the comprehensive description are available in [123]. A simple description of this method is given below.

## Histogram-based Color Correction for Image Stitching

---

Given an image pixel  $I_0(\mathbf{x}_i)$ , the goal is to obtain where it is located relatively in the other image  $I_1(\mathbf{x}_i)$ . The simplest solution is to compute the minimum of the sum of squared difference function:

$$E(u) = \sum_i (I_1(\mathbf{x}_i + \mathbf{u}) - I_0(\mathbf{x}_i))^2 = \sum_i e_i^2, \quad (3.1)$$

where  $\mathbf{u} = (u, v)$  is the displacement vector,  $u \leq m, v \leq n$ ,  $m$  and  $n$  are constant values,  $e_i = I_1(\mathbf{x}_i + \mathbf{u}) - I_0(\mathbf{x}_i)$  is the residual error. To solve this minimization problem, a search algorithm will be adopted. The simplest method is the full search technique. For speeding up the computation, coarse-to-fine techniques based on image pyramids are often used in the practical applications.

### Feature-Based Alignment

The feature-based alignment methods consider extracting distinctive features (interesting points) from each image and matching every feature [74, 12, 108]. Then, the geometric transformation between the considered images is estimated. The most popular feature extraction method is the scale-invariant feature detection [74]. The most widely used solution for feature matching is the indexing schemes based on finding nearest neighbors in high-dimension spaces. For estimating the geometric transformation, a usual method is to use least squares to minimize the sum of squared residuals by

$$E_{LS} = \sum_i \|r_i\|^2 = \sum_i \|\hat{\mathbf{x}}'_i(\mathbf{x}_i; \mathbf{p}) - \hat{\mathbf{x}}'_i\|^2, \quad (3.2)$$

where  $\hat{\mathbf{x}}'_i$  is the detected feature point location corresponding to point  $\mathbf{x}_i$  in other images,  $\hat{\mathbf{x}}'_i$  is the estimated location, and  $\mathbf{p}$  is the estimated motion parameter. Equation (3.2) assumes all feature points are matched with the same accuracy, which does not work well in the real application. Thus, the weighted least square is often used to obtain more robust results via

$$E_{WLS} = \sum_i \sigma_i^{-2} \|r_i\|^2, \quad (3.3)$$

where  $\sigma_i^2$  is a variance estimate.

## 3.3 The Proposed Approach

We proposed a method of color transfer for image stitching using histogram specification and global mapping. There are two given images to be stitched. The image with good visual quality is defined as the reference image, and the other is defined as the test image. Generally speaking, there are four steps in this algorithm. Firstly, overlapping regions between these two images are obtained using a feature-based matching method. Secondly, histogram specification is conducted for the overlapping regions. Thirdly, using corresponding pixels in the overlapping region, which are original pixels and the pixels after histogram specification, the mapping function is computed with an iterative method for minimizing color differences. At last, the whole color transferred image is produced by applying the mapping function to the entire test image.

### 3.3.1 Overview

The notations in this chapter is given below.

$A$  is a reference image,

$B$  is a test image,

$A'$  is the overlapping region in the reference image,

$B'$  is the overlapping region in the test image,

$\hat{B}'$  is the result of histogram specification for  $B'$ ,

$(i, j)$  is the location of pixels in images,

$k$  is the pixel values,  $k \in [0, 1, \dots, 255]$  for 8-bit images,

$\varepsilon(k) := \{(i, j) \in B' \mid B'(i, j) = k\}$ ,

$T$  is a color mapping function,

$\tilde{B}'$  is the result of color transfer for  $B'$  using the color mapping function,

## Histogram-based Color Correction for Image Stitching

$DF$  is the pixel differences between two images,

$PSNR$  is the peak signal-to-noise ratio between two images.

The algorithm framework is described in Figure 3.4.

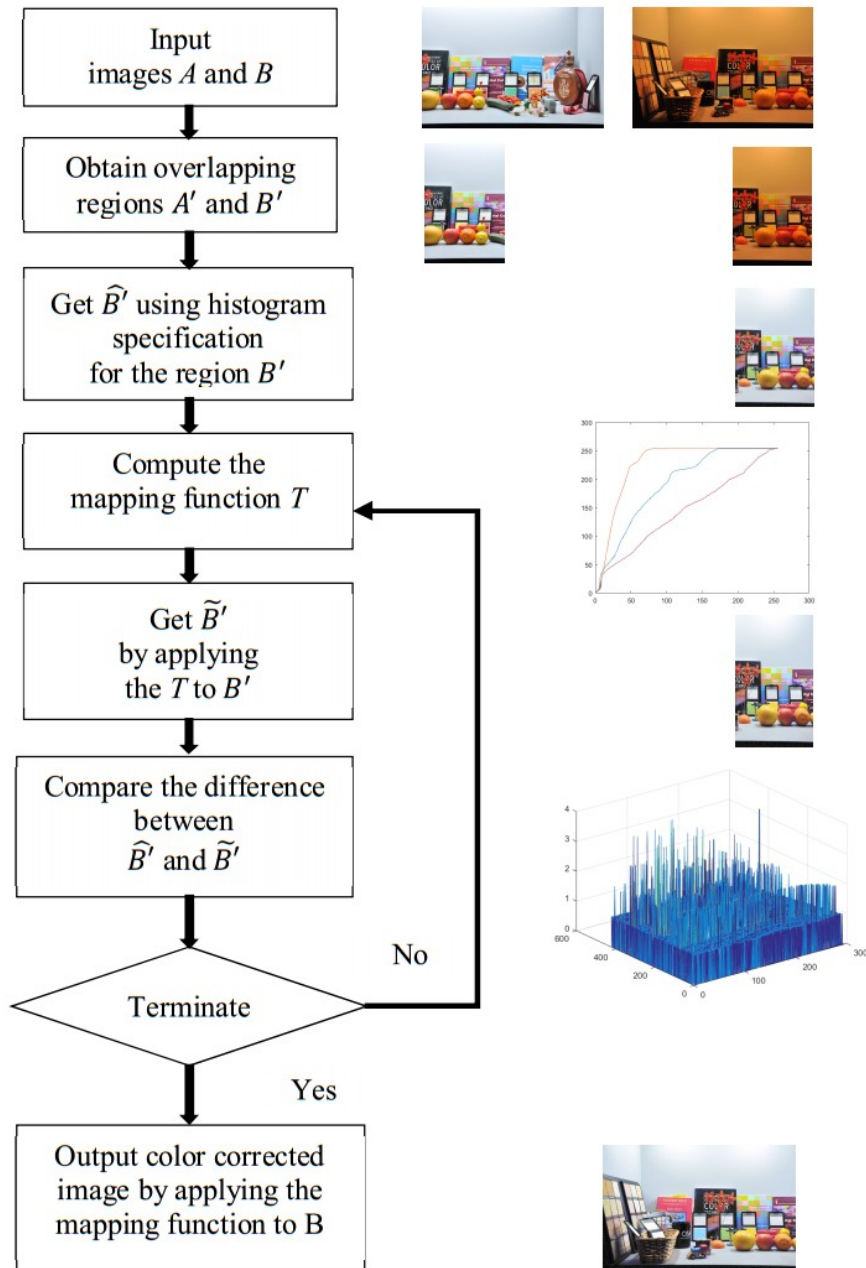


Fig. 3.4 The framework of the proposed algorithm.

#### 3.3.2 The Detailed Description of This Algorithm

In this section, we will describe the proposed algorithm in detail.

##### **Obtain Overlapping Regions between Two Images**

In the application of image stitching, there are overlapping regions between input images. Due to little changes of scenes, differences of image capture angles, differences of focal lengths and other factors, the corresponding overlapping regions are not exactly pixel-to-pixel. Firstly, we find matching points between the reference image and the test image, using the scale-and-rotation-invariant feature descriptor (SURF) [12]. Then, the geometric transformation will be estimated from the corresponding points. In our implementation, the projective transformation is applied. After that, these images can be transformed and placed in the same panorama [123]. At last, we obtain overlapping regions using the image correspondence location information. This part is described in Algorithm 1.

---

**Algorithm 1** Obtain overlapping regions between two images.

---

- 1: Input two images  $A$  and  $B$ , then compute the feature point correspondences  $A_i \leftrightarrow B_i$  using SURF,  $i = 1, 2, \dots, N$ , where  $N$  is the number of feature point correspondences.
- 2: Estimate the geometric transform  $Tr$  using the correspondences, the following term is minimized:

$$\min \sum_{i=1}^N (A_i - Tr(B_i))^2.$$

- 3: Warp these two images and put in the same panorama using the geometric transform  $Tr$ , define two matrixes  $M_1$  and  $M_2$  to store position information.
  - 4: Obtain overlapping regions using the image correspondence location information described in  $M_1$  and  $M_2$ .
-

### Histogram Specification for the Overlapping Region

In this step, we will make exact histogram specification for the overlapping region in the test image to match the histogram of the overlapping region in the reference image. For each channel of the RGB color image, the histogram is calculated as follows:

$$h(k) = \frac{1}{m \times n} \sum_{i=1}^m \sum_{j=1}^n \delta[k, B(i, j)], \quad (3.4)$$

where  $\delta[a, b] = 1$ , if  $a=b$ ;  $\delta[a, b] = 0$ , otherwise.  $B$  is an image,  $k$  are pixel values,  $k \in [0, 1, \dots, 255]$  for 8-bit images,  $m$  and  $n$  are the height and width of the image, and  $i$  and  $j$  are the columns and rows of pixels.

Histogram specification is aimed to transform an input image to an output image fitting a specific histogram. We adopt an algorithm in [87] to perform the histogram specification in overlapping regions between the reference image and the test image. The detailed algorithm is described in Algorithm 2. This algorithm is implemented in the three color channels respectively.

---

**Algorithm 2** Histogram specification for the overlapping region.

---

- 1: Input:  $B'$  is the overlapping region in the test image,  $h$  is the histogram of  $A'$ ,  $u^{(0)} = B'$ ,  $\alpha = 0.05, \beta = 0.1$ , iteration number  $S = 5$ ,  $c_0 = 0$ .
- 2: For  $s = 1, \dots, S$ , compute

$$u^{(s)} = B' - \eta^{-1}(\beta \nabla^T \eta(\nabla u^{(s-1)})),$$

where  $\nabla$  is the gradient operator,  $\nabla^T$  is the transposition of  $\nabla$ ,  $\eta^{-1}(x) = \frac{\alpha x}{1-|x|}$ ,  $\eta(x) = \frac{x}{\alpha+|x|}$ .

- 3: Order the values in  $\Pi_N$  according to the corresponding ascending entries of  $u^{(S)}$ , where  $\Pi_N := \{1, \dots, N\}$  denote the index set of pixels in  $B'$ .
  - 4: For  $k = 0, 1, \dots, 255$ ,  
set  $c_{(k+1)} = c_{(k)} + h_{(k)}$  and  $\hat{B}'[c_{(k)} + 1] = \dots = \hat{B}'[c_{(k+1)}] = k$ .
-

#### Compute the Color Mapping Function

In this step, we will get the color mapping function from corresponding pixels in  $B'$  and  $\hat{B}'$ . This operation is conducted for the three color channels, respectively.

For each color channel, a mapping function is computed as follows:

$$T(k) = \left\lfloor \left( \left( \min_c \sum_{(i,j) \in \varepsilon(k)} (\hat{B}'(i,j) - c)^2 \right) + 0.5 \right) \right\rfloor, \quad (3.5)$$

where  $k \in [0, 1, \dots, 255]$  for 8-bits images,  $\lfloor (x) \rfloor$  is the nearest integer of  $x$  towards minus infinity,  $\varepsilon(k) := \{(i, j) \in B' \mid B'(i, j) = k\}$ . The nearest integer of  $c$  is the mapping value corresponding to  $k$ . In the minimization problem of Equation (3.5), the value of  $c$  is usually not an integer. Thus, we use the nearest integer as the corresponding mapping value of  $k$ .

During the estimation of a color mapping function, we embed some constraint conditions like the related methods [53, 124]. Firstly, the mapping function must be monotonic. We use a post-processing refining method to remove the outliers and make the mapping curve to be monotonic. Secondly, some function values may be obtained by interpolation methods, due to some pixel values  $k$  not existing in the overlapping regions. In our implementation, the simple linear interpolation is used. The detailed algorithm is described in Algorithm 3.

---

**Algorithm 3** Compute the color mapping function.

---

1: Input:  $B'$  is the overlapping region in the test image,  $\hat{B}'$  is the result of histogram specification for  $B'$ . The following steps will be conducted for the three color channels, respectively.

2: For  $k = 0, 1, \dots, 255$ , minimize the function:

$$T(k) = \left\lfloor \left( \left( \min_c \sum_{(i,j) \in \varepsilon(k)} (\hat{B}'(i,j) - c)^2 \right) + 0.5 \right) \right\rfloor.$$

3: For some value of  $k$ , the set  $\varepsilon(k)$  is the empty set. Then, the corresponding  $k$  can not be computed in the above step and will be obtained using interpolation methods.

---



### Minimize Color Differences Using an Iterative Method

Firstly, color transfer is conducted in the overlapping region  $B'$  by the color mapping function obtained at the previous step. The result is denoted as  $\tilde{B}'$ . Secondly, pixel value differences  $DF$ , and the PSNR between  $\hat{B}'$  and  $\tilde{B}'$  is computed. Thirdly, the pixels  $(i, j)$  will be removed from  $\varepsilon(k) := \{(i, j) \in B' \mid B'(i, j) = k\}$ , when  $DF(i, j)$  is larger than the preset threshold  $\text{Thd\_DF}$ , since this kind of pixel is considered to be outliers. Finally, a new color mapping function can be obtained by the algorithm described in Algorithm 3.

Repeat these processes until reaching the preset iteration times or PSNR increase is smaller than the preset threshold  $\text{Thd\_PSNR}$ . After these iterations, the final mapping function is applied to the whole test image. Then, the corrected image shares the same color style with the reference image. In other words, the two images are color consistent, which are suitable for image stitching. The detailed algorithm is described in Algorithm 4.

---

**Algorithm 4** Minimize color differences using an iterative method.

---

- 1: Input:  $\hat{B}'$  is the overlapping region in the test image,  $T$  is the color mapping function obtained in **Algorithm 3**,  $\varepsilon(k) := \{(i, j) \in B' \mid B'(i, j) = k\}$ , maximal iteration number  $S$ ,  $\text{Thd\_Diff}$  is a threshold value,  $\text{Thd\_PSNR}$  is another threshold value.
- 2: Obtain  $\tilde{B}'$  by applying  $T$  to  $B'$ , using

$$\tilde{B}'(i, j) = T(B'(i, j)).$$

- 3: Compute pixel-to-pixel differences by

$$DF(i, j) = \left| \hat{B}'(i, j) - \tilde{B}'(i, j) \right|.$$

- 4: Remove pixels  $(i, j)$  from  $\varepsilon(k)$ , when  $DF(i, j)$  is larger than the preset threshold  $\text{Thd\_Diff}$ .
  - 5: Compute the PSNR increase for  $\tilde{B}'$ .
  - 6: With the new sets  $\varepsilon(k)$ , repeat **Algorithm 3** and steps 2 to 5 in **Algorithm 4** until reaching the maximal iteration number or PSNR increase is smaller than the threshold  $\text{Thd\_PSNR}$ .
-

## 3.4 Experiments

### 3.4.1 Test Dataset and Evaluation Metrics

Both synthetic image pairs and real image pairs are selected to compose the test dataset. Test images in this dataset are chosen from [145, 77, 53, 32]. The synthetic data includes 40 reference/test image pairs. Each pair is from the same image, but with different color style. The image with good visual quality is assigned as a reference image, and the other is assigned as a test image. The real data includes 35 reference/test image pairs. These image pairs are taken under different capture conditions, including different exposures, different illuminations, different imaging devices or different capture time. For each pair, the image of good quality is assigned as a reference image and the other as a test image.

Anbarjafari [8] proposed an objective no-reference measure for illumination assessment. Xu and Mulligan [145] proposed an evaluation method for color correction in image stitching, which has been adopted in our evaluation. This method includes two components: color similarity between a corrected image  $B$  and a reference image  $A$ , and structure similarity between a corrected image  $B$  and a test image  $A$ .

The Color Similarity  $CS(A, B)$  is defined as  $CS(A, B) = PSNR(A', B')$ . PSNR is the **Peak Signal-to-Noise Ratio** [76] and  $A', B'$  are the overlapped regions of  $A$  and  $B$ , respectively. The higher value of  $CS(A, B)$  indicates the more similar color style between the corrected image and the reference image. The definition of  $PSNR$  has been given in Section 2.4.

The structure similarity  $SSIM(A, B)$  is the **Structural SIMilarity** index, which is defined as a combination of luminance, contrast and structure components [139]. The higher value of  $SSIM(A, B)$  indicates the more similar structure between the corrected image and the test image. The definition of  $SSIM$  has been described in Section 2.4.

In the following parts, we compare our algorithm with the methods proposed in [98, 33, 87]. These methods transfer the color style of the whole reference image to the whole test image.

## Histogram-based Color Correction for Image Stitching

---

The source codes of Pitie’s and Nikolova’s methods are downloaded from their homepages. The source code of Fecker’s method is obtained from [145].

### 3.4.2 Experiments on Synthetic Image Pairs

Each synthetic image pair from [145, 77, 2, 1] describes the same scene (exactly pixel-to-pixel) with different color styles. Our algorithm is applied to color correction in image stitching, so we cropped these image pairs to have various overlapping percentages, which simulates the situation in image stitching. Then, color transfer methods are applied to the corresponding image pairs that have different overlapping percentages. In the following experiments, we cropped each image pair with four different overlapping percentages (10%, 30%, 60% and 80%), respectively. Thus, we have  $40 \times 4 = 160$  synthetic pairs to make numerical experiments. As shown in the Table 3.1, our algorithm outperforms other methods in terms of color similarity and structure similarity.

Table 3.1 Comparison for synthetic dataset (average of 40 image pairs for each overlapping percentage). **CS** is the **C**olor **S**imilarity index, **SSIM** is the **S**tructural **S**IMilarity index.

Overlapping Percentage	CS (dB)				SSIM			
	<i>Pitie</i>	<i>Fecker</i>	<i>Nikolova</i>	<i>Proposed</i>	<i>Pitie</i>	<i>Fecker</i>	<i>Nikolova</i>	<i>Proposed</i>
<b>10%</b>	18.21	18.34	18.39	<b>22.03</b>	0.7924	0.8033	0.8165	<b>0.8834</b>
<b>30%</b>	20.16	20.28	20.31	<b>24.11</b>	0.8101	0.8181	0.8299	<b>0.8867</b>
<b>60%</b>	21.93	21.83	22.02	<b>24.19</b>	0.8417	0.8461	0.8545	<b>0.8853</b>
<b>80%</b>	23.39	23.24	23.43	<b>24.31</b>	0.8662	0.8674	0.8721	<b>0.8857</b>

From the experimental results of these algorithms, we can also make a conclusion that our algorithm obtains the better visual quality of correction results even though the overlapping percentage is very small. The ability of color transfer for image pairs having narrow overlapping regions is very important in the application of image stitching. This advantage can make our color correction algorithm more suitable for image stitching. In Table 3.1, we can also observe

that the proposed method is not significantly better than other algorithms when the overlapping percentage is very large. For example, when the overlapping percentage is 80%, the difference between the proposed method and Nikolova's algorithm [87] is very small. Since we adopted Nikolova's algorithm for transferring the color style in the overlapping region, the proposed method is almost the same as Nikolova's algorithm when the overlapping percentage is close to 100%.

Some visual comparisons are shown in Figures 3.5, 3.6, 3.7 and 3.8. In Figure 3.5, the overlapping regions include the information describing the sky, the pyramid and the head of the camel. The red rectangles indicate the transferred color has some distance from the reference color style in the reference image. The yellow rectangle indicates the transferred color by the proposed method is almost the same as the reference color style, according to the visual comparison. We can also observe easily that our algorithm transfers color information more accurately than other algorithms. For more accurate comparison, we show the histograms of the overlapping regions in Figure 3.6. The histograms of the overlapping regions in the reference image and in the test image are totally different. The histograms of the overlapping regions after color transfer algorithms are closer to the reference. In addition, the results by the proposed method are the closest one, which indicates the proposed method outperforms other algorithms.

## Histogram-based Color Correction for Image Stitching

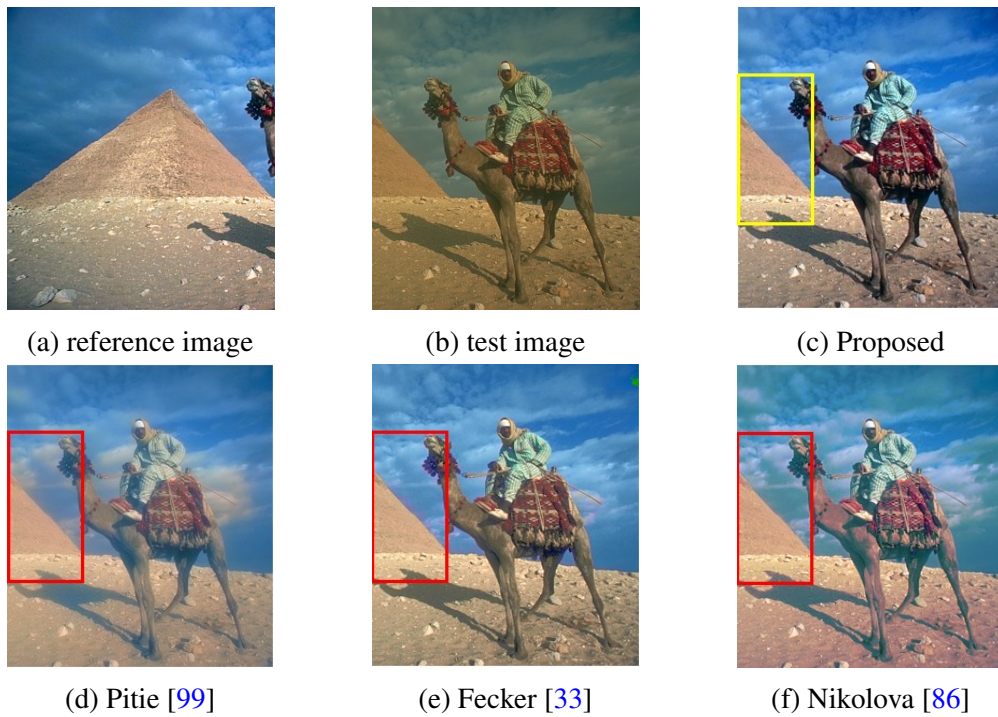


Fig. 3.5 Comparison for the synthetic image pair.

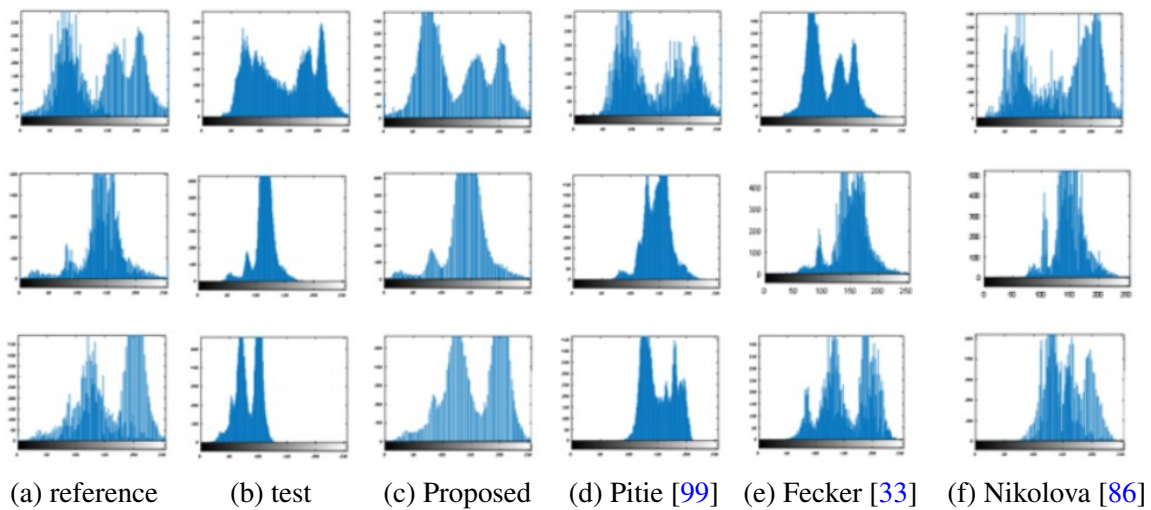


Fig. 3.6 Histogram comparisons for overlapping regions in Figure 3.5. The first row shows the histograms of red channel of corresponding images. The second row shows the histograms of green channel of corresponding images. The third row shows the histograms of blue channel of corresponding images.

In Figure 3.7, the red rectangles show disadvantages of other algorithms, which have transferred the green color to the body of the sheep. The yellow rectangle indicates the advantage of our algorithm, which has transferred the right color to the sheep body. In Figure 3.8, the rectangles describe the airplane body that exists in the overlapping region. The red rectangles show disadvantages of other algorithms that transferred the inconsistent color to the airplane body. The yellow rectangle indicates that the proposed method transfers the consistent color to the airplane body.

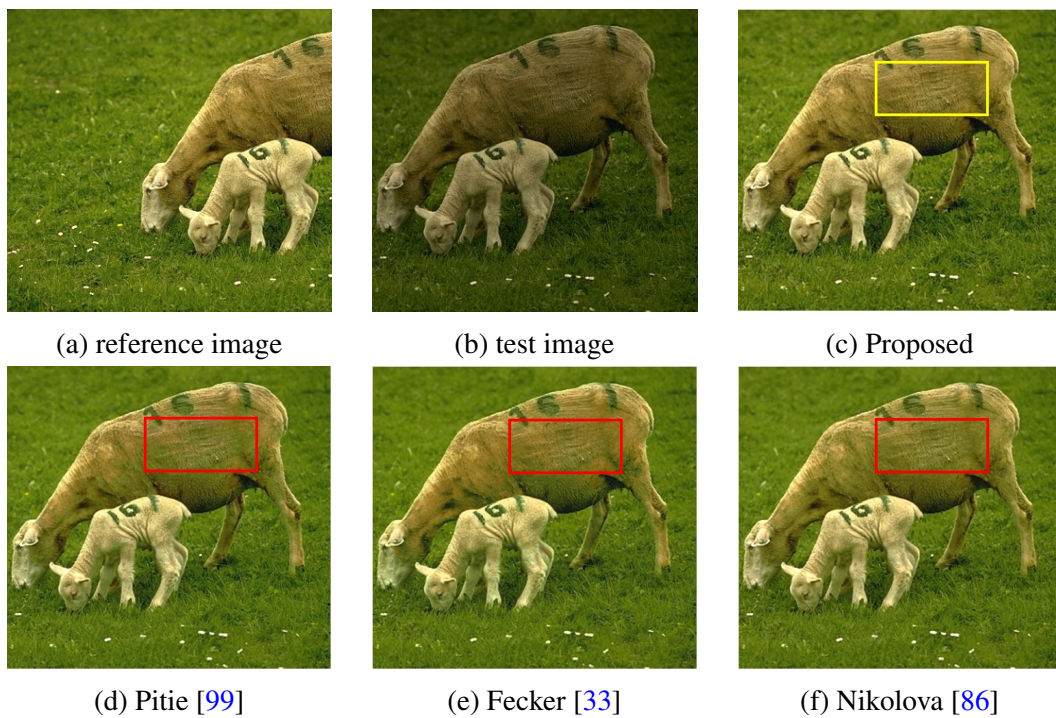


Fig. 3.7 Comparison for the synthetic image pair.

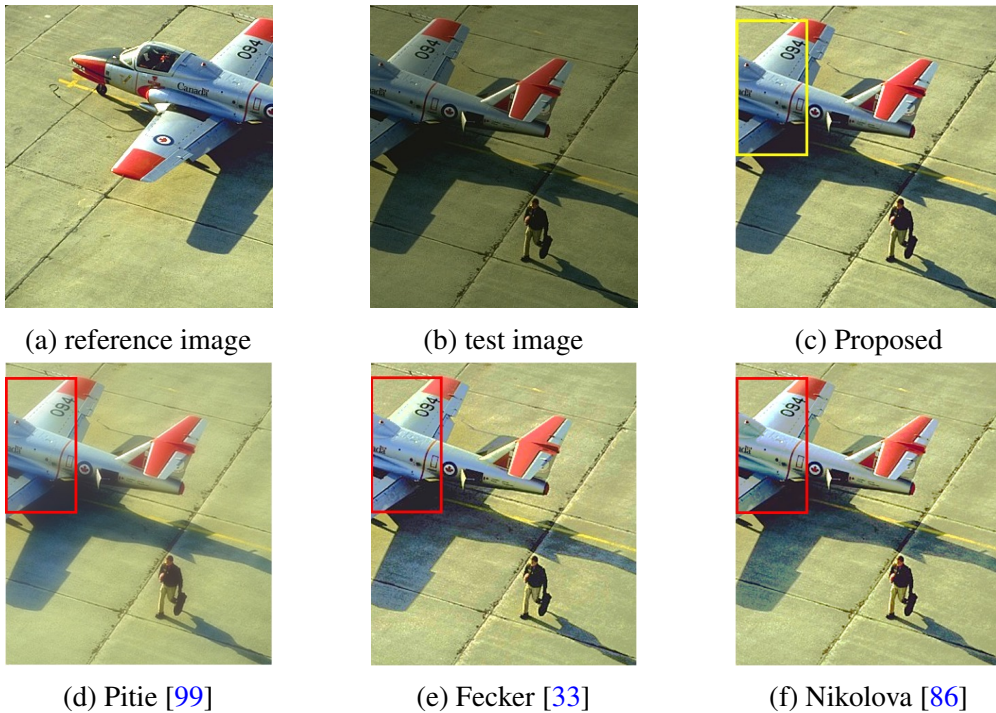


Fig. 3.8 Comparison for the synthetic image pair.

### 3.4.3 Experiments on Real Image Pairs

In the experiments above, we make the comparisons using synthetic image pairs, which have exactly the same overlapping regions. However, overlapping regions are not usually exactly the same (not pixel-to-pixel) in the real application of image stitching. Thus, we now present some experiments for real image pairs.

Objective comparisons are given in Table 3.2, which indicates that our algorithm outperforms other methods in terms of color similarity and structure similarity. Subjective visual comparisons are also presented in Figures 3.9, 3.10, 3.11 and 3.12. In Figure 3.9, the red rectangles show disadvantages of other algorithms, which have transferred the green color to the tree body and the windows. The yellow rectangles indicate the advantage of our algorithm, which transfers the right color to the mentioned regions. The histogram comparisons for the overlapping regions are shown in Figure 3.10, which indicates the proposed method outper-

forms other algorithms. More results and the comparisons are given in Figure 3.11 and Figure 3.12.

Table 3.2 Comparison for real image pairs (Average of 35 pairs).

	<i>Pitie</i>	<i>Fecker</i>	<i>Nikolova</i>	<i>Proposed</i>
<b>CS(dB)</b>	18.98	19.04	19.12	<b>21.19</b>
<b>SSIM</b>	0.8162	0.8334	0.8255	<b>0.8531</b>

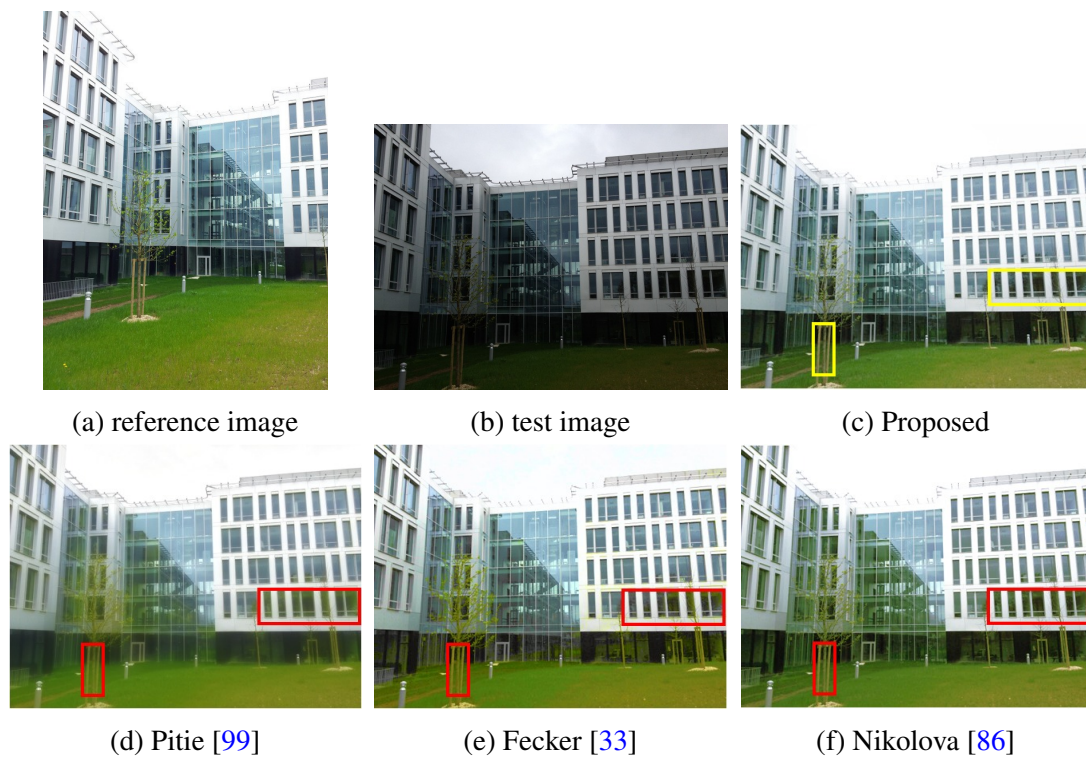


Fig. 3.9 Comparison for the real image pair.



## Histogram-based Color Correction for Image Stitching

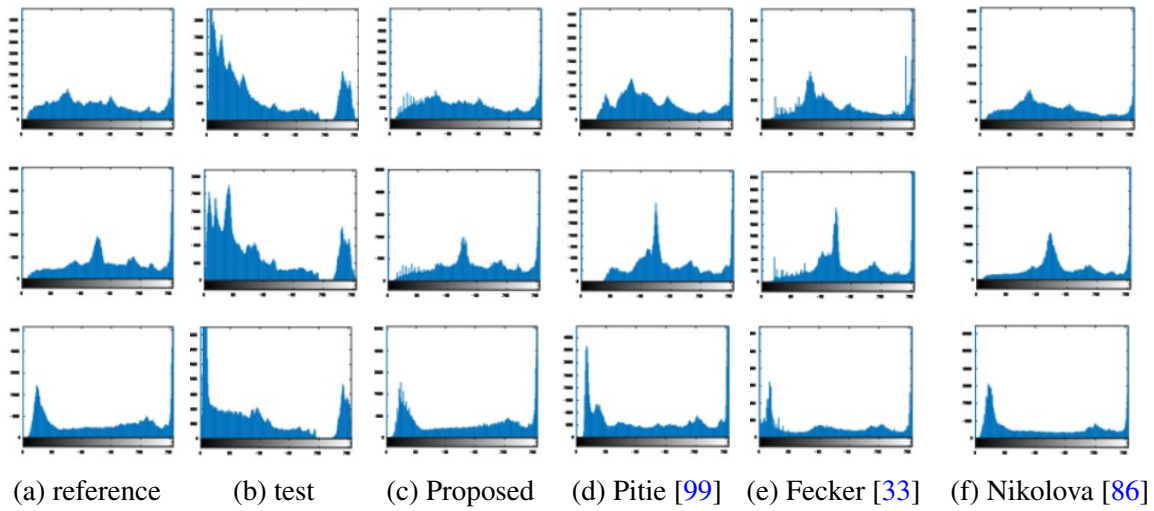


Fig. 3.10 Histogram comparisons for overlapping regions in Figure 3.9. The first row shows the histograms of red channel of corresponding images. The second row shows the histograms of green channel of corresponding images. The third row shows the histograms of blue channel of corresponding images.

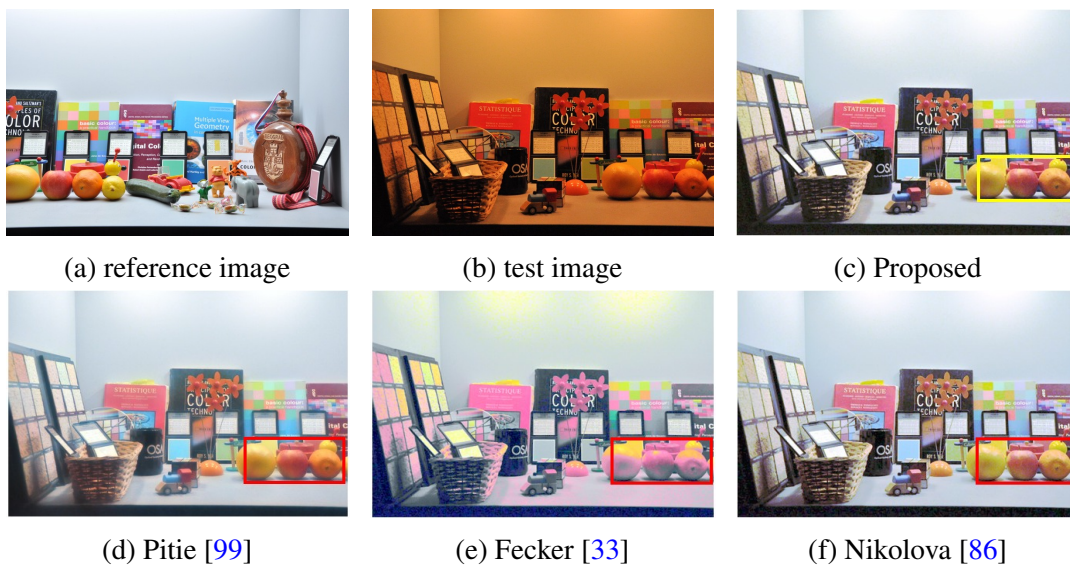


Fig. 3.11 Comparison for the real image pair.

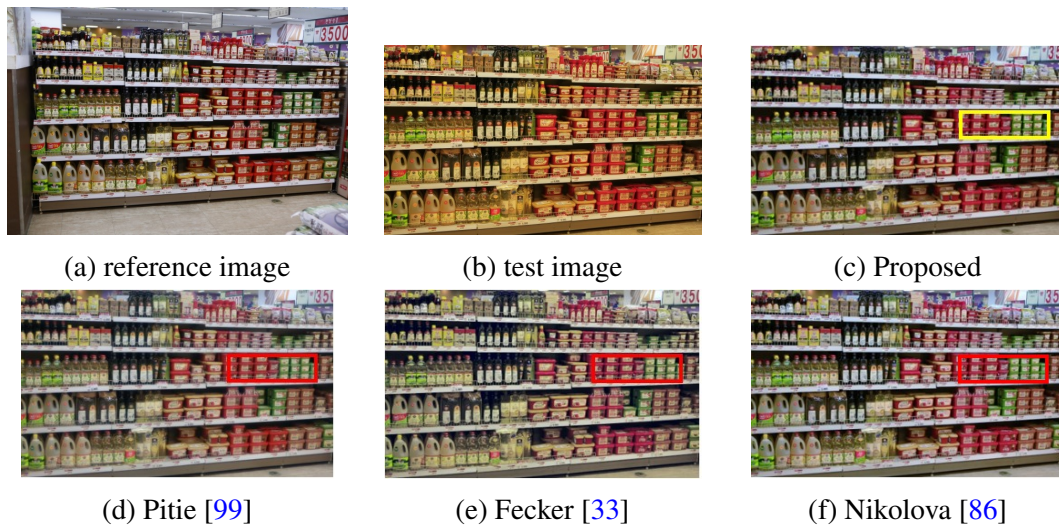


Fig. 3.12 Comparison for the real image pair.

### 3.4.4 An Example of Stitching More Than Two Images

In real application, there are usually more than two images need to stitch. Our method is also able to deal with this kind of real problem. An example is given in Fig. 3.13. This result demonstrates our color corrected method is also useful in the image stitching with more than two images.

## 3.5 Discussion

In this chapter, we have proposed an efficient color transfer method for image stitching, which combines the ideas of histogram specification and global mapping. The main contribution of the proposed method is using original pixels and the corresponding pixels after histogram specification to compute a global mapping function with an iteration method, which can effectively minimize color differences between a reference image and a test image. The color mapping function can spread well the color style from the overlapping region to the whole image. The experiments also demonstrate the advantages of our algorithm in terms of objective evaluation and subjective evaluation.

## Histogram-based Color Correction for Image Stitching

---

As our work relies on the exact histogram specification, bad results of histogram specification will decrease the visual quality of our results. Even though the problem of histogram specification has received considerable attention and has been well studied during recent years, some future work can be conducted to improve the results of this kind of algorithm.

In the detailed description of the proposed algorithm, we have shown that our method is building the color mapping functions using the global information and without using the local neighbor information. In future work, we will consider the information of local patches [26] to construct the color mapping functions, which may be more accurate to transfer colors. Another problem is that the mapping function is computed for each color channel. This simple processing does not consider the relation of the three color channels, and this may produce some color artifacts. In our future work, we will try to obtain the color mapping function considering the relation of the three color channels. The minimization is completed with an iteration framework, and the termination conditions include computing PSNR. These operations need high computation, so a fast minimization method will also be considered in the future work.



(a) Original images



(b) Color corrected images



(c) Stitching with the original images



(d) Stitching with the color corrected images

Fig. 3.13 An example of stitching more than two images.



# Chapter 4

## Color Consistency for Photo Collections without Gamut Problems

### Contents

---

<b>4.1</b>	<b>Introduction</b>	<b>63</b>
<b>4.2</b>	<b>Related work</b>	<b>65</b>
4.2.1	Color Enhancement for a Single Image	65
4.2.2	Color Transfer Between Two Images	66
4.2.3	Color Balance for Image Collections	66
<b>4.3</b>	<b>Overview</b>	<b>67</b>
<b>4.4</b>	<b>Color Consistency without Gamut Problems</b>	<b>68</b>
4.4.1	Image Quality Assessment by Non-Reference Measures	68
4.4.2	Color Balance without Gamut Problems	70
4.4.3	Color Transfer without Gamut Problems	72
<b>4.5</b>	<b>Experiments</b>	<b>73</b>
4.5.1	Image Datasets	73
4.5.2	Results	74

**Color Consistency for Photo Collections without Gamut Problems**

---

**4.6 Conclusion . . . . . 77**

---

## Abstract

In this chapter, we present a color consistency technique, which was also introduced in our research paper [126]. This method can make images in the same collection share the same color style and avoid gamut problems. Some previous methods define simple global parameter-based models and use optimizing algorithms to obtain the unknown parameters, which usually cause gamut problems in bright and dark regions. Our method is based on a range-preserving histogram specification and can enforce images to share the same color style, without resulting in gamut problems. We divide the input images into two sets having respectively high visual quality and low visual quality. The high visual quality images are used to make color balance. And then the low visual quality images are color transferred using the previous corrected high quality images. Our experiments indicate that such histogram-based color correction method is better than the compared algorithm.

## 4.1 Introduction

With the popularity of digital cameras, online photo albums and social networks, we can easily find thousands of photos of the same scenes, especially for the famous landmarks. And these kinds of photo collections have been applied in high level computer vision problems, including visual photo tourism [120], scene completion [49], landmark recognition [46], image retrieval [70, 52], photo stitching [118], and time-lapse [78]. However, these online images are usually taken with different capture devices [32], different illuminations, and different views, which are the reasons for the different color styles in the same photo collection.

In order to obtain better results of the above mentioned interesting computer vision applications, the color consistency or color correction is an essential pre-processing procedure before implementing the main algorithms. The most simple color correction method is the auto color adjustment technique [114], which is implemented in most commercial photo editing tools. However, this kind of method makes the color correction for each image independently,



## Color Consistency for Photo Collections without Gamut Problems

---

not considering the color distribution relations among all images in the same collection. Another kind of method is manually adjusting all images by professional photographers, which requires a significant amount of processing time for a large number of photos.

Recently, Park et al. [93] proposed a method to optimize color consistency in community photo collections depicting the same scenes. Their method is based on the assumption of a color correction model, which is a simple combination of white balance and gamma correction. Park et al.'s method is globally making color mapping in the three color channels respectively, and may cause gamut problems [85, 121]. Gamut problem is also called saturated problem, which results in over-enhancement. An example of gamut problem is shown in Fig. 4.1, from which we can see some regions of the bright sky are saturated to 255, and some regions of the dark tree are saturated to 0. In Park et al.'s simple global parameter-based model, the dark pixel values are easily saturated to 0 and the bright pixel values are easily saturated to 255. In other words, this method produced gamut problems. Another disadvantage of their algorithm is that the final results are highly depending on the color distribution of all images. In other words, some low quality images with bad color distribution will affect the quality of other images in the same collection.

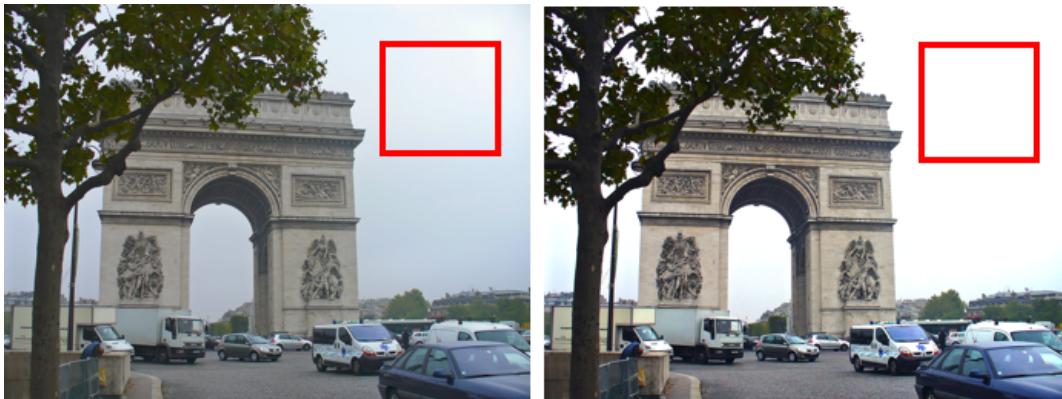


Fig. 4.1 An example of gamut problems.

In order to avoid gamut problems and reduce the effects from bad quality images, we present an automatic color consistency algorithm for photo collections based on image quality assessment and range-preserving histogram specification. In our method, input images are

divided into two sets, namely high quality image set and low quality image set. And then the images having high quality will be used to produce corresponding color balanced images. At last, the images classified in the low quality image set will be color transferred with the corrected high quality images as the reference. These three stages can obtain color consistency among the whole set of images and not cause the disadvantages existing in Park et al.'s method.

The rest of this chapter is organized as follows. The relevant previous work is summarized in Section 4.2. The overview of the proposed algorithm is described in Section 4.3 and the detailed description is given in Section 4.4. The experiments and comparisons are shown in Section 4.5. Finally, we give the conclusion and discuss the future work in Section 4.6.

## 4.2 Related work

In this section, we summarize the previous related work and categorize these methods by the number of input images. Color image enhancement is an ancient image processing technique, which is normally applied to a single image based on the statistic information of the input image or some specialized filters. Color transfer is a technique of transferring the color style of a reference image to a test image. Color balance for image collections is a new and interesting problem, which can enforce thousands of images to share the same color style.

### 4.2.1 Color Enhancement for a Single Image

Color image enhancement is an ancient and challenging task in image processing. Histogram equalization [115] is a useful method for image enhancement. Sapiro and Caselles [116] proposed a PDE-based image histogram modification method, which was further extended to color image enhancement by many researchers [90, 102, 87, 86, 97]. The automatic color enhancement (ACE) algorithm [114] is a popular method, which has been used in many photo editing software. Recently, Yuan and Sun [149] proposed an automatic exposure correction method, which was based on region-level exposure evaluation and detail-preserving S-curve

## Color Consistency for Photo Collections without Gamut Problems

---

adjustment. This kind of algorithm operates on each image independently, so they can not obtain color consistency among all images in the same collection. More details related to color image enhancement can be found in Section 5.2, Section 7.2 and Section 8.2.

### 4.2.2 Color Transfer Between Two Images

Color transfer between two images has received significant attention in recent years. The goal of this kind of algorithm is transferring the color style of a reference image to a test image, which can enforce the corresponding two images to share the same color style. Reinhard et al. [110] proposed a simple statistics-based algorithm to transfer colors between two images, which was also extended by many researchers. Papadakis et al. [92] proposed a variational model for color image histogram transfer, which used the energy functional minimization to obtain the goal of transferring the image color style and maintaining the image geometry. Hristova et al. [50] presented a style-aware robust color transfer method, which was based on the style feature clustering and the local chromatic adaptation transform. Hwang et al. [53] proposed a geometry-based color transfer algorithm using probabilistic moving least squares. More details related to color transfer can be found in Section 2.3.

### 4.2.3 Color Balance for Image Collections

Automatic color consistency for photo collections firstly obtained attention in HaCohen et al. [45]. Their method used the non-rigid dense correspondence algorithm [44] to obtain matched features, and then constructed a graph with edges linking image pairs sharing the similar contents. Color consistency was achieved by globally optimizing three piece-wise quadratic curves over the whole graph, which can minimize the color difference between all correspondences. However, their method is highly depending on dense and accurate correspondences (high computational complexity), which makes this algorithm unsuitable for a large number of images in photo collections.

A more efficient and robust color consistency algorithm for photo collections was proposed by Park et al. [93]. They firstly recovered sparse point correspondences in the same image collection, and then constructed a simple color correction model which can be considered the combination of white balance and gamma correction. Then a robust low-rank matrix factorization method was used to estimate the unknown parameters of the defined model. However, this correction model does not consider gamut problems and negative effects resulting from low quality images in the same collection.

### 4.3 Overview

Given an input photo collection as a sequence of images  $\mathbf{I} = \{\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3, \dots, \mathbf{I}_n\}$  which describe the same scene with different views, different capture devices or different illustrations, our goal is to make these images share the same color style and to be color consistent in the shared contents.

Our method is inspired by [93], which has given a whole framework to minimizing color difference among all input images. However, we do not adopt the simple global parameter-based model to correct colors, which may result in gamut problems. The contributions of our work are classifying input images based on image quality metrics and finding suitable target histograms for the range-preserving histogram specification.

Fig. (4.2) illustrates the overall framework of our color consistency algorithm, which consists of three main stages.

**1. Image quality assessment:** use non-reference measures to assess the image visual quality, and then construct two image sets having respectively high quality and low quality.

**2. Color balance:** use matched points between images having high quality to construct correspondences, and then obtain early corrected images with linear transforms. These early images can produce the target histograms. At last, the range-preserving histogram specification is applied to each image.

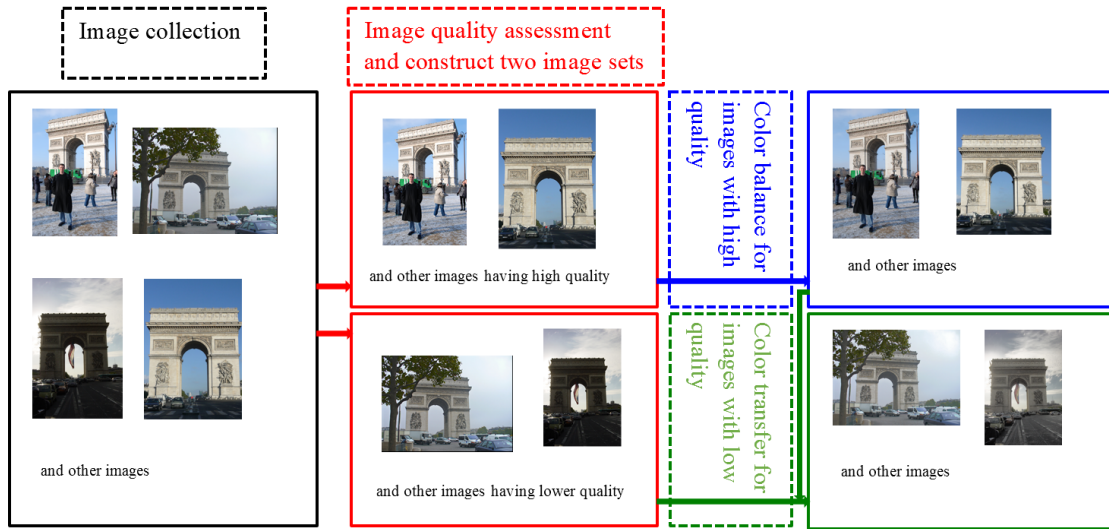


Fig. 4.2 The overall framework of the proposed method

**3. Color transfer:** use matched points between low quality images and corrected high quality images to construct correspondences, and then obtain final corrected images with linear transforms (can produce target histograms) and the range-preserving histogram specification.

## 4.4 Color Consistency without Gamut Problems

### 4.4.1 Image Quality Assessment by Non-Reference Measures

As discussed in Section 4.1, the results of Park et al.’s method [93] depend on the color distribution of all images in the same collection. This kind of algorithm may obtain some bad results when there are many low quality images in the same image collection. So we firstly make quality assessment for input images, which can sort the images by their visual quality. Then we make color balance for the images ranking high quality. At last, this kind of color style obtained from high visual quality images will be propagated to the images which are ranked lower visual quality in the assessment procedure. This kind of processing can reduce bad effects from lower visual quality images.

#### 4.4 Color Consistency without Gamut Problems

Much effort [91, 17, 43] has been made in recent years to design non-reference image quality assessment metrics. Panetta et al. [91] proposed a non-reference color image quality measurement combining the contrast, colorfulness and sharpness metrics. In other words, this measurement is a linear weighting of three terms assessing the contrast, color and edge information respectively. We simplify this assessment method and adopt the contrast and the sharpness metrics in our method. The measurement IQA (Image Quality Assessment) is written by

$$IQA = w_1 * Contrast + w_2 * Sharpness, \quad (4.1)$$

where  $w_1$  is the weighting of the contrast measure,  $w_2$  is the weighting of the sharpness measure, *Contrast* is defined in Eq. (4.2), *Sharpness* is defined in Eq. (4.3).

$$Contrast = AME(Y),$$

$$AME(Y) = \frac{1}{b_1 * b_2} \sum_{q=1}^{b_1} \sum_{p=1}^{b_2} \left( \log \left( \frac{Y(max, p, q) + Y(min, p, q)}{Y(max, p, q) - Y(min, p, q)} \right) \right)^{-0.5}, \quad (4.2)$$

where AME is the Michelson-Law measure of enhancement [4],  $Y$  is the Y channel of the input image in the YCbCr color space, the image is divided into  $b_1 * b_2$  blocks,  $Y(min, p, q)$  is the minimum of the block  $(p, q)$  in  $Y$ ,  $Y(max, p, q)$  is the maximum of the block  $(p, q)$  in  $Y$ ,  $p$  and  $q$  are the row and column index of blocks in the image.

$$Sharpness = \sum_{c=1}^3 \lambda_c EME(Edge_c),$$

$$EME(Edge_c) = \frac{2}{b_1 * b_2} \sum_{q=1}^{b_1} \sum_{p=1}^{b_2} \log \left( \frac{Edge_c(max, p, q)}{Edge_c(min, p, q)} \right), \quad (4.3)$$

where  $c$  is the index of the color channel, EME is the measure of enhancement [3],  $Edge_c$  is the edge map of the corresponding color channel,  $\lambda_c$  is the weighting of each color channel, the

image is divided into  $b_1 * b_2$  blocks.  $Edge(min, p, q)$  and  $Edge(max, p, q)$  are respectively the minimum and maximum of the block  $(p, q)$  in  $Edge$ ,  $p$  and  $q$  are the row and column index of blocks in the image.

After this kind of quality assessment, we obtain the corresponding visual quality values of each image, which are written by  $IQA = \{IQA_1, IQA_2, IQA_3, \dots, IQA_n\}$ . Then these images can be sorted by descending the values of  $IQA$ . Some best quality images  $\mathbf{I}_{high} = \{\mathbf{I}_{high(1)}, \mathbf{I}_{high(2)}, \dots, \mathbf{I}_{high(s)}\}$  will be chosen for make color balance in the next stage.  $s$  is the total number of images in the set  $\mathbf{I}_{high}$ . The rest images are labeled by  $\mathbf{I}_{low} = \{\mathbf{I}_{low(1)}, \mathbf{I}_{low(2)}, \dots, \mathbf{I}_{low(t)}\}$ , where  $t = n - s$ .

### 4.4.2 Color Balance without Gamut Problems

In this stage, the goal is to make color balance for the image set  $\mathbf{I}_{high}$ . We adopt the global color correction method, which is robust to feature matching errors and has low computational complexity. We do not define the simple correction models which were defined in [44, 45, 93]. For example, the correction model in [93] is the simulation of white balance and gamma correction, which is depending on only two parameters for each image and may result in gamut problems. Our color balance method consists of two parts, linear transforms to obtain target histograms and range-preserving histogram specifications to produce corrected images. The detailed algorithm is described in **Algorithm 5**.

For the step 7 in **Algorithm 5**, we combine the hue-preserving color image enhancement framework [85] and the fast exact histogram specification [87, 86], which can avoid gamut problems.

Many color image processing methods treat the three color channels separately, which will change the hue of the original images and produce gamut problem. Hue preservation is an important technique to avoid this problem. There are different definitions of hue. Since HSI (Hue-Saturation-Intensity) [41] color space is a common color model in many computer vision applications, the definition of hue in HSI model is adopted in our method. Giving a single RGB

## 4.4 Color Consistency without Gamut Problems

---

### Algorithm 5 Color Balance without Gamut Problems

---

- 1: **Input:**  $\mathbf{I}_{high} = \{\mathbf{I}_{high(1)}, \mathbf{I}_{high(2)}, \dots, \mathbf{I}_{high(s)}\}$ .
  - 2: **Extract SIFT features** in  $\mathbf{I}_{high(i)}$ , where  $i \in [1, 2, \dots, s]$ .
  - 3: **Feature matching** between  $\mathbf{I}_{high(i)}$  and  $\mathbf{I}_{high(j)}$ , where  $i, j \in [1, 2, \dots, s]$  and  $i \neq j$ , store matching results in a sparse Matrix  $M_1$  with size  $k \times s \times 3$ ,  $k$  is the number of matching points in the same scene.
  - 4: **Correction for the sparse Matrix  $M_1$ :** find the non-zero values in each row of  $M_1$ , compute the mean of these non-zero values and replace the original non-zero values, which produces a new sparse Matrix  $M_2$ .
  - 5: **Compute linear transforms  $T(i)$**  for each image:  $M_2(i) = M_1(i) \bullet T(i)$ , the sizes of  $M_1(i)$  and  $M_2(i)$  both are  $k \times 3$ , the size of  $T(i)$  is  $3 \times 3$ .
  - 6: **Compute transformed images:**  $\mathbf{I}_{Trans(i)} = \mathbf{I}_{high(i)} \bullet T(i)$ .
  - 7: **Histogram Specification** for  $\mathbf{I}_{high(i)}$  with the histogram of  $\mathbf{I}_{Trans(i)}$ , the result is  $\mathbf{I}_{Correction(i)}$ .
  - 8: **Output:**  $\mathbf{I}_{Correction(i)}$ .
- 

color pixel  $p$  with values  $(r, g, b)$ , the hue of  $p$  is defined by Eq. (4.4).

$$hue(p) = \begin{cases} 0 & \text{if } r = g = b, \\ \theta & \text{if } b \leq g, \\ 2\pi - \theta & \text{if } b > g, \end{cases}$$

where

$$\theta = \arccos \frac{\frac{1}{2}((r-g) + (r-b))}{((r-g)^2 + (r-b)(g-b))^{\frac{1}{2}}}. \quad (4.4)$$

**Proposition 1.** *The single pixel  $p_1$  with values  $(r_1, g_1, b_1) \in [0, L-1]^3$  and the other single pixel  $p_2$  with valuse  $(r_2, g_2, b_2) \in [0, L-1]^3$  have the same hue if and only if there exist  $a, d \in \mathbb{R}$  such that  $(r_1, g_1, b_1) = a(r_2, g_2, b_2) + d\mathbf{1}_3^T$ , where  $\mathbf{1}_3 := (1, 1, 1)^T$ ,  $L$  is the range of pixel values,  $L=256$  for 8-bit images. The proof of this proposition can be found in [34].*

The above proposition is a basic theory on hue preservation.

Given a color image  $\mathbf{I}$ , we firstly get the corresponding intensity image  $Y$  using Eq. (4.5).

$$Y = 0.299 * I_r + 0.587 * I_g + 0.114 * I_b, \quad (4.5)$$



## Color Consistency for Photo Collections without Gamut Problems

---

where  $I_r, I_g, I_b$  are respectively the red color channel, green color channel and blue color channel of the corresponding image  $\mathbf{I}$ .

Then the histogram specification will be applied to  $Y$ , the result is  $\hat{Y}$ .

At last, we use the hue-preserving enhancement framework to obtain the final corrected color image  $\hat{\mathbf{I}}$ , which is computed using the Eq. (4.6) for the three color channels respectively. Nikolova et al. [86] have analyzed and proven the efficiency of hue preservation with this equation. The hue-preserving enhancement framework is also analyzed in [85], which demonstrates that this kind of framework is better than the traditional channel-by-channel enhancements or methods only enhancing the intensity channel.

$$\begin{aligned} \hat{I}_c(k) &= \frac{\hat{Y}(k)}{Y(k)} I_c(k), & \text{if } \frac{\hat{Y}(k)}{Y(k)} \leq 1, \\ \hat{I}_c(k) &= \frac{255 - \hat{Y}(k)}{255 - Y(k)} (I_c(k) - Y(k)) + \hat{Y}(k), & \text{if } \frac{\hat{Y}(k)}{Y(k)} > 1, \end{aligned} \quad (4.6)$$

where  $I_c$  is the corresponding color channel of the image  $\mathbf{I}$ ,  $\hat{I}_c$  is the corresponding color channel of the final corrected image  $\hat{\mathbf{I}}$ ,  $k$  is the index of pixels in each gray-scale image.

### 4.4.3 Color Transfer without Gamut Problems

In the first stage, we divided the input image collection into two image sets, based on a non-reference image quality assessment method. The first image set has been color balanced in the previous stage. And the other image set having lower quality will be color corrected in this stage. We use the idea of color transfer or color propagation between two images to finish the task at this stage. The detailed algorithm is described in **Algorithm 6**.

---

**Algorithm 6** Color Transfer without Gamut Problems

---

- 1: **Input:**  $\mathbf{I}_{low} = \{\mathbf{I}_{low(1)}, \mathbf{I}_{low(2)}, \dots, \mathbf{I}_{low(t)}\}$ .
  - 2: **Extract SIFT features** in  $\mathbf{I}_{low(j)}$ , where  $j \in [1, 2, \dots, t]$ .
  - 3: **Feature matching** between  $\mathbf{I}_{low(j)}$  and  $\mathbf{I}_{high(i)}$ , where  $j \in [1, 2, \dots, t]$ ,  $i \in [1, 2, \dots, s]$ ,  $\mathbf{I}_{high(h(j))}$  is the best corresponding image pair of  $\mathbf{I}_{low(j)}$ , the corresponding values are stored in two Matrices  $M_j$  and  $M_{h(j)}$ .
  - 4: **Compute linear transforms**  $T(j)$  for each image:  $M_{h(j)} = M_j \bullet T(j)$ .
  - 5: **Compute transformed images:**  $\mathbf{I}_{Trans(j)} = \mathbf{I}_{low(j)} \bullet T(j)$ .
  - 6: **Histogram Specification** for  $\mathbf{I}_{low(j)}$  with the histogram of  $\mathbf{I}_{Trans(j)}$ , the result is  $\mathbf{I}_{Correction(j)}$ .
  - 7: **Output:**  $\mathbf{I}_{Correction(j)}$ .
- 

For the step 6 in **Algorithm 6**, we adopt the same method described in the previous stage, which can avoid gamut problems.

## 4.5 Experiments

### 4.5.1 Image Datasets

We had run our algorithm and the comparison algorithm [93] on the landmark images download from the website FLICKR, which were also collected as a public test dataset on the project website (landmark3d.codeplex.com) [46]. This dataset was popularly used as a benchmark for evaluating and comparing different computer vision algorithms. In our experiments, four landmarks had been chosen to test color consistency algorithms. ARC DE TRIOMPHE, NOTRE DAME CATHEDRAL, STATUE OF LIBERTY, TREVI FOUNTAIN are the names of these landmarks. For each landmark, we chose 20 images having different color styles, which were captured with different cameras, different illuminations, different views by different photographers. Some examples will be shown in the following part.

### 4.5.2 Results

For the comparison algorithm, we use the original codes shared on the author’s homepage and the parameters are the default values. Our method is implemented on the Matlab platform. Fig. 4.3, Fig. 4.4, Fig. 4.5, and Fig. 4.6 show the results of Park et al.’s method and our method. Since there is no efficient object evaluation metric to assess the performance of color consistency algorithms for photo collections, we compare the results with the subject method based on the color distribution and visual quality of corrected images.

The results shown in Fig. 4.3 demonstrate that our approach can enforce the image collection to share a similar color style and not cause gamut problems. The matched patches from the original images and the corrected images can easily describe the color consistency after our method. The yellow squares indicate that the compared algorithm causes gamut problems in the dark regions. In the same way, the red squares indicate that it causes gamut problems in the bright regions. Our method do not result in this kind of disadvantage, since we adopt a range preserving exact histogram specification in the proposed algorithm.

In Fig. 4.4, the results of Park et al.’s method and our approach show these two methods both enforce the images to share a similar color style. However, our method outperforms the compared algorithm on the bright sky regions, which is easy to cause gamut problems in Park et al.’s method. The results shown in Fig. 4.5 are similar to the results of Fig. 4.4, which indicates that the two approaches both make color consistency well and Park et al.’s method can not correct pixels in bright and dark regions.

In Fig. 4.6, it is not easy to compare the results from the whole images on the left of this figure. However, we can know that our results are slightly better than the compared algorithm, from the re-sized matched patches on the right of the figure.

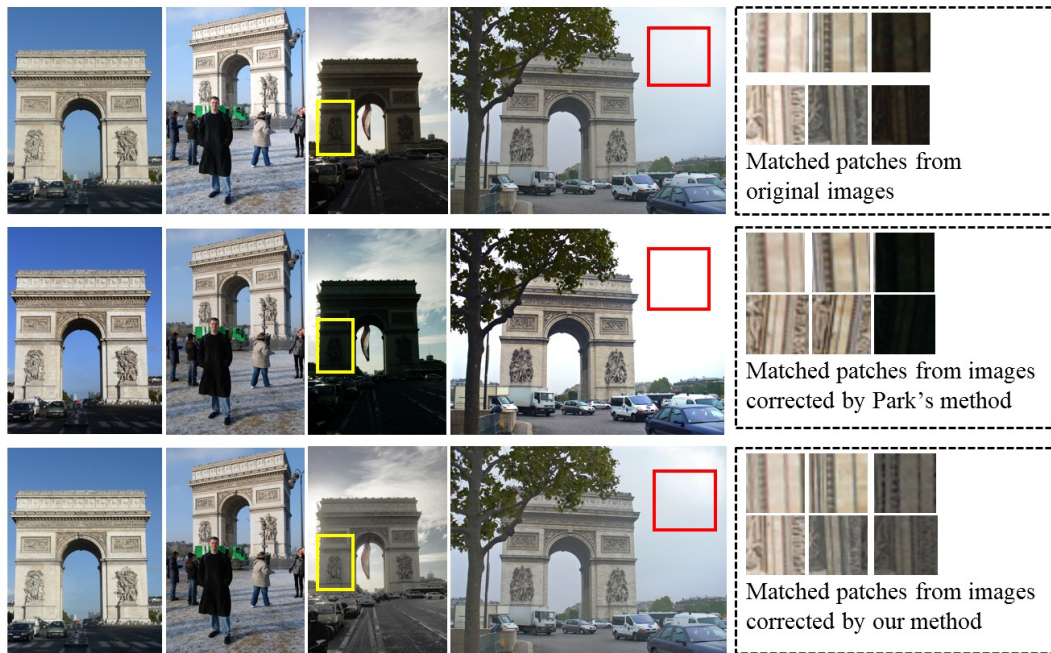


Fig. 4.3 Results on the photo collection ARC DE TRIOMPHE, only four images are shown. The upper row shows the original images, the middle row shows the results by Park et al.'s method [93], the lower row shows our results. Red and yellow squares indicate gamut problems in Park et al.'s method.

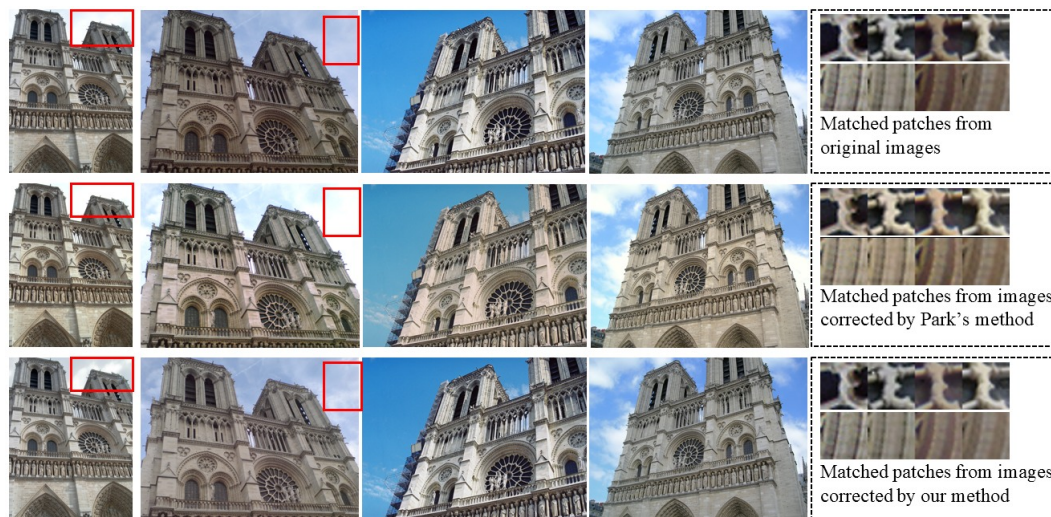


Fig. 4.4 Results on the photo collection NOTRE DAME CATHEDRAL, only four images are shown. The upper row shows the original images, the middle row shows the results by Park et al.'s method [93], the lower row shows our results. Red squares indicate gamut problems in Park et al.'s method.

## Color Consistency for Photo Collections without Gamut Problems

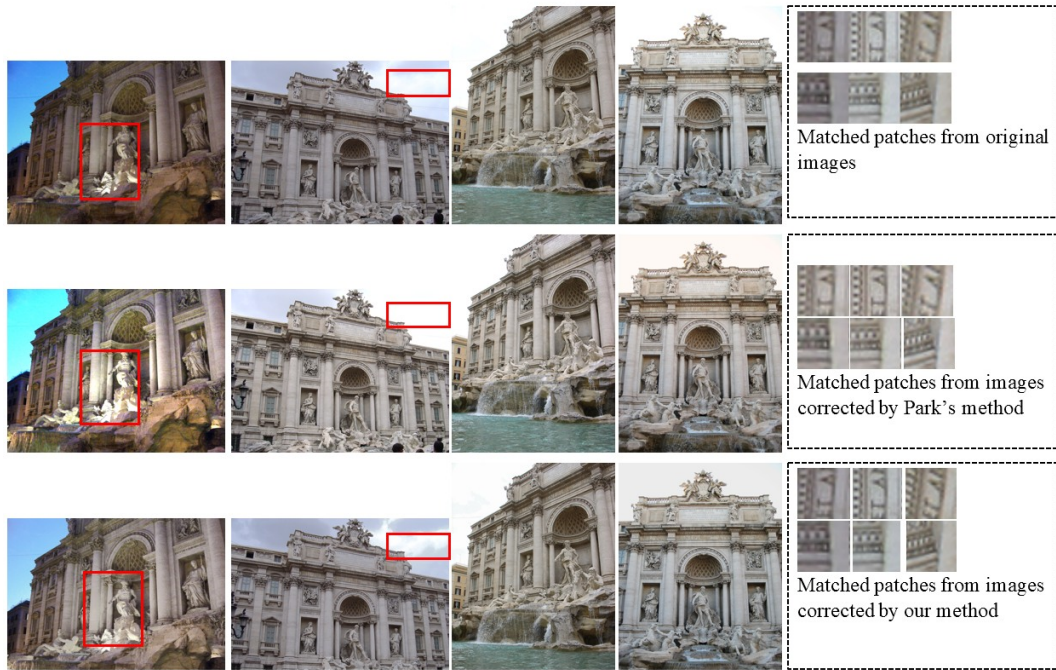


Fig. 4.5 Results on the photo collection TREVI FOUNTAIN, only four images are shown. The upper row shows the original images, the middle row shows the results by Park et al.'s method [93], the lower row shows our results. Red squares indicate gamut problems in Park et al.'s method.



Fig. 4.6 Results on the photo collection STATUE OF LIBERTY, only five images are shown. The upper row shows the original images, the middle row shows the results by Park et al.'s method [93], the lower row shows our results.

### 4.6 Conclusion

In this work, we have proposed a color consistency approach for image collections, based on range-preserving histogram specification. This method can enforce the same image collection to share the same color style and not to cause gamut problems. The main contributions of our work are reducing the effects of bad visual quality images to the whole image collection based on non-reference image quality assessment method, and finding suitable target histograms for range-preserving histogram specifications. The experiments demonstrate the proposed method outperforms the compared algorithm in terms of color consistency and avoiding gamut problems.

The proposed method is also based on a global model, since the global histogram specification is adopted. Generally speaking, global model may result in some color artifacts when the input images have some bright and dark regions. So we will focus on the local-based model in the future.



## **Part II**

# **Contrast Enhancement for Natural Images and Videos**





# Chapter 5

## A Simple Review of Contrast Enhancement

### Contents

---

<b>5.1</b>	<b>Introduction</b>	<b>82</b>
<b>5.2</b>	<b>Contrast Enhancement Methods</b>	<b>83</b>
5.2.1	Histogram-based Methods	83
5.2.2	Retinex-based Methods	87
5.2.3	Learning-based Methods	90
<b>5.3</b>	<b>Quantitative Measures</b>	<b>91</b>
<b>5.4</b>	<b>Application of Contrast Enhancement</b>	<b>93</b>
<b>5.5</b>	<b>Conclusions</b>	<b>95</b>

---

### Abstract

With the popularity of professional digital imaging devices, it is very convenient to capture images. However, some images are usually not desirable in terms of the visual quality. Because these images are captured in poor illumination conditions, by low quality cameras, or with bad parameter settings. Image enhancement is an important and challenging technique to deal with this problem. Contrast enhancement is a kind of image enhancement method for improving the contrast and the visibility of the considered images. This technique is one of the most important and challenging task in image processing research and consumer imaging systems. In this chapter, we give a simple review of image contrast enhancement, which lets the readers to quickly understand the relevant work. Firstly, we introduce the backgrounds of image contrast enhancement. Secondly, we summarize three kinds of contrast enhancement approached, including histogram-based methods, retinex-base methods, and learning-based methods. Then, five image quality assessment metrics are described for measuring the performance of different algorithms. Some relevant applications of contrast enhancement are also given to indicate the useful of this kind of technique. Finally, we conclude this chapter.

### 5.1 Introduction

Image enhancement is the technique to improve the visual quality of the considered images. There are several kinds of enhancement approaches to deal with this problem. One of the most popular technique is the method to improve the contrast, which makes the considered image to be more visible. Due to the limitations of imaging devices and illuminations, the contrast of captured images is usually unsatisfied. This makes contrast enhancement techniques to be received important attention.

Contrast enhancement methods make the considered images to be more closed to human perception, which contains similar information as the real scene provided. Based on this property, a number of contrast enhancement methods are developed to adjust the global contrast

and the local contrast of images. Generally, contrast enhancement is conducted by a transform function, which is described in Eq. 5.1.

$$\mathbf{F}(\mathbf{x}) = T(\mathbf{I}(\mathbf{x})), \quad (5.1)$$

where  $\mathbf{I}$  is the original low contrast image,  $\mathbf{F}$  is the enhanced image,  $\mathbf{x}$  are the locations of pixels in the considered images.  $T$  is the enhancement operation.

Usually, contrast enhancement methods define a contrast measure and try to optimize this value. Histogram-based algorithms are designed to modify the image histogram for improving the visibility. A typical method is the histogram equalization [41], which modifies the image histogram to be close to a uniform distribution. An example of histogram equalization is shown in Fig. 5.1. Another kind of widely used contrast enhancement method is based on the retinex theory [67], which derives from that the human perception of each pixel value depends on its surrounding pixels. Learning-based contrast methods are proposed to deal with this problem, due to the powerful learning ability of estimating the relationship between low contrast images and high visual quality images.

## 5.2 Contrast Enhancement Methods

There are lots of contrast enhancement methods proposed in the literature. We simply summarize three kinds of enhancement algorithms in the following part.

### 5.2.1 Histogram-based Methods

#### **Histogram Equalization**

The most popular histogram-base enhancement method is Histogram Equalization (HE) [41], which is a widely used for improving image visual quality. HE modifies the original histograms of images to an approximate uniform histogram, which stretches pixel value range

## A Simple Review of Contrast Enhancement

---

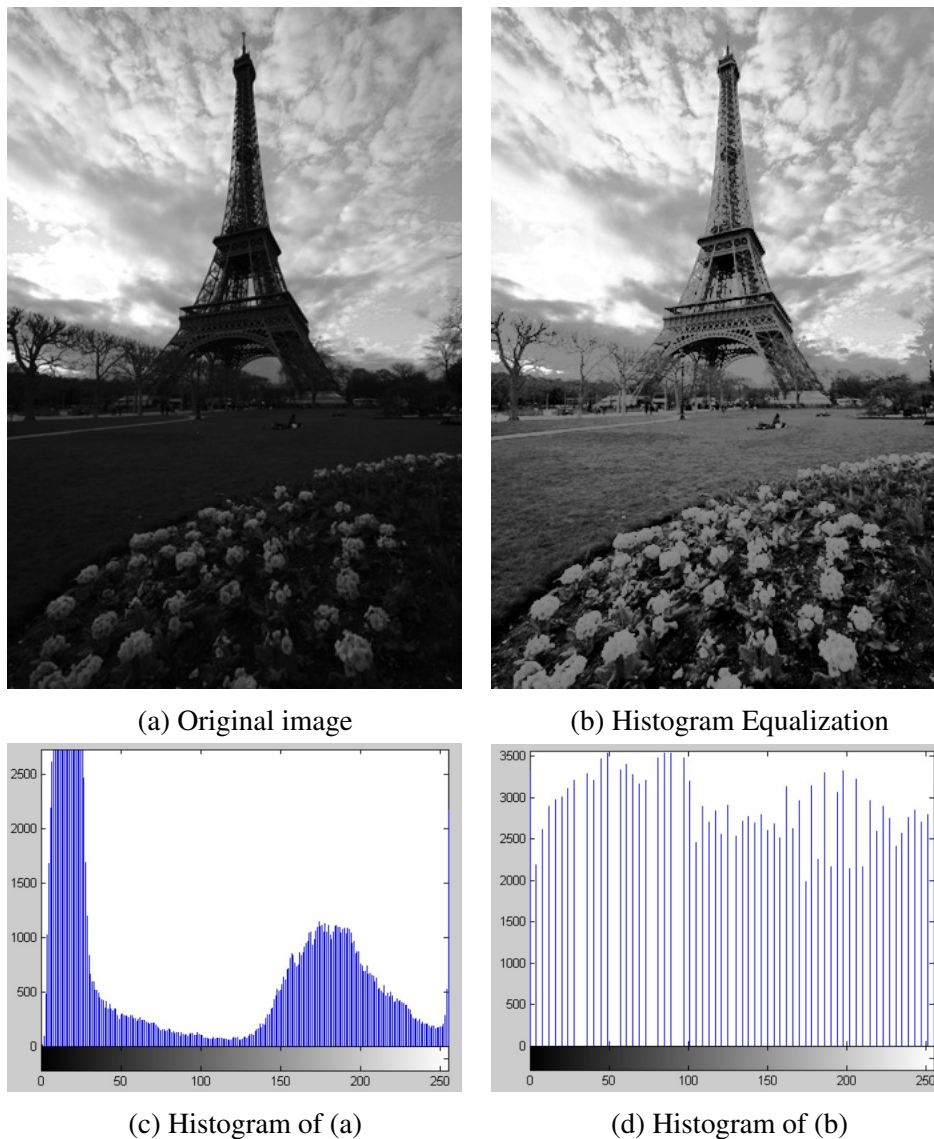


Fig. 5.1 An example of histogram equalization.

of images. This method uses the original histogram of the considered image to obtain the mapping function.

Given a gray image  $f$ , with a total number of  $N$  pixels and an intensity level range of  $[0, 255]$ . The normalized histogram  $h_f$  of the image  $f$  is computed by

$$h_f(s) = \frac{n_s}{N}, \quad (5.2)$$

where  $s \in [0, L - 1]$  is pixel values, and  $n_s$  is the total number of pixels having the same value  $s$ .

The mapping function  $T$  for the image  $f$  is obtained by

$$T(i) = \left\lfloor 255 \cdot \sum_{j=0}^i h_f(j) + 0.5 \right\rfloor, \quad (5.3)$$

where  $i \in [0, 255]$  is the input integer for the mapping function, and  $\lfloor \cdot \rfloor$  computes the nearest integer of the considered value towards minus infinity.

Histogram equalization (HE) tries to create a uniform histogram for enhanced images via considering a cumulative histogram as the corresponding mapping function. It often produces enhanced images with visual artifacts. To avoid this problem, Arici et al. [10] proposed a general histogram modification framework for contrast enhancement. The modified histogram  $h$  should be closer to the normalized uniform histogram  $h_U$  and the value of the residual  $h - h_f$  should be also small. The problem of obtaining the optimal modified histogram  $\tilde{h}$  is regarded as a bi-criteria optimization problem. An analytical solution of this problem can be obtained when the squared sum of the  $L_2$  norm is adopted. This problem is written in

$$\tilde{h} = \arg \min_h (||h - h_f||_2^2 + \lambda ||h - h_U||_2^2). \quad (5.4)$$

where  $||h - h_f||_2^2$  is a  $L_2$  norm of  $h - h_f$ ,  $||h - h_U||_2^2$  is a  $L_2$  norm of  $h - h_U$ , and the parameter  $\lambda > 0$  adjusts the trade-off between the contrast enhancement and the data fidelity.

### Histogram Specification

In order to modify the image to match a specific histogram, Nikolova et al. [88, 87, 86]<sup>1</sup> proposed an exact histogram specification method for improving image contrast. This method is aimed to transform an input image to an output image fitting a specific histogram. The detailed algorithm is described in Algorithm 7. This method is also extended to enhance color image [86]. An example is shown in Fig. 5.2.

---

<sup>1</sup>Prof. Mila Nikolova is a very excellent mathematician and researcher of the Center for Mathematics and Applications (CMLA), ENS Cachan. It is my great honor to have attended Prof. Nikolova's course "Optimization. Applications in image processing" at ENS Cachan. When I prepared this thesis, I was deeply saddened to hear that she left us on June 20th 2018.

## A Simple Review of Contrast Enhancement

---

**Algorithm 7** Nikolova's Histogram Specification Method [86].

---

1: Input:  $f$  is a test image to be enhanced,  $hist$  is the histogram of a reference image  $g$ ,

$$u^{(0)} = f, \alpha = 0.05, \beta = 0.1, \text{ iteration number } S = 5, c_0 = 0.$$

2: For  $s = 1, \dots, S$ , compute

$$u^{(s)} = f - \eta^{-1}(\beta \nabla^T \eta(\nabla u^{(s-1)})),$$

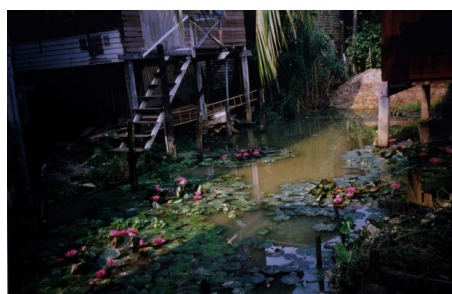
where  $\nabla$  is the gradient operator,  $\nabla^T$  is the transposition of  $\nabla$ ,  $\eta^{-1}(x) = \frac{\alpha x}{1-|x|}$ ,  $\eta(x) = \frac{x}{\alpha+|x|}$ .

3: Order the values in  $\Pi_N$  according to the corresponding ascending entries of  $u^{(S)}$ , where  $\Pi_N := \{1, \dots, N\}$  denote the index set of pixels in  $f$ .

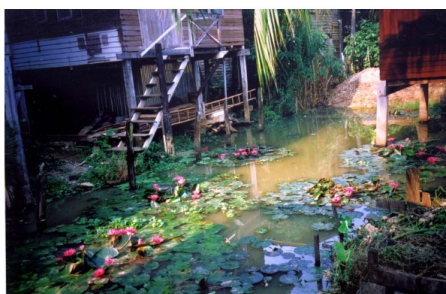
4: For  $k = 0, 1, \dots, 255$ ,

set  $c_{(k+1)} = c_{(k)} + hist_{(k)}$  and  $Y[c_{(k)} + 1] = \dots = Y[c_{(k+1)}] = k$ .  $Y$  is the enhanced result having the similar histogram to  $hist$ .

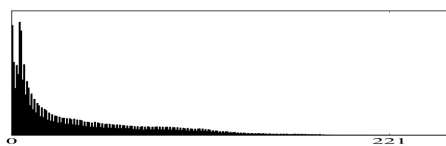
---



(a) Original image



(b) Histogram Specification



(c) Histogram of (a)



(d) Target histogram

Fig. 5.2 An example of histogram specification [86].

### Contrast-Limited Adaptive Histogram Equalization

The above methods are based on global histograms. There are a number of enhancement algorithms based on local histograms. Contrast-Limited Adaptive Histogram Equalization (CLAHE) [100] is a traditional local histogram-based enhancement algorithm. It considers histogram equalization in each local region. In other words, CLAHE defines a local transform function for each local region based on the pixel value distribution. This method is able to obtain more detailed information than global histogram-based enhancement methods. In order to control the whole brightness and preserve the naturalness of the enhanced results, researchers proposed some other local histogram-based algorithms [21, 61, 22, 119, 113, 73].

### 5.2.2 Retinex-based Methods

Inspired by the retinex theory [67], there are many retinex-based contrast enhancement algorithms. This kind of enhancement methods is based on the observation that the human perception of each pixel depends on the corresponding neighboring pixels. Land et al. [67] addressed that the human visual system does not perceive an absolute brightness but rather a relative brightness, which has a relation of the corresponding surrounding pixels. They presented a complex method involving image paths to obtain the relative brightness. Later on, they proposed an alternative technique [66] for computing the designator in the retinex theory. This method obtains the brightness by computing the logarithm of the ratio between the pixel value and the weighted average value of the neighboring pixels.

Considering a Gaussian kernel to build the relationship between the center pixel and surround pixels, Jobson et al. [57] proposed a classic multi-scale retinex-based enhancement method. They extend a previously single-scale retinex [58] to a multi-scale which achieves simultaneous dynamic range compression, color consistency, and tonal rendition. The results are more similar to the human visual perception.

Kimmel et al. [64] introduced a variational model to the retinex enhancement via a quadratic programming optimization. For a given image  $I$ , there are two different corresponding



## A Simple Review of Contrast Enhancement

---

images, including the reflectance image  $R$ , and the illumination image  $L$ . A first step taken by most retinex-based algorithms is the conversion to the logarithmic domain by  $s = \log S, l = \log L, r = \log R$ , and thereby  $s = l + r$ . The general framework of retinex-based methods is illustrated in Fig. 5.3. Before defining the minimization functional, they gave five assumptions. (1). The first important assumption about the illumination is its spatial smoothness. (2). Since the reflectance image  $R$  is restricted to the unit interval, they add the constraint  $L \geq S$ . Since the log function is monotone, they also have  $l \geq s$ . (3). By setting  $l = Const$ , where  $Const$  is any constant above the maximal value of  $s$ , they get a trivial solution that satisfies the two previous assumptions. They therefore add the assumption that the illumination image  $L$  is close to the intensity image  $s$ , i.e., it minimizes a penalty term of the form  $dist(l, s)$ , e.g., the  $L_2$  norm  $(l - s)^2$ . (4). The reflectance image  $r = s - l$  can be assumed to have a high prior probability. One of the simplest prior functions used for natural images assigns high probability to spatially smooth images. (5). They assume that the illumination continues smoothly as a constant beyond the image boundaries. This is an artificial assumption required for boundary conditions that would have minor effect on the final results. After collecting all these assumptions into one expression, they define a penalty functional to achieve the goal of contrast enhancement.

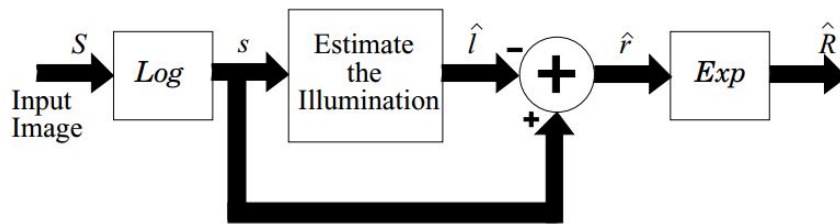


Fig. 5.3 The general framework of retinex-based methods.

Provenzi et al. [107] considers color correction and local contrast improvement for color image enhancement. In order to produce more robust and better-enhanced results, they combine the random spray retinex method and the automatic color equalization. Specifically, the distinct nonlinear and differential mechanisms of these two algorithms have been fused with the spray technique and local average operations. In addition, they considered a local and global contrast-

based and image-driven regulation method which achieves color correction. An example of image enhancement by the randoms spray retinex, the automatic color equalization, and Provenzi et al.'s method is shown in Fig. 5.4.

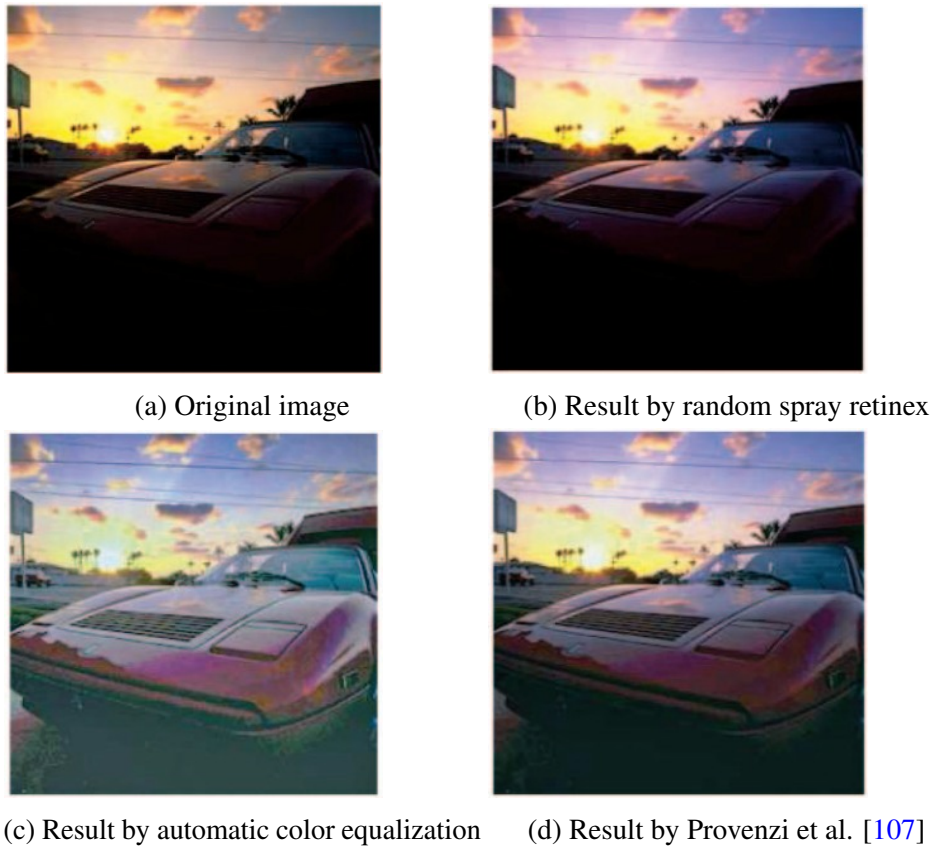


Fig. 5.4 Image enhancement by the randoms spray retinex, the automatic color equalization, and Provenzi et al.'s method.

Palma-Amestoy et al. [90] proposed a variational framework for color image enhancement, which is inspired by the basic phenomenology of color perception. They designed a kind of energy functional to simulate the perceptually inspired image color and contrast information. The minimization is obtained via a gradient descent method.

Recently, Pierre et al. [96] propose a hue-preserving variational contrast enhancement method, which enables users to control the contrast improvement levels. Since lots of contrast enhancement methods produced over-enhancement artifacts, they allows users to manually control the contrast enhancement level and the scale of enhanced detail information via a

## A Simple Review of Contrast Enhancement

---

variational framework. Moreover, the hue preservation is considered in the enhancement framework for processing color images.

### 5.2.3 Learning-based Methods

Machine learning is a very popular and powerful technique in the domains of computer vision and image processing. It achieves better performance than traditional algorithms in lots of research topics. Recently, there are also some learning-based image contrast enhancement methods in the literature.

Bychkovsky et al. [19] proposed a learning photographic global tonal adjustment approach, which can obtain desirable enhanced results. They firstly created a dataset including 5 sets of 5000 example input-output pairs which can be used for supervising the learning framework. Then, they applied the dataset to build a global tonal adjustment model with a number of features.

Ignatov et al. [54] proposed an end-to-end deep convolutional network to improve photo visual quality, especially for contrast enhancement. The learning-based method can improve both image contrast and color rendition. They designed a perceptual error function combining image content loss, color loss and texture loss. A large-scale dataset is collected captured from different imaging devices. Then, the enhancement network model is build with the collected dataset. The overall framework of the proposed learning-based enhancement method is presented in Fig. 5.5.

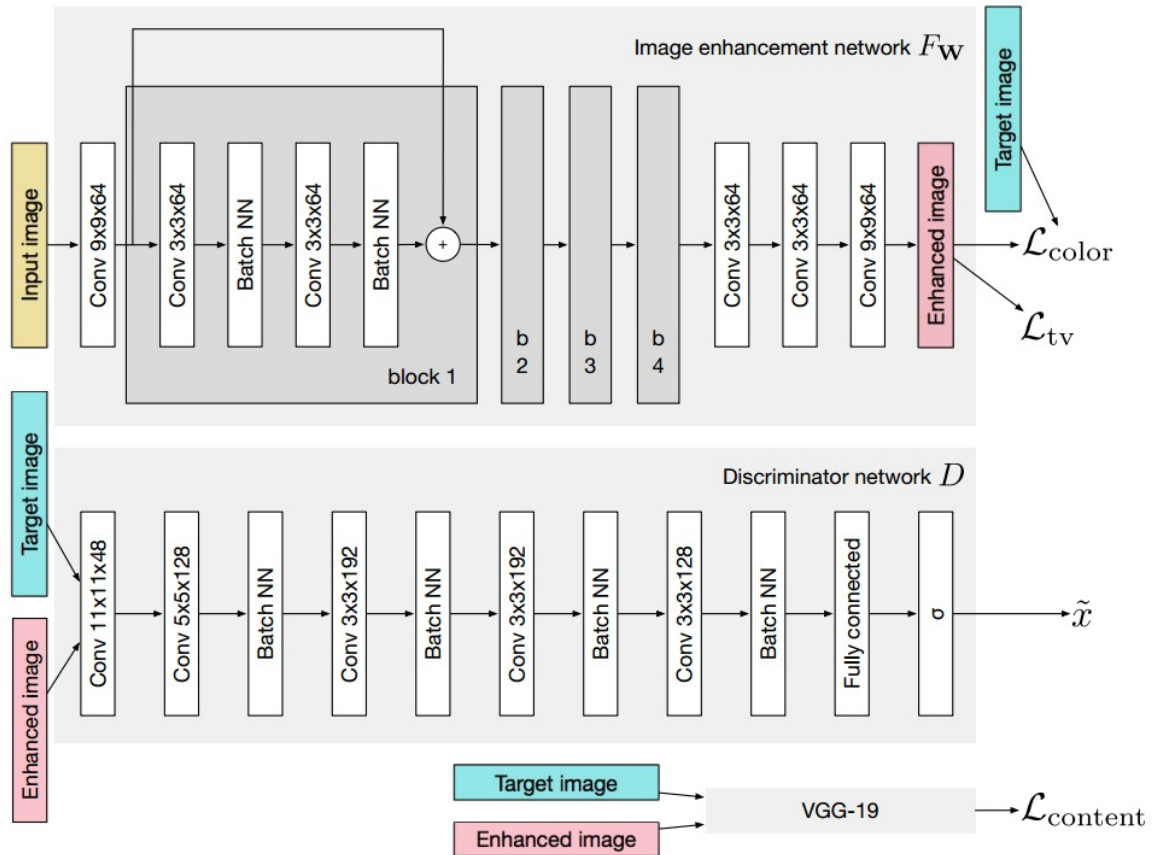


Fig. 5.5 The overall architecture of the learning-based enhancement in [54].

## 5.3 Quantitative Measures

The quality of the contrast enhanced images can be assessed in many aspects. We summarize some popularly used metrics in the following part.

- **Peak Signal-to-Noise Ratio (PSNR)**

PSNR [41] is the most popular full-reference metrics to assess image quality. PSNR is usually used to measure the pixel value fidelity between the enhanced images and the corresponding high-quality reference images. The definition of *PSNR* has been given in Section 2.4.

- **Structural Similarity Index (SSIM)**

SSIM [139] is usually used to measure the structure fidelity between the enhanced images and the reference images. The definition of *SSIM* has been described in Section 2.4.

- **Visible Edges Assessment (VEA)**

Hautière et al. [48] proposed a contrast evaluation method via Visible Edges Assessment (VEA). This metric evaluates the contrast improvement with three indicators. The first indicator  $e$  evaluates the ability for restoring edges. The second indicator  $\bar{r}$  is the mean ratio of gradients in visible edges. The third indicator  $\Sigma$  represents the percentage of pixels becoming saturated after the enhancement. The higher values of  $e$  and  $\bar{r}$  present the better contrast improvement. The lower value of  $\Sigma$  indicates the better ability of pixel value range preservation.

- **Statistical Naturalness Measure (SNM)**

Yeganeh et al. [146] proposed a Statistical Naturalness Measure (SNM) model for evaluating the image quality. Since there are lots of image quality metrics not considering the naturalness of the enhanced results, SNM is also able to assess the performance of different enhancement algorithms. Yeganeh et al. considered the global intensity distributions of a large number of images and built a model to assess the image naturalness. The range of SNM is  $[0, 1]$ . The higher value of SNM means the better naturalness of the considered image.

- **Color image Quality measurement (CQE)**

Panetta et al. [91] proposed a color image quality measurement (CQE) combining the contrast, sharpness and colorfulness metrics. CQE is the weighted sum of the three metrics. The contrast is represented by the Michelson-Law measure of enhancement AME [4] of the intensity component. The sharpness is represented by the Weber contrast based measure of enhancement EME [3] of each gray edge map. The colorfulness is

represented with the statistical information [47] of the opponent color components. The higher value of CQE means the better quality of the considered color images enhanced by corresponding methods.

### 5.4 Application of Contrast Enhancement

- **Photography**

With the popularity of digital cameras, it is very convenient to capture photos by ourselves. However, the obtained photos are usually not desirable resulting from the imaging device quality, the environmental illuminations, or the photography experience. So contrast enhancement is considered to improve the visibility of images. Kaufman et al. [60] presented a content-aware automatic photo enhancement method. An enhanced result by this method is shown in Fig. 5.6.



(a) Original image



(b) Enhanced by Photoshop Elements



(c) Enhanced by Google Picasa



(d) Enhanced by [60]

Fig. 5.6 Contrast enhancement in photography.

## A Simple Review of Contrast Enhancement

---

- **Medical Imaging**

Image contrast enhancement methods can improve the contrast and visual quality of magnetic resonance (MR) images. For example, some contrast enhancement methods are applied in brain tumor MR imaging to improve the visibility, which is helpful to distinguish between the normal and abnormal regions in MR images. Fig. 5.7 shows an example of contrast enhancement in medical imaging.

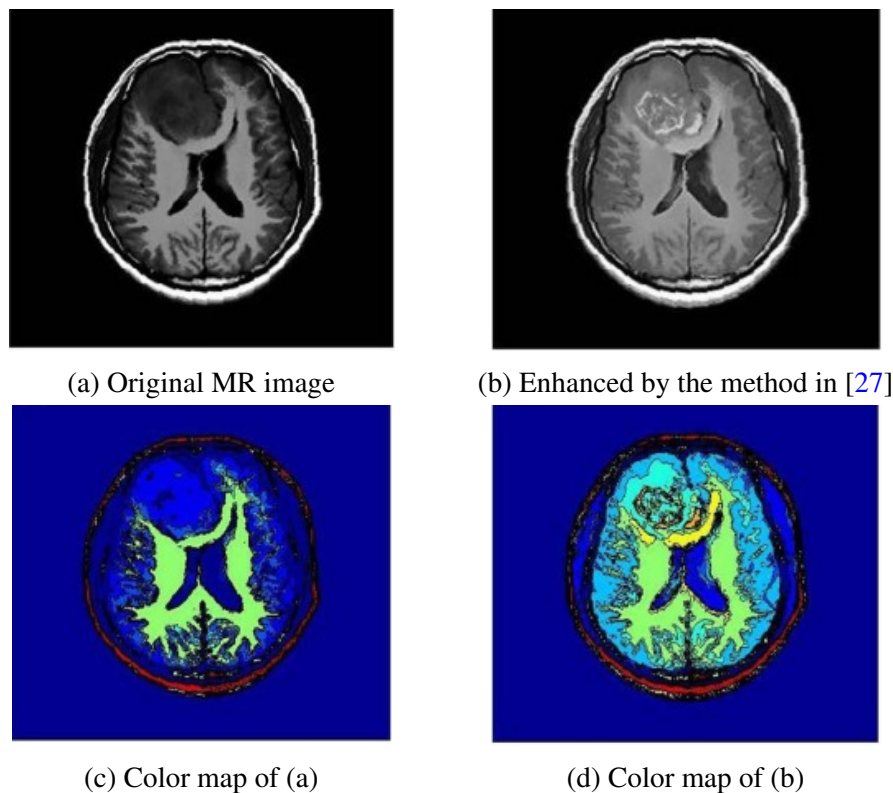
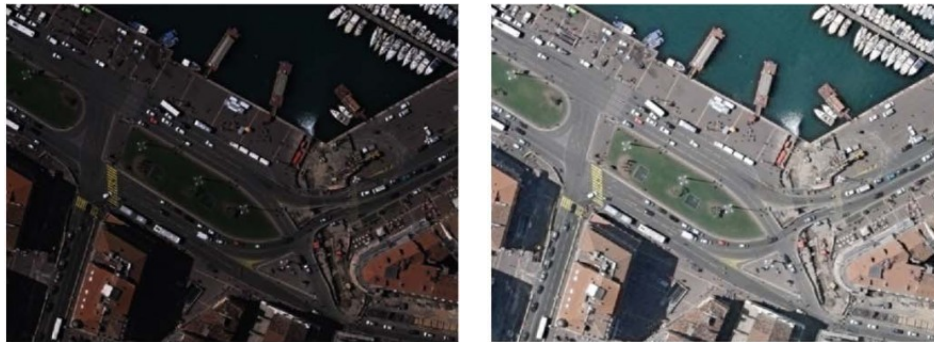


Fig. 5.7 Contrast enhancement in medical imaging

- **Remote Sensing Imaging**

Remote sensing images can provide us with more information about the land, water, and buildings in the earth. However, resulting from this unknown perspective and the image data obtained from radiation outside the visible portion of the electromagnetic spectrum, this kind of images need to improve the contrast. Fig. 5.8 shows an example contrast enhancement in remote sensing images.



(a) Original image

(b) Enhanced by a method in [72]

Fig. 5.8 Contrast enhancement in remote sensing imaging [72]

## 5.5 Conclusions

This chapter simply reviews the relevant work of image contrast enhancement. Firstly, we introduce the background of image contrast enhancement. Then, three kinds of enhancement methods are summarized. Besides, several image quality assessment metrics are described. We expect that this simple review could make the readers understand the research background easily. This basic knowledge of image contrast enhancement can be also regarded as a supplementary description of the work in the following chapters.





# Chapter 6

## A Global Naturalness Preservation

## Contrast Enhancement Method

### Contents

---

<b>6.1</b>	<b>Introduction</b>	<b>98</b>
<b>6.2</b>	<b>Proposed Method</b>	<b>101</b>
6.2.1	Overview	101
6.2.2	A Global Naturalness Preservation Contrast Enhancement Method	101
<b>6.3</b>	<b>Results</b>	<b>104</b>
6.3.1	Performance Criteria	104
6.3.2	Result Analysis	105
<b>6.4</b>	<b>Conclusions and Future Work</b>	<b>109</b>

---

### Abstract

Contrast enhancement is a technique for enhancing image contrast to obtain better visual quality. Since many existing contrast enhancement algorithms usually produce over-enhanced results, the naturalness preservation is needed to be considered in the framework of image contrast enhancement. This chapter proposes a naturalness preserving contrast enhancement method (presented in our contribution [129]), which adopts histogram matching to improve the contrast and uses the image quality assessment to automatically select the optimal target histogram. The contrast improvement and the naturalness preservation are both considered in the target histogram, so this method can avoid the over-enhancement problem. In the proposed method, the optimal target histogram is a weighted sum of the original histogram, the uniform histogram, and the Gaussian-shaped histogram. Then the structural metric and the statistical naturalness metric are used to determine the weights of corresponding histograms. At last, the contrast-enhanced image is obtained via matching the optimal target histogram. The experiments demonstrate the proposed method outperforms the compared histogram-based contrast enhancement algorithms.

### 6.1 Introduction

With the popularity of professional digital cameras and smartphone cameras, it is very convenient to capture images. However, some images are usually not desirable in terms of the visual quality. Because these images are captured in poor illumination conditions, by low quality cameras, or with bad parameter settings. Image enhancement is an important and challenging technique to deal with this problem. This technique has been successfully applied in the relevant domains, such as camera photographing [54], medical imaging [51], and remote sensing imaging [72]. It makes the considered images more clear, so image enhancement works as a very important pre-processing step in these applications. Contrast enhancement is a kind

of image enhancement method for improving the contrast and the visibility of the considered images.

There are many different kinds of methods [41, 107, 94, 81, 127, 129] having been proposed for image contrast enhancement. Histogram-based approaches is a very popular kind of enhancement method and can be categorized into two subgroups: global methods and local methods. Global methods analyze the global histogram of the whole image, and local methods utilize the information of local histograms in the considered image. Although local methods [61, 106, 90, 96] can usually obtain good enhancement results with carefully tuning parameters, these methods are highly depended on the suitable parameter settings. Unsuitable parameters will result in artifacts decreasing the visual quality of the considered images.

One of the most popular global contract enhancement methods is histogram equalization [100], which modifies different kinds of histograms to uniform histograms and produces higher visual contrast. For some color images, traditional histogram equalization will result in unnatural artifacts (over enhancement) and change original hue, which can be clearly seen in Fig. 6.1.



Fig. 6.1 Traditional histogram equalization for a color image. The over-enhancement problem can be observed obviously.

## A Global Naturalness Preservation Contrast Enhancement Method

---

Various related methods have been proposed to avoid these kinds of disadvantages. Stark [122] proposed an adaptive image contrast enhancement method based on a generalization of histogram equalization. By setting different forms of mapping functions, this algorithm can result in corresponding different degrees of contrast enhancement. A more general framework of Stark's method is proposed by T. Arici [10]. Recently, Xu [144] proposed a generalized equalization model combining white balance and contrast enhancement. Jiang [56] proposed a brightness preservation method for color image enhancement. Jung [59] proposed an optimized perception tone mapping method for contrast enhancement. Local contrast enhancement methods [61, 90, 96] can usually obtain good enhancement results with carefully tuning parameters. However, this kind of methods are highly depend on the suitable parameter settings. Unsuitable parameters will result in artifacts decreasing the visual quality of the considered images.

Many previous histogram-based contrast enhancement algorithms, including global methods and local methods, usually need to select the parameters carefully or result in over-enhancement problems. To avoid these issues, a naturalness preservation automatic contrast enhancement approach (also presented in our research paper [129]) is proposed in this chapter. This method automatically chooses the optimal target histogram considering the image structure and statistical naturalness. Then the target histogram is used to enhance the image contrast via histogram matching methods.

The rest of this chapter is organized as follows. The detailed description of the proposed approach is given in Section 6.2. The numerical experiments and performance comparisons are shown in Section 6.3. Finally, we give the conclusions in Section 6.4.

## 6.2 Proposed Method

### 6.2.1 Overview

We present the overview of the proposed naturalness preservation contrast enhancement method, which is shown in Fig. 6.2. Given a low contrast image  $\mathbf{I}$  (RGB color space), it firstly converted to the full value range  $[0, 255]$  with the linear stretching. Then the stretched image is converted to HSV color space. The  $V$  channel is enhanced with histogram matching methods. Different target histograms can produce different enhanced  $V_M$ . The optimal target histogram can be obtained based on the structure measure (between  $V_M$  and  $V_L$ ,  $V_L$  is the enhanced result by contrast limit adaptive histogram equalization) and the naturalness measure (for  $V_M$ ). After computing the enhanced  $V_E$  with the optimal target histogram, the final enhancement result  $\mathbf{F}$  is produced using HSV-RGB color space conversion.

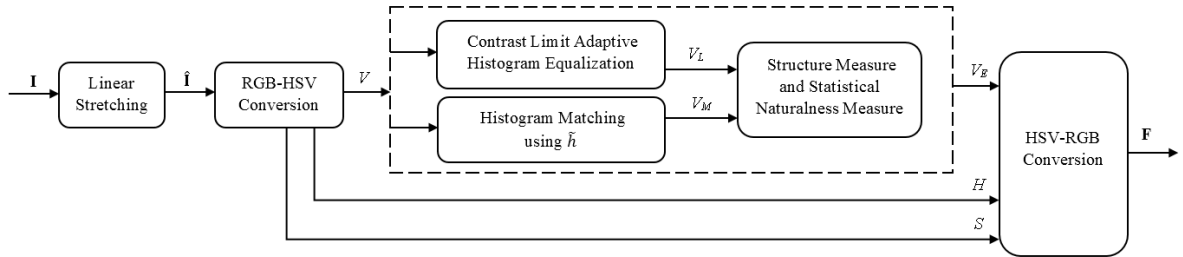


Fig. 6.2 The overall framework of the proposed enhancement method.

### 6.2.2 A Global Naturalness Preservation Contrast Enhancement Method

In the above subsection, we give an overview of the proposed naturalness preservation contrast enhancement approach. Since the linear stretching, RGB-HSV conversion and HSV-RGB conversion are basic image processing techniques, we will not give the detailed description of these operations. In this section, we will present the method obtaining the enhanced  $V_E$

## A Global Naturalness Preservation Contrast Enhancement Method

---

with the optimal target histogram and the intensity channel  $V$ . The key contributions are the definition of the target histogram and computing the optimal weights of the components of the target histogram. Considering a gray image  $V$  with a total number of  $N$  pixels, the normalized histogram is defined by

$$h_V(k) = \frac{n_k}{N}, \quad (6.1)$$

where  $k \in [0, 255]$  is pixel values,  $n_k$  is the total number of pixels having the same value  $k$ .

Histogram-based contrast enhancement methods use different kinds of histograms to obtain the corresponding mapping functions for modifying the pixel values and enhancing the contrast of the considered image. Traditional histogram equalization algorithm uses the original histogram of the considered image to obtain the mapping function. It tries to create a uniform histogram for the enhanced image via considering a cumulative histogram as the corresponding mapping function. This kind of histogram equalization algorithm often produces over-enhancement problems. To avoid this problem, Arici et al. [10] considered the weight sum of the original histogram and the uniform histogram. The weighted histogram is used to create the mapping function. The over-enhancement problem can be decreased to a certain extent. Inspired by this idea, we consider a more complex histogram modification, which is a weight sum of the original histogram, the uniform histogram and the Gaussian-shaped histogram. In [146], the authors analyzed about 3000 gray images and build a statistical naturalness model. They found that the histograms of the means of these images can be well fitted using a Gaussian function. The similar conclusion can be also found in [80], which adopts a Gaussian curve to assess the well-exposed pixels. So, we adopt the Gaussian-shaped histogram to make the enhancement results more natural. Based on the above analysis, the modified histogram  $h$  should be closer to the normalized uniform histogram  $h_u$  and normalized Gaussian-shaped histogram  $h_g$ , the residual  $h - h_V$  should be also small. We define a target histogram  $\tilde{h}$  which can be formulated as the minimization problem:

$$\tilde{h} = \arg \min_h ((1 - \alpha - \beta) \|h - h_V\|_2^2 + \alpha \|h - h_u\|_2^2 + \beta \|h - h_g\|_2^2), \quad (6.2)$$

where  $h_u$  is the normalized uniform histogram,  $h_g$  is the normalized histogram with the Gaussian curve shape,  $\alpha$  and  $\beta$  are the corresponding weights,  $\alpha + \beta \in [0, 1]$ . In the implement, we use the Gaussian curve  $\exp\left(-\frac{(i-0.5)^2}{2\sigma^2}\right)$ ,  $\sigma = 0.2$ .

The equation 6.2 is a quadratic optimization problem, and the solution is given by

$$\tilde{h} = (1 - \alpha - \beta)h_v + \alpha h_u + \beta h_g, \quad (6.3)$$

The target histogram  $\tilde{h}$  is a weighted sum of  $h_v$ ,  $h_u$ , and  $h_g$ . There are two parameters  $\alpha$  and  $\beta$  to be tuned in this solution. Different  $\alpha$  and  $\beta$  can produce different target histogram  $\tilde{h}$ , which will generate different contrast enhanced images. Generally speaking,  $\alpha$  controls the contrast enhancement, and  $\beta$  controls the naturalness preservation. Our goal is to automatically enhance the contrast of the considered image. To deal with this automatic problem, we adopt the structure measure and the statistical naturalness measure [146] to guide the optimization. SSIM [139] was used to measure the structure. The detail description of this measure has been given in Section 2.4. The statistical naturalness measure is described in Section 5.3.

The Contrast Limit Adaptive Histogram Equalization (CLAHE) can produce satisfying local structure of the considered image. We use the CLAHE enhancement result  $V_L$  to guide the image structure. And use the statistical naturalness measure to achieve the task of the naturalness preservation. Based on the experience, we can give some candidates of  $\alpha$  and  $\beta$ . Each pair of  $\alpha$  and  $\beta$  can produce an enhancement result  $V_M$ . The corresponding structure measure between  $V_M$  and  $V_L$ , and the statistical naturalness measure of  $V_M$  can be both obtained. Then we can get the optimal  $\alpha$  and  $\beta$  based on the best structure measure and the statistical naturalness measure. After determining  $\alpha$  and  $\beta$ , the corresponding optimal enhancement result  $V_E$  can be found.



### 6.3 Results

We ran the traditional Histogram Equalization algorithm (HE) [41], Contrast Limit Adaptive Histogram Equalization (CLAHE) [41], Histogram Modification Framework (HMF) [10] and the proposed Naturalness Preservation Contrast Enhancement method on five test images from the image dataset TID2013 [101] and CSIQ [68]. The test images and corresponding reference images are both available in these datasets. By decreasing the contrast, these low contrast test images were obtained from the corresponding high contrast reference images. The reference images are also given to evaluate the algorithm performance. For the traditional histogram equalization algorithm, we use the function `histeq` in the MATLAB Image Processing Tool. For the Contrast Limit Adaptive Histogram Equalization algorithm, we use the function `adaphisteq` in the MATLAB Image Processing Tool. For the histogram modification method [10], we reproduce this algorithm and set the parameter  $\lambda = 1$  for all experiments. We also implement the proposed method using MATLAB. For all algorithms, the test image is firstly converted from the RGB color space to the HSV color space. Then the  $V$  channel is processed using the corresponding enhancement algorithms. At last, the enhanced HSV image is converted to the RGB color space.

#### 6.3.1 Performance Criteria

The quality of the contrast enhanced images can be assessed in many aspects. The performance metrics used in our experiments are Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [139], which are the most popular metrics to assess image quality and compare the performance of different image enhancement algorithms. In our experiment, we use the metric PSNR to measure the pixel value fidelity between the enhanced images and the corresponding high-quality reference images, and use the metric SSIM to measure the structure fidelity between the enhanced images and the reference images. The definitions of *PSNR* and *SSIM* have been described in Section 2.4.

### 6.3.2 Result Analysis

To evaluate the performance of the proposed enhancement method, both qualitative comparisons and quantitative assessments are considered in the following parts.

- **Qualitative Comparisons**

To compare different enhancement algorithms qualitatively, we show some test images and the corresponding enhanced images in following figures. The reference images are also given to evaluate whether the corresponding results are over-enhancement or not. In Fig. 6.3, HE makes the histograms of the enhanced results as uniform as possible. It produces some regions to be brighter or darker, which makes the results un-natural. These issues can be found in the region of the ref door and the white ball (in Fig. 6.3a), the region of the sky (in Fig. 6.4a), the regions of the fruit (in Fig. 6.5a), the region of the building (in Fig. 6.6a), and the region of the wall (in Fig. 6.7a) . Compared with HE, the results of CLAHE and HMF avoid the over-enhancement (un-naturalness) problem to some extent. However, the slight un-naturalness issue can be observed in the results of CLAHE and HMF. The reason is that these two methods do not consider the naturalness preservation. Compared our results with the others, we can conclude that the proposed method preserves the naturalness better. This conclusion can be also supported by comparing the enhancement results with the high-quality reference images. More result comparisons are show in Fig. 6.4, Fig. 6.5, Fig. 6.6, and Fig. 6.7.

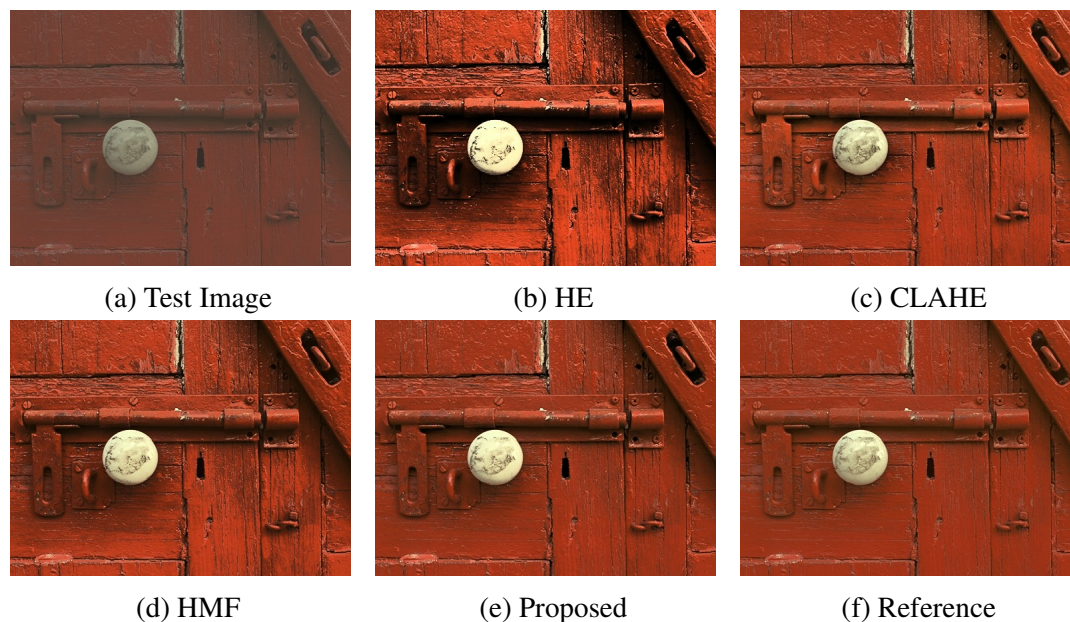


Fig. 6.3 Results of different enhancement algorithms for the image "Door".

### • Quantitative Comparisons

To compare different enhancement algorithms quantitatively, two widely adopted image quality assessment metrics (PSNR and SSIM) are considered below. The detailed definitions of these metrics are given in Section 2.4. The PSNR comparisons of different enhancement algorithms (including HE, CLAHE, HMF and the proposed method) on the five test images are shown Table 6.1. We can know that the proposed method obtains the best PSNR for all test images, which indicates the ability of image pixel value fidelity. In Table 6.2, we give the SSIM comparisons of different enhancement methods. The results demonstrate the proposed approach outperforms other enhancement algorithms in terms of SSIM. This indicates the ability of image structure fidelity of our method.

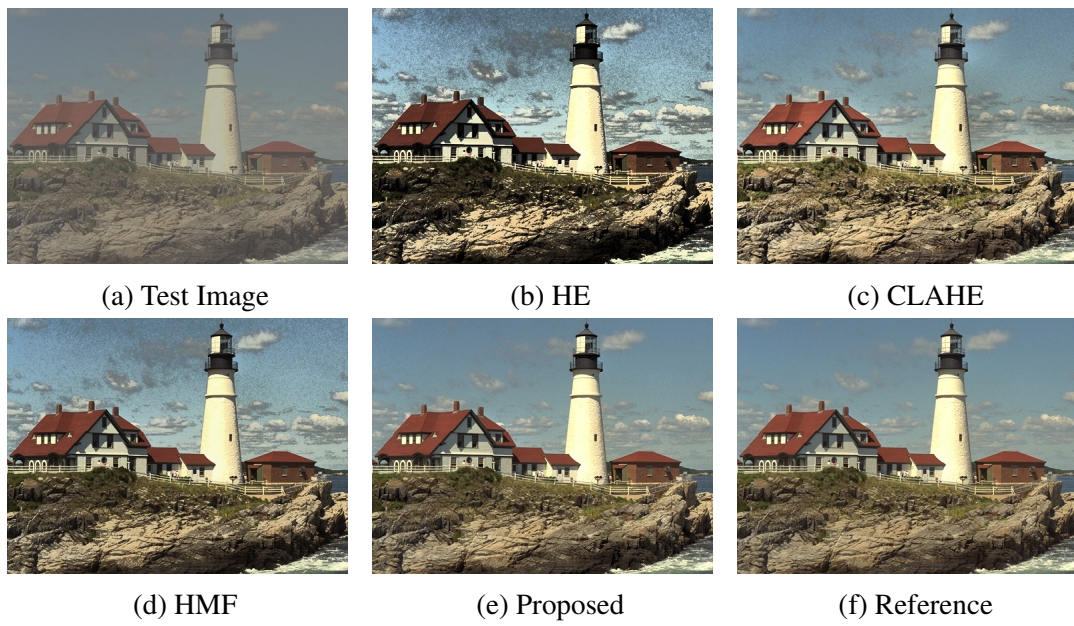


Fig. 6.4 Results of different enhancement algorithms for the image "Lighthouse".

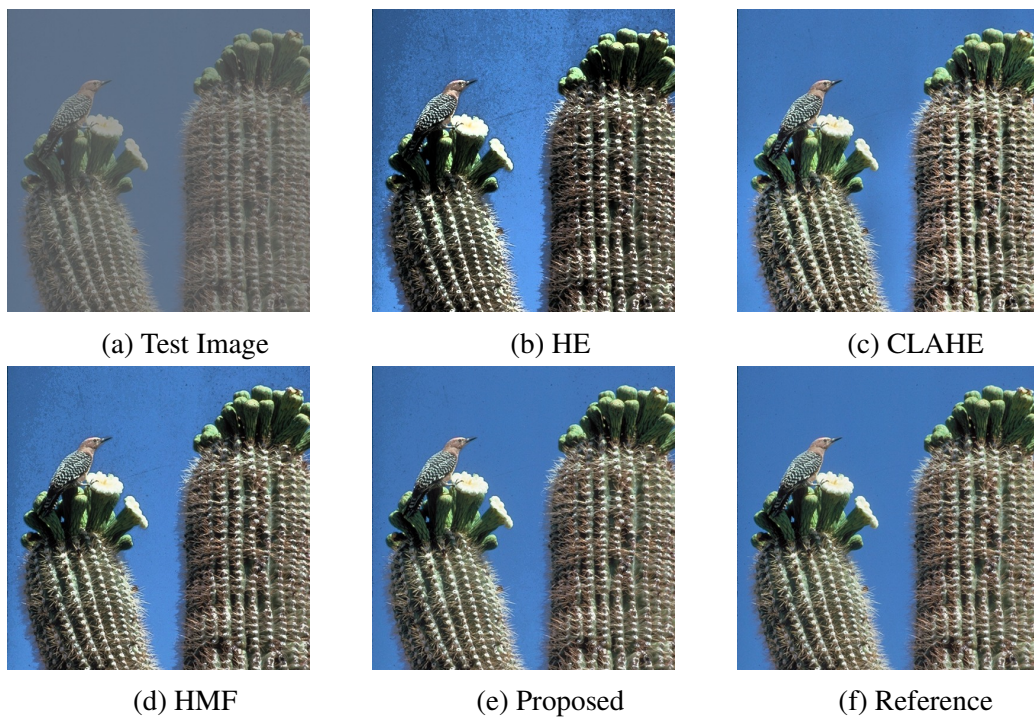


Fig. 6.5 Results of different enhancement algorithms for the image "Cactus".

## A Global Naturalness Preservation Contrast Enhancement Method

---

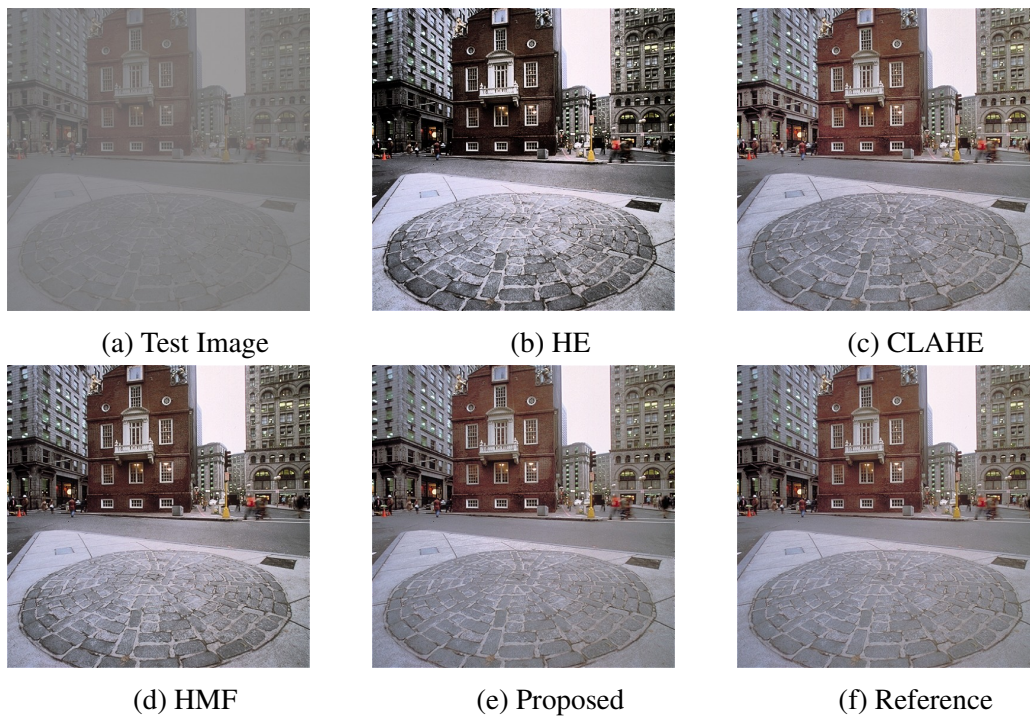


Fig. 6.6 Results of different enhancement algorithms for the image "Boston".

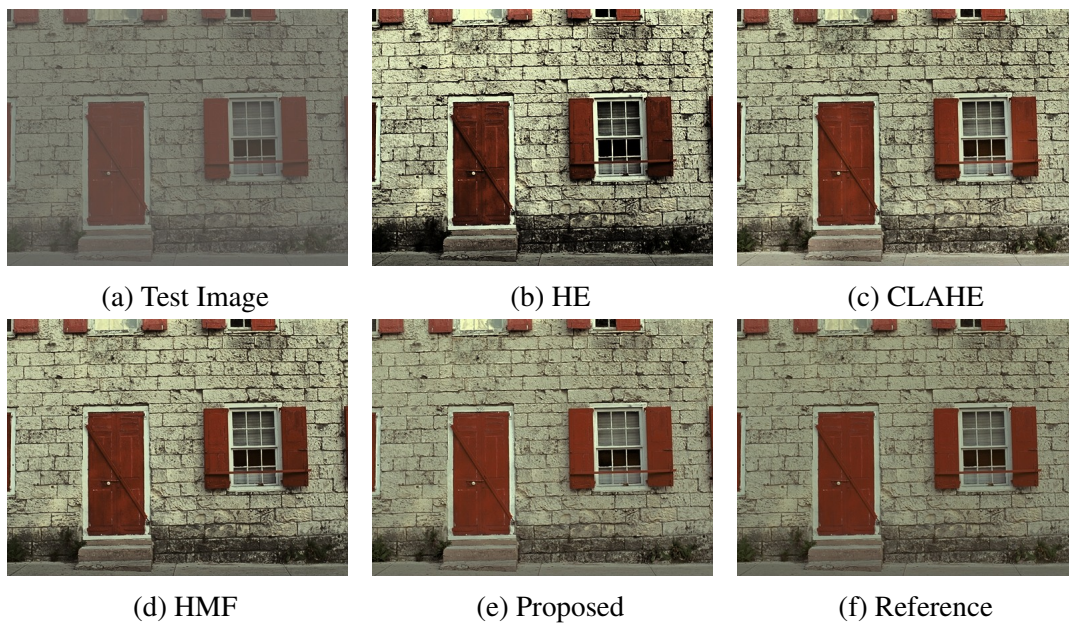


Fig. 6.7 Results of different enhancement algorithms for the image "Wall".

## 6.4 Conclusions and Future Work

	HE	CLAHE	HMF	Proposed
Image Door	17.90	27.63	24.12	<b>29.92</b>
Image Lighthouse	17.84	23.94	23.94	<b>35.92</b>
Image Cactus	20.33	25.99	26.67	<b>34.90</b>
Image Boston	17.34	28.23	23.89	<b>34.74</b>
Image Wall	16.31	19.60	21.08	<b>25.81</b>

Table 6.1 The comparison of different enhancement algorithms in terms of PSNR.

	HE	CLAHE	HMF	Proposed
Image Door	0.7690	0.9788	0.9442	<b>0.9818</b>
Image Lighthouse	0.7225	0.9439	0.9067	<b>0.9925</b>
Image Cactus	0.8887	0.9713	0.9752	<b>0.9941</b>
Image Boston	0.7125	0.9645	0.9072	<b>0.9865</b>
Image Wall	0.7416	0.8819	0.9097	<b>0.9779</b>

Table 6.2 The comparison of different enhancement algorithms in terms of SSIM.

## 6.4 Conclusions and Future Work

In this chapter, we have proposed a naturalness preservation automatic contrast enhancement method. The main contributions of this method are: (a). defining the weight sum of the original histogram, the uniform histogram and the Gaussian-shaped histogram as the optimal target histogram for contrast enhancement. (b). using the structure measure and the statistical naturalness measure to determine the optimal parameters. The proposed method considers the trade-off between the contrast enhancement and the naturalness preservation.

We try some candidate parameters to find the optimal target histogram, which is a time-consuming method. In the future work, we will find a more direct and faster way to select the optimal parameters.



# Chapter 7

## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

### Contents

---

<b>7.1</b>	<b>Introduction</b>	<b>113</b>
<b>7.2</b>	<b>Related Work</b>	<b>116</b>
7.2.1	Global Enhancement Methods	116
7.2.2	Local Enhancement Methods	116
7.2.3	Image Fusion	117
<b>7.3</b>	<b>The Proposed Method</b>	<b>118</b>
7.3.1	Global Contrast Adaptive Enhancement	118
	Overview	118
	Global Contrast Adaptive Enhancement for Gray Images	120
7.3.2	Local Contrast Adaptive Enhancement	122



---

## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

---

7.3.3	A Variational Method for Fusion via Contrast Optimization and Color Correction . . . . .	123
	Variational-based Fusion Model . . . . .	124
	Numerical Method . . . . .	127
	Parameters Setting . . . . .	127
7.3.4	Fusion with other Global Enhancement and Local Enhancement Methods . . . . .	128
<b>7.4</b>	<b>Experiments and Comparisons . . . . .</b>	<b>130</b>
7.4.1	Qualitative Comparisons . . . . .	130
7.4.2	Quantitative Comparisons . . . . .	137
<b>7.5</b>	<b>Conclusions . . . . .</b>	<b>138</b>

---

## Abstract

Non-uniform illumination images have limited visibility due to under-exposure, over-exposure, or a combination of them. Enhancement of this kind of images is a very challenging task in image processing. Although there are lots of enhancement methods to improve the visual quality of images, many of these methods produce undesirable results in the aspect of contrast improvement or saturation improvement. In order to improve the visibility of images without over-enhancement or under-enhancement, a variational-based fusion method (presented in our contribution [130]) is proposed for adaptively enhancing the non-uniform illumination images. Firstly, a hue-preserving global contrast adaptive enhancement algorithm obtains the globally enhanced image. Secondly, a hue-preserving local contrast adaptive enhancement method produces the locally enhanced image. Finally, the enhanced result is obtained by a variational-based fusion model with contrast optimization and color correction. The final enhanced result represents a trade-off between global contrast and local contrast, and also maintains the color balance between the globally enhanced image and the locally enhanced image. This method produces the desirable visual quality in terms of contrast improvement and saturation improvement. Experiments are conducted on a dataset including different kinds of non-uniform illumination images. Results demonstrate the proposed method outperforms the compared enhancement algorithms both qualitatively and quantitatively.

## 7.1 Introduction

With the development of digital cameras, it is very convenient to obtain images. However, the captured images are usually lack of detailed information, which results from the limitations of imaging devices or environmental illuminations. To improve the visibility of images, many enhancement methods [151, 122, 85, 107, 10, 11, 148, 54] are proposed. Enhancement methods are able to improve the visual quality of the considered images, so they have been widely applied to the area of imaging, such as photographing [149], medical imaging[51], and remote-

## **A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement**

sensing imaging [72]. Since image enhancement methods can improve the visibility of images, they are often used for pre-processing images in some other computer vision applications, including object segmentation [117], face recognition [62], and high dynamic range image rendering [111, 6, 7, 5]. Moreover, this kind of methods is also applied in post-processing images and videos.

Images captured in uniform illumination environment can be enhanced well in terms of contrast improvement. However, most of the enhancement algorithms fail to process non-uniform illumination images. Some existing methods [151, 122, 85, 10, 54, 41] either under-enhance dark regions or over-enhance bright regions of images. Generally speaking, enhancement methods are categorized into two kinds: global enhancement algorithms and local enhancement algorithms. Usually, global enhancement methods produce over-enhancement results in the bright regions of images. Local enhancement algorithms obtain under-enhancement results in the dark regions of images. An example is shown in Fig. (7.1), from which we can know that the global enhancement method Histogram Equalization (HE) [41] over-enhanced the bright regions and the local method Contrast-Limited Adaptive Histogram Equalization (CLAHE) [100] under-enhanced the dark regions.

Inspired by the idea of exposure fusion [80], we [127] proposed an enhancement method combining globally enhanced images and locally enhanced images. This method improves the contrast both in dark regions and bright regions of images. Following the enhancement framework in [127], we consider a variational model [104] in the fusion to improve more visibility of images. Specifically, a hue-preserving global contrast adaptive enhancement method is applied to the original non-uniform illumination color images. Then, a hue-preserving local contrast adaptive enhancement method is conducted on the original images. Finally, the enhanced results are obtained via a variational-based fusion algorithm considering contrast optimization [90, 96] and color correction [128, 126].

The main contributions of the proposed enhancement method include presenting an adaptive global contrast enhancement method, considering hue preservation in the enhancement

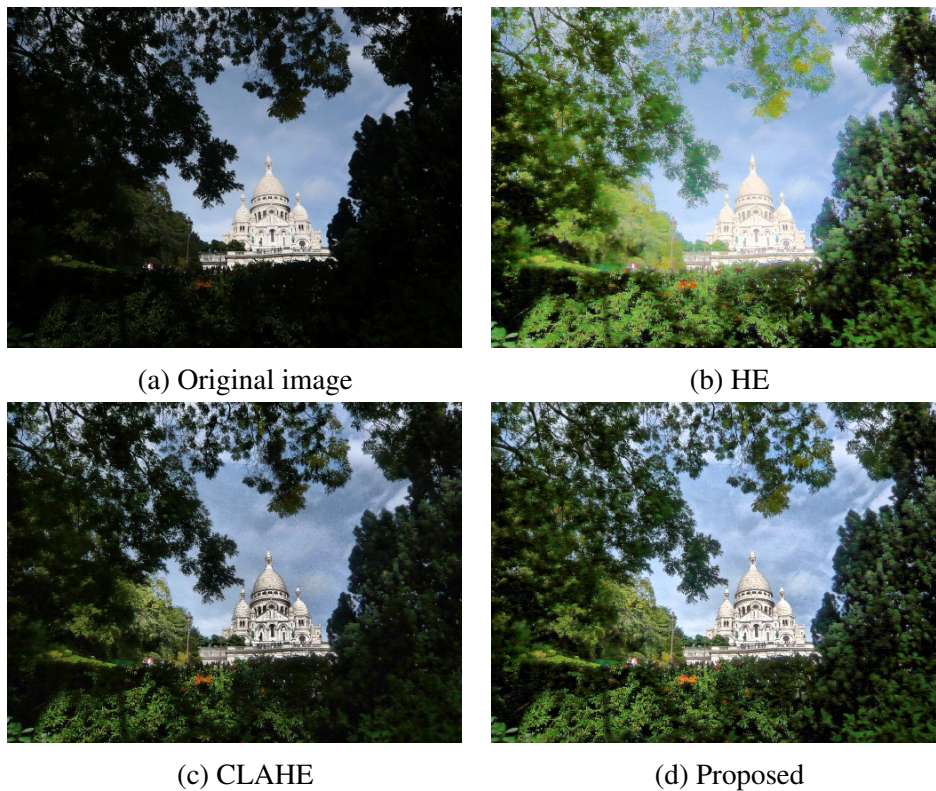


Fig. 7.1 Enhancement results by the global method Histogram Equalization (HE), local method Contrast-Limited Adaptive Histogram Equalization (CLAHE), and the proposed method. The bright regions (white building) are over-enhanced by HE. The dark regions (under-exposed tree) are under-enhanced by CLAHE. The bright regions and dark regions are both enhanced well by the proposed method.

framework, and developing a variational-based fusion model via contrast optimization and color correction.

This chapter is an extended version of our previous work [127]. Compared with [127], a variational-based fusion model considering contrast optimization and color correction is proposed in this work. The proposed variational-based fusion method produces better results than [127] in terms of contrast improvement. The rest of this chapter is organized as follows. The related work is briefly summarized in Section 7.2. The detailed description of the proposed method is presented in Section 7.3. The numerical experiments and performance evaluations are shown in Section 7.4. Finally, we give the conclusions and the future work in Section 7.5.

## 7.2 Related Work

The proposed image enhancement method combines the results of a global enhancement method and a local enhancement method, with a variational-based image fusion framework. In this part, we will introduce some related techniques, including global enhancement methods, local enhancement methods, and image fusion models.

### 7.2.1 Global Enhancement Methods

Global image enhancement methods conduct the same operation on the same pixel value regardless of the corresponding neighbor pixel distribution. The simplest one is the piece-wise linear transformation [41], which defines a poly-line as the mapping function. In order to obtain more visibility of images, some global enhancement methods use various curves to map the considered images. For example, power-law functions, log functions, and gamma functions are often used for non-linear mappings, which produce better results than linear mappings. Global histogram of images also can be used for driving enhancement. Histogram Equalization (HE) [41] is a widely used technique for image contrast enhancement. HE modifies the original histograms of images to an approximate uniform histogram, which stretches pixel value range of images. The traditional HE might produce over-enhancement results. To avoid this problem, some improved histogram equalization methods are proposed. Arici et al. [10] proposed a general histogram equalization framework for image contrast enhancement via optimizing cost functions. In Chapter 6, we presented a naturalness preservation histogram-based enhancement method using structure measure and statistical naturalness measure.

### 7.2.2 Local Enhancement Methods

Contrast-Limited Adaptive Histogram Equalization (CLAHE) [100] is another traditional histogram-based enhancement algorithm. CLAHE considers histogram equalization in each local region. This kind of local enhancement methods [21, 119, 113, 73] can obtain more

details of images, and preserve the image naturalness. Inspired by the retinex theory [67], there are many retinex-based contrast enhancement algorithms. Considering a Gaussian kernel to build the relationship between the center pixel and surround pixels, Jobson et al. [57] proposed a classic retinex-based enhancement method. Recently, Petro et al. [95] improve the multiscale retinex model for image enhancement. In order to obtain better visual quality, Kimmel et al. [64] introduced a variational model to the retinex enhancement via a quadratic programming optimization. Moreover, Morel et al. [82] explored some new alternative kernels for the retinex model, which are suitable for different kinds of enhancement applications. Banić and Lončarić [11] proposed a fast retinex implementation for brightness adjustment and color correction, which avoids some disadvantages of traditional retinex enhancement methods. Provenzi et al. [107] combines color correction and local contrast improvement for color image enhancement. Palma-Amestoy et al. [90] proposed a variational framework for color image enhancement, which is inspired by the basic phenomenology of color perception. Recently, Pierre et al. [96] propose a hue-preserving variational contrast enhancement method, which enables users to control the contrast improvement levels.

### 7.2.3 Image Fusion

Image fusion [89] is a technique for combining useful information from different images, which describe the same scene. The fusion result contains better visibility than any input images. The fusion can be conducted on various levels, such as signal-level, pixel-level, feature-level, symbol-level [15]. No matter which level is selected, the fusion results should meet the following two conditions: (1) the fusion image preserves as much as possible information of the input images; (2) the fusion image does not contain new artifacts or noisy. Mertens et al. [80] proposed a practical pixel-level exposure fusion method for generating high dynamic range images. The results can maintain the useful information in each image sequence using weighted blending. Ma et al. [75] proposed a feature-level robust exposure fusion model for avoiding ghosting effect. Wang et al. [137] proposed a variational method for fusing

multi-focus images. A family of weight functions using the local average modulus of gradients and the power transform is adopted in Wang et al.'s method. Fu et al. [36] proposed a fusion method for combining three illumination components. This method can obtain good results for weakly-illuminated images. Inspired by the human visual system, Ying et al. [147] proposed a multi-exposure fusion method for low-light image enhancement, which can produce enhanced results with small lightness distortion.

### 7.3 The Proposed Method

Let  $\mathbf{I} = (I_r, I_g, I_b) : \Omega \rightarrow [0, 255]^3$  be the considered RGB color image, where  $\Omega \subset \mathbb{R}^2$  is the image domain.  $\mathbf{x} = (x_1, x_2)$  denotes the position in the image domain  $\Omega$ . Our goal is to obtain the enhanced color image  $\mathbf{F} = (F_r, F_g, F_b)$ . The overall framework of the proposed variational-based fusion method for non-uniform illumination image enhancement via contrast optimization and color correction is illustrated in Fig. (7.2). The considered non-uniform illumination color image  $\mathbf{I}$  is processed by a global enhancement method and a local enhancement method, respectively. Then the globally enhanced color image  $\mathbf{G}$  and the locally enhanced color image  $\mathbf{E}$  are fused to produce a well-enhanced color image  $\mathbf{F}$ . The detailed description of the proposed method is presented below.

#### 7.3.1 Global Contrast Adaptive Enhancement

##### Overview

The overall framework of the global contrast adaptive enhancement method is shown in Fig. (7.3). The brief introduction will be given below.

In our global contrast adaptive enhancement method, the pixel value range of a color image  $\mathbf{I}$  is firstly converted to the full range  $[0, 255]$  with the linear stretching [9] via

$$\hat{\mathbf{I}} = 255 \cdot \frac{\mathbf{I} - I_{min}}{I_{max} - I_{min}}, \quad (7.1)$$

## 7.3 The Proposed Method

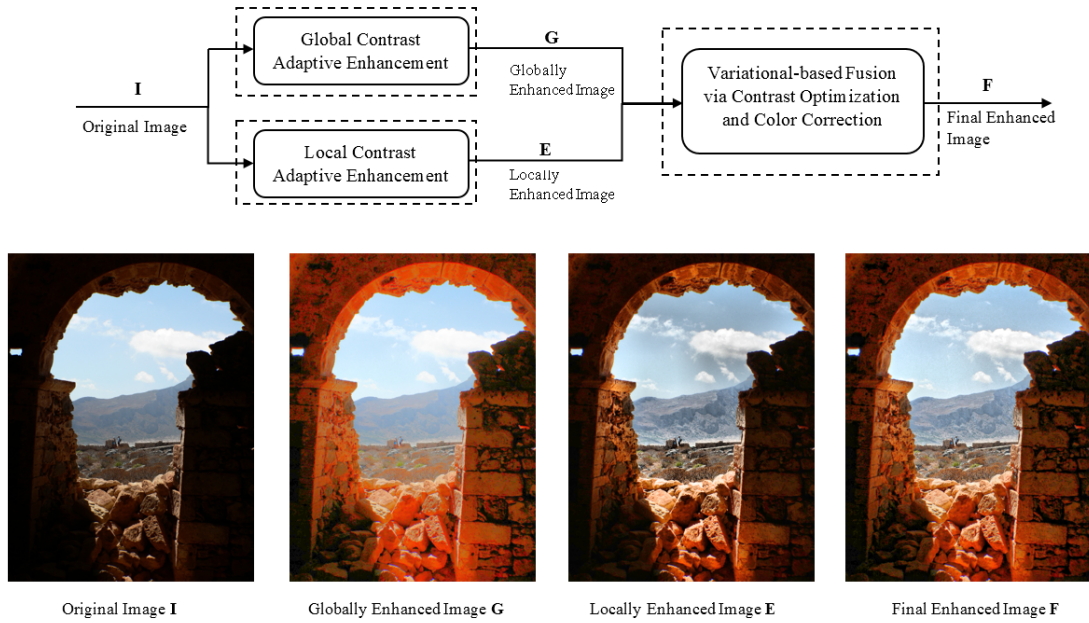


Fig. 7.2 The overall framework of the proposed enhancement method. The original image **I** has low contrast. The globally enhanced image **G** has good global contrast. However, the detailed structure information is not desirable (over-enhancement) in some regions. The local enhanced image **E** increased the detailed structure information. However, the visual quality is not desirable (under-enhancement). The final enhanced image **F** represents a trade-off between the global contrast and the local contrast.

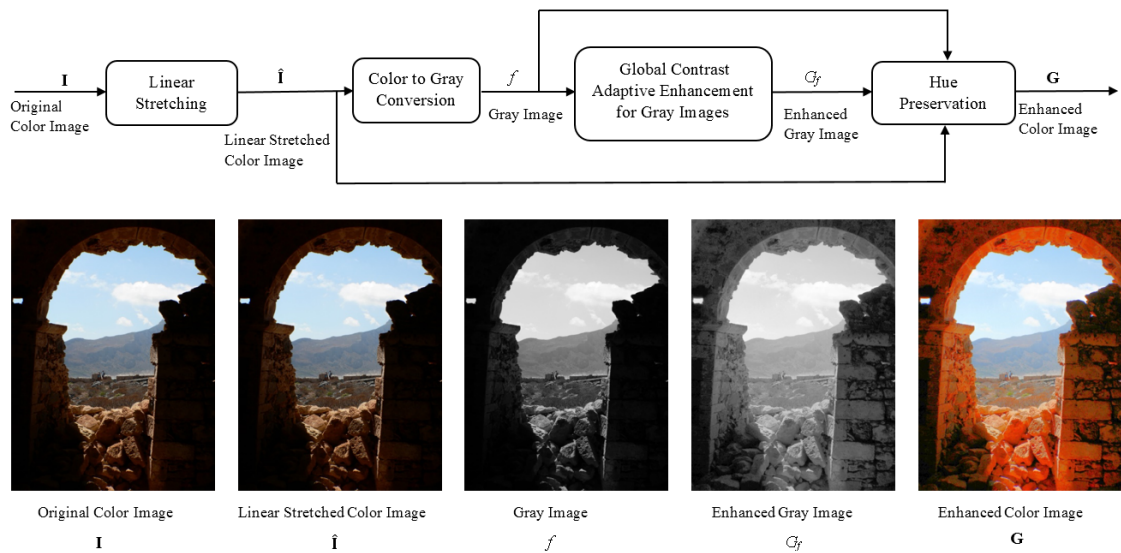


Fig. 7.3 The overview of the global contrast adaptive enhancement method.



## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

where  $I_{min}$  and  $I_{max}$  are the minimal and the maximal intensity values among the three color channels of the image  $\mathbf{I} = (I_r, I_g, I_b)$ .  $\hat{\mathbf{I}} = (\hat{I}_r, \hat{I}_g, \hat{I}_b)$  is the stretched color image.

The stretched color image  $\hat{\mathbf{I}}$  is converted to the corresponding intensity image  $f$  using

$$f = 0.299 \cdot \hat{I}_r + 0.587 \cdot \hat{I}_g + 0.114 \cdot \hat{I}_b, \quad (7.2)$$

where  $\hat{I}_r, \hat{I}_g, \hat{I}_b$  are the three color channels of the stretched color image  $\hat{\mathbf{I}}$ .

Then a global contrast adaptive enhancement is conducted on  $f$  to obtain the corresponding enhanced intensity image  $G_f$ . The detailed description of this global enhancement algorithm is given in the following subsection. At last, we use the hue preservation enhancement framework to obtain the enhanced color image  $\mathbf{G}$  with

$$\mathbf{G}(\mathbf{x}) = \begin{cases} \frac{G_f(\mathbf{x})}{f(\mathbf{x})} \hat{\mathbf{I}}(\mathbf{x}), & \text{if } \frac{G_f(\mathbf{x})}{f(\mathbf{x})} \leq 1, \\ \frac{255 - G_f(\mathbf{x})}{255 - f(\mathbf{x})} (\hat{\mathbf{I}}(\mathbf{x}) - f(\mathbf{x})) + G_f(\mathbf{x}), & \text{if } \frac{G_f(\mathbf{x})}{f(\mathbf{x})} > 1, \end{cases} \quad (7.3)$$

where  $\mathbf{G}(\mathbf{x}) = (G_r(\mathbf{x}), G_g(\mathbf{x}), G_b(\mathbf{x}))$  represents the globally enhanced color image,  $G_r(\mathbf{x})$ ,  $G_g(\mathbf{x})$ ,  $G_b(\mathbf{x})$  are the three color channels of  $\mathbf{G}$ , and  $\mathbf{x}$  denotes the positions of pixels on the image domain. Nikolova et al. [86] have analyzed and proved the efficiency of the hue preservation with this equation. Hue-preserving enhancement framework is also analyzed in [85], which demonstrates this kind of framework is better than the traditional channel-by-channel enhancements or methods only enhancing the intensity channel.

### Global Contrast Adaptive Enhancement for Gray Images

The overall pipeline of the global contrast adaptive enhancement has been given in the above subsection. As mentioned above, we will describe the global contrast adaptive enhancement, which is able to obtain  $G_f$  from  $f$ . Given a gray image  $f$ , with a total number of  $N$  pixels and an intensity level range of  $[0, 255]$ .  $h_f$  is the normalized histogram of the image  $f$ .

Traditional histogram equalization algorithm uses the original histogram of the considered image to obtain the mapping function. The mapping function  $T$  for the image  $f$  is given by

$$T(i) = \left\lfloor 255 \cdot \sum_{j=0}^i h_f(j) + 0.5 \right\rfloor, \quad (7.4)$$

where  $i \in [0, 255]$  is the input integer for the mapping function, and  $\lfloor \cdot \rfloor$  computes the nearest integer of the considered value towards minus infinity.

The traditional histogram equalization (HE) [41] tries to create a uniform histogram for enhanced images via considering a cumulative histogram as the corresponding mapping function. It often produces enhanced images with visual artifacts. To avoid this problem, Arici et al. [10] proposed a general histogram modification framework for contrast enhancement. The modified histogram  $h$  should be closer to the normalized uniform histogram  $h_U$  and the value of the residual  $h - h_f$  should be also small. The problem of obtaining the optimal modified histogram  $\tilde{h}$  is regarded as a bi-criteria optimization problem, which can be formulated as a weighted sum of two terms shown in

$$\min_h (||h - h_f|| + \lambda ||h - h_U||), \quad (7.5)$$

where  $||h - h_f||$  is a norm of  $h - h_f$ ,  $||h - h_U||$  is a norm of  $h - h_U$ , and the parameter  $\lambda > 0$  adjusts the trade-off between the contrast enhancement and the data fidelity. An analytical solution of Eq. (7.5) will be obtained when the squared sum of the  $L_2$  norm is adopted. This problem is rewritten in

$$\tilde{h} = \arg \min_h (||h - h_f||_2^2 + \lambda ||h - h_U||_2^2). \quad (7.6)$$

This is a quadratic optimization problem, and the solution of Eq. (7.6) is given by

$$\tilde{h} = \left( \frac{1}{1 + \lambda} \right) h_f + \left( \frac{\lambda}{1 + \lambda} \right) h_U. \quad (7.7)$$

## **A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement**

---

The parameter  $\lambda$  needs to be carefully selected for obtaining satisfied enhancement results. Different values of  $\lambda$  can produce corresponding modified histograms, thus generate different enhanced images.

In [10], the authors manually gave the parameter  $\lambda$ . In order to develop an adaptive enhancement method, we adopt the tone distortion of the mapping function  $T$  to guide the optimization. The tone distortion measure [142] is defined by

$$D(T) = \max_{0 \leq j \leq i \leq 255} \{i - j; T(i) = T(j), h_f(i) > 0, h_f(j) > 0\}. \quad (7.8)$$

We are able to know that the smaller the tone distortion  $D(T)$  the smoother the tone reproduced by the mapping function  $T$ , from the definition in Eq. (7.8). The smoother tone means less unnatural looking in the results. In other words, a small tone distortion is able to avoid unnatural artifacts. The tone distortion measure  $D$  is obtained from the mapping function  $T$ , which is computed with the optimally modified histogram  $\tilde{h}$ . And the histogram  $\tilde{h}$  depends on the weighted parameter  $\lambda$ . So we can use the tone distortion to select the optimal weighted parameter  $\lambda$ , which produces the optimal modified histogram and the final mapping function. This mapping function is utilized to produce the globally enhanced image  $G_f$ .

### **7.3.2 Local Contrast Adaptive Enhancement**

The proposed global contrast adaptive enhancement method can improve the global contrast and brightness of the whole image. However, it is essentially a global method, which may reduce the local contrast or the detail information in the original image. So we consider a local contrast adaptive enhancement to improve the local contrast and preserve the detail information.

In this method, we combine the hue preservation enhancement framework described in Section 7.3.1 and the Contrast-Limited Adaptive Histogram Equalization method (CLAHE) [100] to improve the local contrast and preserve the hue of the images. The locally enhanced

gray image  $E_f$  is obtained using CLAHE. Then, we can produce the locally enhanced color image  $E$  via the Eq. (7.9).

$$\mathbf{E}(\mathbf{x}) = \begin{cases} \frac{E_f(\mathbf{x})}{f(\mathbf{x})} \hat{\mathbf{I}}(\mathbf{x}), & \text{if } \frac{E_f(\mathbf{x})}{f(\mathbf{x})} \leq 1, \\ \frac{255-E_f(\mathbf{x})}{255-f(\mathbf{x})} (\hat{\mathbf{I}}(\mathbf{x}) - f(\mathbf{x})) + E_f(\mathbf{x}), & \text{if } \frac{E_f(\mathbf{x})}{f(\mathbf{x})} > 1, \end{cases} \quad (7.9)$$

where  $\mathbf{E}(\mathbf{x}) = (E_r(\mathbf{x}), E_g(\mathbf{x}), E_b(\mathbf{x}))$  represents the locally enhanced color image,  $E_r(\mathbf{x})$ ,  $E_g(\mathbf{x})$ ,  $E_b(\mathbf{x})$  are the three color channels of  $\mathbf{E}$ , and  $\mathbf{x}$  denotes the positions of pixels on the image domain.

The overall framework of this method is shown in Fig. (7.4). This framework is similar to the framework shown in Fig. (7.3). The only difference is that the step Contrast-Limited Adaptive Histogram Equalization takes the place of the step Global Contrast Adaptive for Gray Images. The detailed description of the Contrast-Limited Adaptive Histogram Equalization method (CLAHE) can be found in the paper [100]. In our method, we adopted the Matlab Image Processing Function `adapthisteq` to implement CLAHE. All parameters of CLAHE are the defaults. The number of rectangular contextual regions is  $8 \times 8$ . *ClipLimit* is a contrast factor that prevents over-enhancement of the image, specifically in homogeneous regions. It is equal to 0.01 with the default setting. *NBins* is equal to 256, which results in greater dynamic range. *Range* is set to *full*, which means the full range [0,255] is used for enhanced images.

### 7.3.3 A Variational Method for Fusion via Contrast Optimization and Color Correction

Inspired by the idea of exposure fusion [80] and variational-based enhancement [90], we develop a variational-based fusion method [130] considering contrast optimization and color correction to obtain the final enhanced image  $\mathbf{F}$  with the globally enhanced image  $\mathbf{G}$  and the locally enhanced image  $\mathbf{E}$ . This fusion framework can obtain desirable contrast and saturation

## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

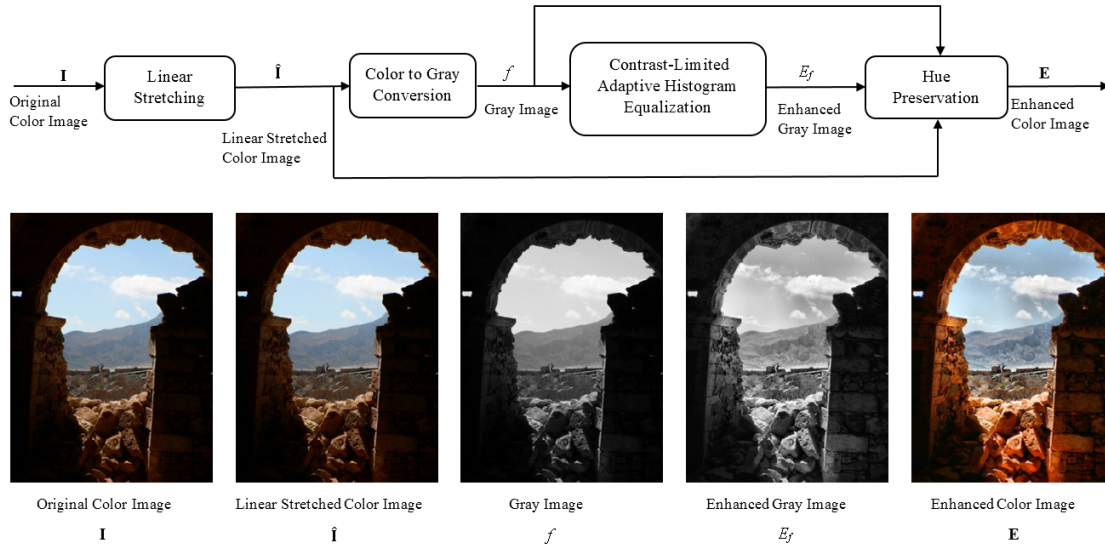


Fig. 7.4 The overview of the local contrast adaptive enhancement method.

for each pixel, since we adopt pixel-level weights to fuse every pixel via contrast optimization and color correction.

### Variational-based Fusion Model

The goal is to fuse the globally enhanced image  $G$  and the locally enhanced image  $E$  to a final enhancement result  $F$  which obtains the optimal contrast and maintains the color balance. We deal with the three color channel respectively. Due to the hue-preserving framework analyzed in Section 7.3.1, we only compute the weight maps for the intensity images of the globally enhanced color image and the locally enhanced color image, and then apply the same weight maps to the three color channels. In the following part, we give the variational-based fusion model for the gray-scale images corresponding to the color channels.

The variational-based fusion model via contrast optimization and color correction is achieved by minimizing the following energy functional:

$$\begin{aligned} \mathbf{F} = \arg \min_{\mathbf{Z}} \left\{ \alpha \int_{\Omega} \left( \omega_{\mathbf{G}(\mathbf{x})} (\mathbf{Z}(\mathbf{x}) - \mathbf{G}(\mathbf{x}))^2 + \omega_{\mathbf{E}(\mathbf{x})} (\mathbf{Z}(\mathbf{x}) - \mathbf{E}(\mathbf{x}))^2 \right) d\mathbf{x} \right. \\ \left. + \beta \int_{\Omega} \left( \frac{1}{2} (\mathbf{Z}(\mathbf{x}) - \hat{\mathbf{G}}(\mathbf{x}))^2 + \frac{1}{2} (\mathbf{Z}(\mathbf{x}) - \hat{\mathbf{E}}(\mathbf{x}))^2 \right) d\mathbf{x} \right. \\ \left. - \gamma \int_{\Omega} \int_{\Omega} g_{\sigma}(\mathbf{x}, \mathbf{y}) \Psi_{\varepsilon} (\mathbf{Z}(\mathbf{x}) - \mathbf{Z}(\mathbf{y})) d\mathbf{x} d\mathbf{y} \right\} \end{aligned} \quad (7.10)$$

where,  $\mathbf{G}(\mathbf{x})$  and  $\mathbf{E}(\mathbf{x})$  are the globally enhanced image and the locally enhanced image,  $\omega_{\mathbf{G}(\mathbf{x})}$  and  $\omega_{\mathbf{E}(\mathbf{x})}$  are the corresponding weight maps, and  $\hat{\mathbf{G}}(\mathbf{x})$ ,  $\hat{\mathbf{E}}(\mathbf{x})$  are the corresponding color correction results via midway image equalization [24] for each color channel. The function  $g_{\sigma}(\mathbf{x}, \mathbf{y})$  is a Gaussian curve, where  $\mathbf{x}$  and  $\mathbf{y}$  denote the positions of two pixels on the image domain.  $\Psi_{\varepsilon}$  is a non-linear function.  $\alpha$ ,  $\beta$  and  $\gamma$  are the three parameters to control the data fidelity, the color consistency, and the local contrast.

*Data Fidelity.* The first part of the energy functional (the first line in Eq. (7.10)) is to achieve the data fidelity. This term can be considered as a general fusion framework, which produces a trade-off fusion result between the globally enhanced image  $\mathbf{G}(\mathbf{x})$  and the locally enhanced image  $\mathbf{E}(\mathbf{x})$ . This processing provides an attachment to the original data.

The weight maps of the globally enhanced image and the locally enhanced image are computed by

$$\begin{aligned} W_d = \min\{C_d, B_d\}, \quad d \in \{\mathbf{G}, \mathbf{E}\}, \\ \omega_d = \frac{W_d}{W_{\mathbf{G}} + W_{\mathbf{E}}}, \quad d \in \{\mathbf{G}, \mathbf{E}\}, \end{aligned} \quad (7.11)$$

where  $W_d$  is the weight map,  $\omega_d$  is the normalized weight map,  $C_d$  is the contrast measure,  $B_d$  is the brightness measure, and the operation  $\min$  can efficiently penalize the corresponding low-contrast, low brightness (under-exposure) or high brightness (over-exposure).  $C_d$  is obtained by a Laplacian filter, which can assign high weights to edges and textures in the corresponding

## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

image.  $B_d$  is computed by a Gaussian curve  $\exp\left(-\frac{(i-0.5)^2}{2\sigma_1^2}\right)$  and  $\sigma_1 = 0.2$  in our experiments, which can assign high weights to pixel values close to 0.5 and define low weights to pixel values near 0 (under-exposure) or near 1 (over-exposure).

*Color Consistency.* The second part of the energy functional (the second line in Eq. (7.10)) is to maintain the color consistency. Most previous research [13, 107, 90, 96] considers the grey world principle to achieve the color consistency in image enhancement. Actually, the grey world principle is not always working well for color consistency. We apply the color balance [126] as the solution.  $\hat{\mathbf{G}}(\mathbf{x})$  and  $\hat{\mathbf{E}}(\mathbf{x})$  are the corresponding color correction results of  $\mathbf{G}(\mathbf{x})$  and  $\mathbf{E}(\mathbf{x})$  after the midway image equalization.  $\hat{\mathbf{G}}(\mathbf{x})$  and  $\hat{\mathbf{E}}(\mathbf{x})$  share the same cumulative histogram, which makes them having the same color style. The final enhanced result  $\mathbf{F}$  can maintain color consistency with  $\hat{\mathbf{G}}(\mathbf{x})$  and  $\hat{\mathbf{E}}(\mathbf{x})$  via this strategy.

*Local Contrast Improvement.* The third part of the energy functional (the third line in Eq. (7.10)) is to improve the local contrast of the final enhanced result  $\mathbf{F}$ . The Gaussian function  $g_\sigma(\mathbf{x}, \mathbf{y})$  is given in Eq. (7.12).

$$g_\sigma(\mathbf{x}, \mathbf{y}) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{|\mathbf{x} - \mathbf{y}|^2}{2\sigma^2}\right), \quad (7.12)$$

where  $\sigma$  is a parameter representing the size of the Gaussian kernel, and  $\mathbf{x}, \mathbf{y}$  denote the positions of two pixels on the image domain. The function  $\Psi_\varepsilon(z)$  is given in Eq. (7.13).

$$\Psi_\varepsilon(z) = \sqrt{z^2 + \varepsilon^2}, \quad (7.13)$$

where  $\varepsilon$  is a small constant. This equation describes a non-linear function. Its sigmoid-shaped derivation  $\Psi'_\varepsilon(z) = \frac{z}{\sqrt{z^2 + \varepsilon^2}}$  appearing in Eq. (7.14) provides the non-linear response of the human visual system, in the sense of a contrast enhancement function [13, 79].

### Numerical Method

The problem of Eq. (7.10) can be solved with the gradient descent method. With the iteration index  $t$  and the time step  $\tau$ , the solution is described in Eq. (7.14).

$$\begin{aligned} \mathbf{Z}^{t+1}(\mathbf{x}) = & \mathbf{Z}^t(\mathbf{x}) \left( 1 - 2(\alpha + \beta)\tau \right) \\ & + \left( 2\alpha\mathbf{Q}(\mathbf{x}) + 2\beta\hat{\mathbf{Q}}(\mathbf{x}) \right. \\ & \left. + 2\gamma \int_{\Omega} g_{\sigma}(\mathbf{x}, \mathbf{y}) \Psi'_{\varepsilon}(\mathbf{Z}^t(\mathbf{x}) - \mathbf{Z}^t(\mathbf{y})) d\mathbf{y} \right) \tau \end{aligned} \quad (7.14)$$

where  $\mathbf{Q}(\mathbf{x}) = \omega_{\mathbf{G}}(\mathbf{x}) \cdot \mathbf{G}(\mathbf{x}) + \omega_{\mathbf{E}}(\mathbf{x}) \cdot \mathbf{E}(\mathbf{x})$ ,  $\hat{\mathbf{Q}}(\mathbf{x}) = \frac{1}{2}(\hat{\mathbf{G}}(\mathbf{x}) + \hat{\mathbf{E}}(\mathbf{x}))$ ,  $\mathbf{Z}^0(\mathbf{x}) = \mathbf{Q}(\mathbf{x})$ . After each gradient descent step, we account for a simple constraint that  $\mathbf{Z}^t(\mathbf{x})$  should be in the pixel value range  $[0, 255]$ . Since there are not many pixel intensities falling outside  $[0, 255]$ , a direct clipping strategy is adopted as the projection operation. Because a linear mapping may decrease the whole contrast of enhanced results, we do not use it for projecting pixel values.

### Parameters Setting

The proposed variation-based fusion model produces enhanced images via minimizing the energy functional described in Eq. (7.10). The solution of this model is given in Eq. (7.14). There are some parameters that need to be selected carefully.  $\alpha$ ,  $\beta$  and  $\gamma$  are the three parameters to control the data fidelity, the color consistency, and the local contrast. The larger the values the more influence their term has in the final enhanced images. In our implement, we set  $\alpha = 0.5, \beta = 0.5, \gamma = 1$  to achieve the balance of data fidelity, color consistency, and local contrast improvement. The function  $g_{\sigma}(\mathbf{x}, \mathbf{y})$  is a Gaussian curve given in Eq. (7.12). The parameter  $\sigma$  represents the size of the Gaussian kernel. The smaller the value of  $\sigma$  the more local contrast improvement. However, a smaller  $\sigma$  might produce unnatural enhanced results. In order to make a trade-off, we set  $\sigma$  to be equal to the  $\min(\text{high}, \text{width})/20$ . *high* and *width*



## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

are the height and the width of images, respectively. The function  $\Psi'_\varepsilon(z) = \frac{z}{\sqrt{z^2 + \varepsilon^2}}$  appearing in Eq. (7.14) provides the non-linear response of the human visual system, in the sense of a contrast enhancement function. The parameter  $\varepsilon$  is a small constant, which controls the non-linearity. In our implement, we set  $\varepsilon = 0.1$ .

The parameter  $\tau$  is the gradient descent step, which is a very important parameter impacting the minimization. In order to select a suitable  $\tau$  for obtaining satisfied enhanced results, we give the relation between the final iteration numbers and the values of  $\tau$  in Table (7.1). The iteration will be stopped when the mean difference (absolute value) between the previous iteration and the current iteration is less than  $\Delta = 0.0002$ , or the iteration reaches the maximum number  $Iter = 100$ . From the Table (7.1), we can know that smaller  $\tau$  results in needing too many iterations for the convergence. In our implementation with Matlab codes, each iteration needs around 8 seconds for the test image  $I$  (resolution:  $432 \times 576$ ) shown in Fig. 7.1. The computation time can be improved by using other approximation minimization solutions and C++ programming. In our testing, we also know that larger  $\tau$  might produce over-enhanced results. In order to make a balance between the convergence speed and the naturalness of the enhanced images, we set  $\tau = 0.02, \Delta = 0.001, Iter = 20$  for all the experiments in the following part. For the dataset mentioned above, the average iteration stop number is 15.

Step $\tau$	0.01	0.02	0.03	0.04	0.05
Iteration Stop Number	96	74	60	50	44

Table 7.1 The relation between the final iteration stop numbers and the steps  $\tau$ . The test image  $I$  is shown in Fig. 7.1. The image size is  $432 \times 576$ .

### 7.3.4 Fusion with other Global Enhancement and Local Enhancement Methods

One of the contributions of this chapter is combining globally enhanced images and locally enhanced images. The global contrast adaptive enhancement method in section 7.3.1

is developed from Arici et al's Histogram Modification Framework (HMF) [10], Wu's tone distortion measure [142], and Nikolova et al's hue preservation method [86]. The local contrast adaptive enhancement method in section 7.3.2 is developed from the traditional CLAHE [100] and Nikolova et al's hue preservation method [86]. Any other global enhancement method and local enhancement method can replace the method in section 7.3.1 and section 7.3.2, respectively. For example, Arici et al's contrast enhancement method using Histogram Modification Framework (HMF) [10] can replace the global enhancement method in section 7.3.1. Banić et al's Smart Light Random Memory Sprays Retinex (SLRMSR) [11] can replace the local enhancement method in section 7.3.2. The final enhanced results can be produced via the fusion model in section 7.3.3. We give the comparison in Fig. (7.5), in which the proposed method outperforms the compared method in terms of contrast improvement.

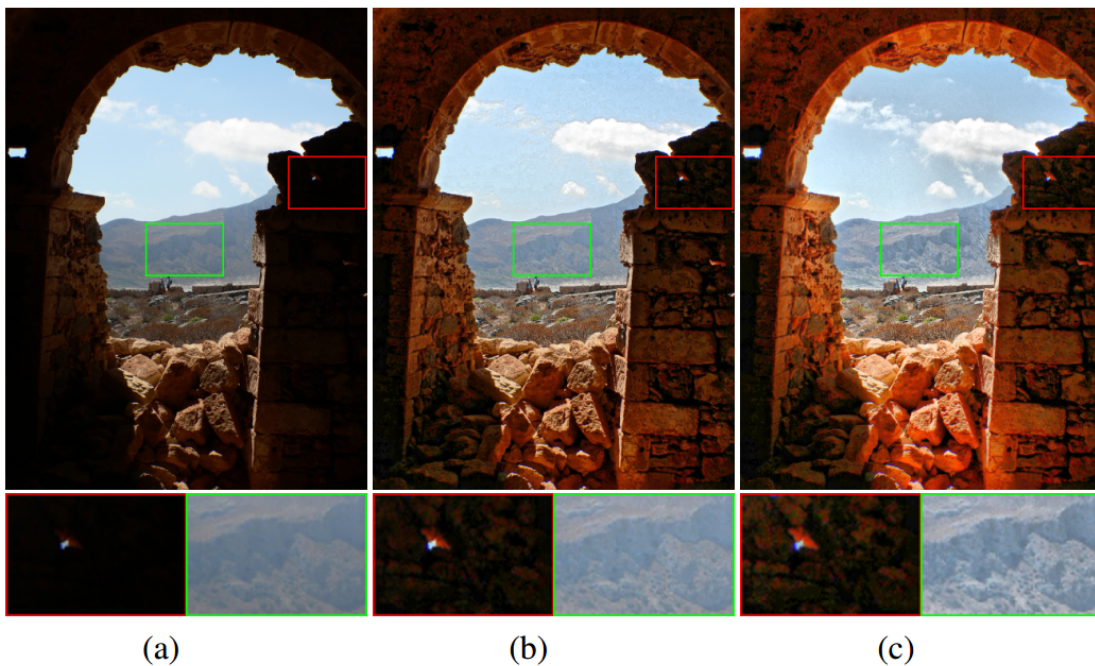


Fig. 7.5 Final enhanced results via the fusion model with different global enhancement methods and local enhancement methods. (a). Original image; (b). Fusion with HMF [10] and SLRMSR [11]; (c). Fusion with the method in section 7.3.1 and the method in section 7.3.2. For the visual comparison, the regions in the red and green rectangles are enlarged and shown below the corresponding images.

### 7.4 Experiments and Comparisons

We ran the proposed method and several state-of-the-art image enhancement methods on a dataset [134, 133] including 24 non-uniform illumination color images. This test dataset is a collection of challenging cases for image enhancement. Each image in this dataset has the regions correctly exposed and other regions severely under-exposed or over-exposed. A good enhancement algorithm should enhance the under-exposed regions and the over-exposed regions. Meanwhile, the well-exposed regions should not be affected.

The comparison algorithms include Arici et al.’s contrast enhancement method using Histogram Modification Framework (HMF) [10], Banić et al.’s Smart Light Random Memory Sprays Retinex (SLRMSR) [11], Ignatov et al.’s enhancement method with Deep Convolutional Networks (DeepNet) [54], Fu et al.’s Weighted Variational Model for image enhancement (WVM) [37], Ying et al.’s Bio-Inspired Multi-Exposure Fusion framework for image enhancement (BIMEF) [148, 147], and Tian et al.’s Global-Local Fusion method for contrast enhancement (GLF) [127]. The source codes or executable demos of SLRMSR, DeepNet, WVM, and BIMEF are available on the corresponding project homepages. We reproduced the method HMF with the parameter  $\lambda = 1$  for all experiments. The codes of GLF and the proposed method will be available on the project homepage <sup>1</sup>. The parameter settings of the proposed method are analyzed in section 7.3.3.

To evaluate the performance of the proposed adaptive enhancement method, both qualitative comparisons and quantitative assessments are considered in the following parts.

#### 7.4.1 Qualitative Comparisons

In this part, we show some original test images (non-uniform illumination color images) and the corresponding enhanced images to subjectively compare the performances of these enhancement algorithms. The contrast enhancement and detailed information preservation are considered in the comparisons.

---

<sup>1</sup>[www.ceremade.dauphine.fr/~tian/non-uniform-illumination-image-enhancement.html](http://www.ceremade.dauphine.fr/~tian/non-uniform-illumination-image-enhancement.html)

Fig. (7.6) shows the enhanced results on the image Arch (Fig. (7.6)-(a)), which contains the high illumination on the sky region and the low illumination on the arch region. Our goal is to enhance the bright regions (high illuminations) and the dark regions (low illuminations), without reducing the details in the bright regions. HMF (Fig. (7.6)-(b)) and SLRMSR (Fig. (7.6)-(c)) slightly enhances the bright regions and the dark regions. DeepNet (Fig. (7.6)-(d)) over-enhances the bright regions (mountain, sky, and so on) and fails in the dark regions. WVM (Fig. (7.6)-(e)) over-enhances the bright regions (mountain, sky, and so on) and obtains good results in the dark area. BIMEF (Fig. (7.6)-(f)) also over-enhances the bright regions (mountain, sky, and so on) and obtains good results in the dark regions. GLF (Fig. (7.6)-(g)) produces good results both in the bright regions and the dark regions. In the bright regions and the dark regions, the proposed method (Fig. (7.6)-(h)) obtains desirable results in terms of improving contrasts and preserving details. From the enlarged bright regions, we can observe that the proposed method obtains better contrasts than the results of GLF. Our method generates the best results both in the dark regions and in the bright regions, resulting from combining the globally enhanced image and the locally enhanced image via contrast optimization and color correction.

Some other results are shown in Fig. (7.7), Fig. (7.8), Fig. (7.9) and Fig. (7.10), which demonstrate the proposed method can obtain the best results both in the bright regions and in the dark regions. HMF, SLRMSR, DeepNet, WVM, BIMEF either slightly enhance the dark regions or over-enhance the bright areas, which produce undesirable enhanced results. GLF can obtain good results both in the bright regions and in the dark regions. However, the results produced by GLF is slightly worse than the proposed method in terms of contrast improvement. The proposed method obtains more local contrast than GFL. Since the difference is not easy to observe in this chapter, the visual comparisons are also given on the project homepage.

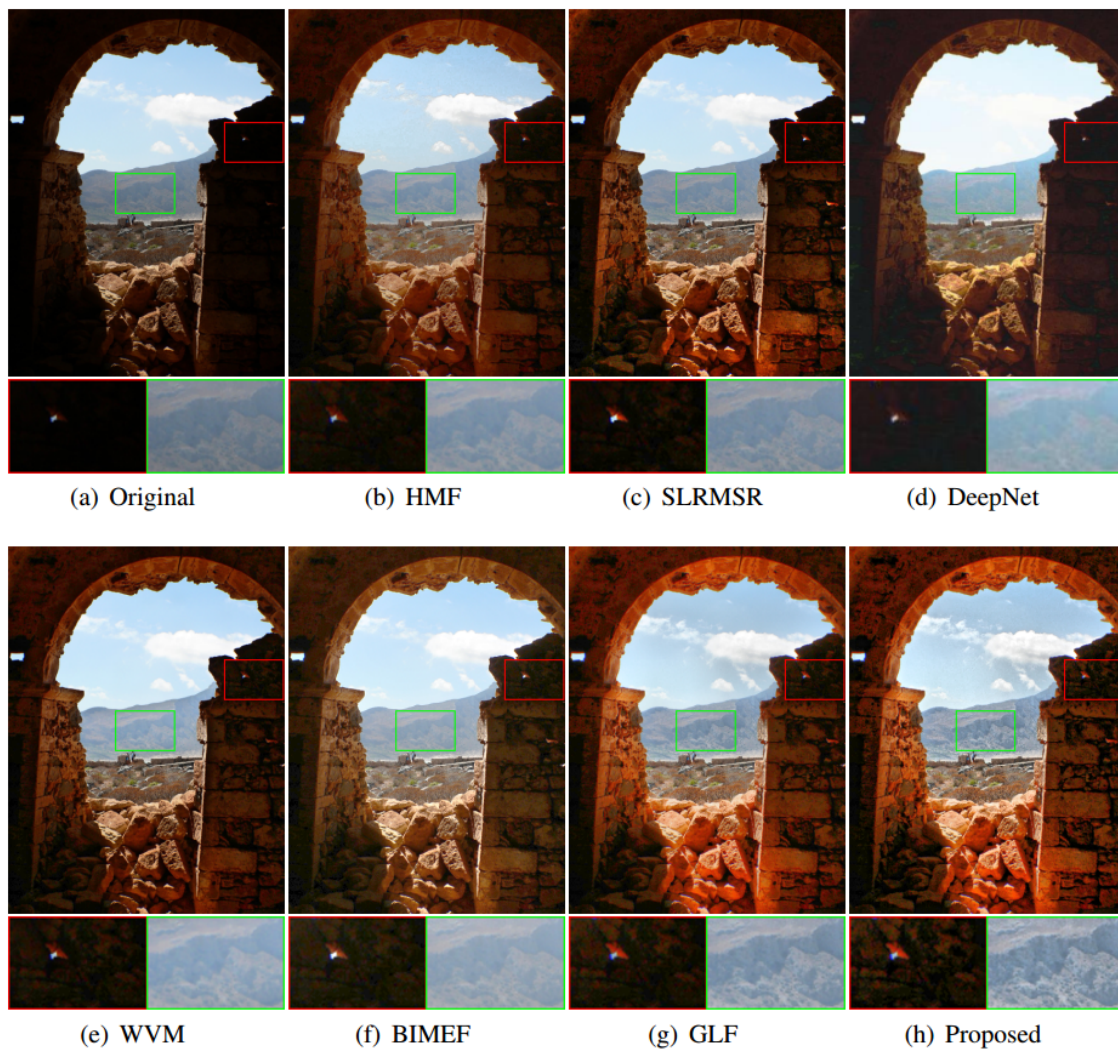


Fig. 7.6 Enhanced results of the image Arch. (a). Original image; (b)-(h). Results enhanced respectively by HMF [10], SLRMSR [11], DeepNet [54], WVM [37], BIMEF [147], GLF [127] and the proposed method. For the visual comparison, the regions in the red and green rectangles are enlarged and shown below the corresponding images.



Fig. 7.7 Enhanced results of the image Man1. (a). Original image; (b)-(h). Results enhanced respectively by HMF [10], SLRMSR [11], DeepNet [54], WVM [37], BIMEF [147], GLF [127] and the proposed method.

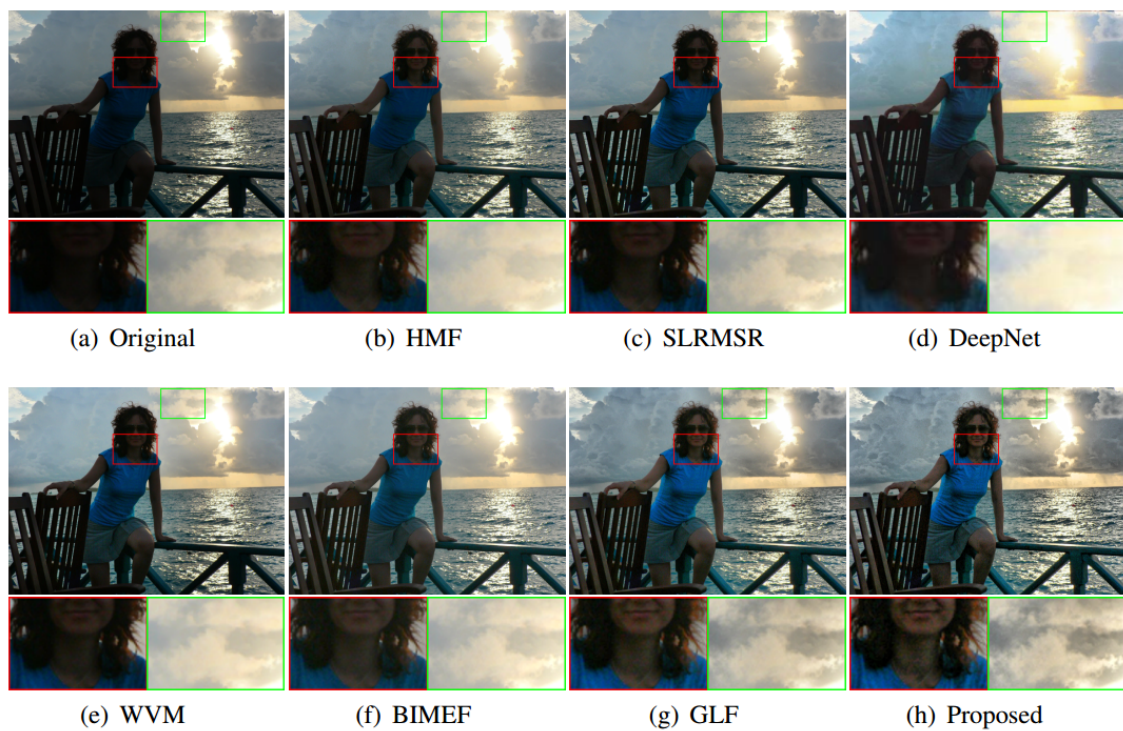


Fig. 7.8 Enhanced results of the image Woman1. (a). Original image; (b)-(h). Results of HMF [10], SLRMSR [11], DeepNet [54], WVM [37], BIMEF [147], GLF [127], and the proposed method, respectively.

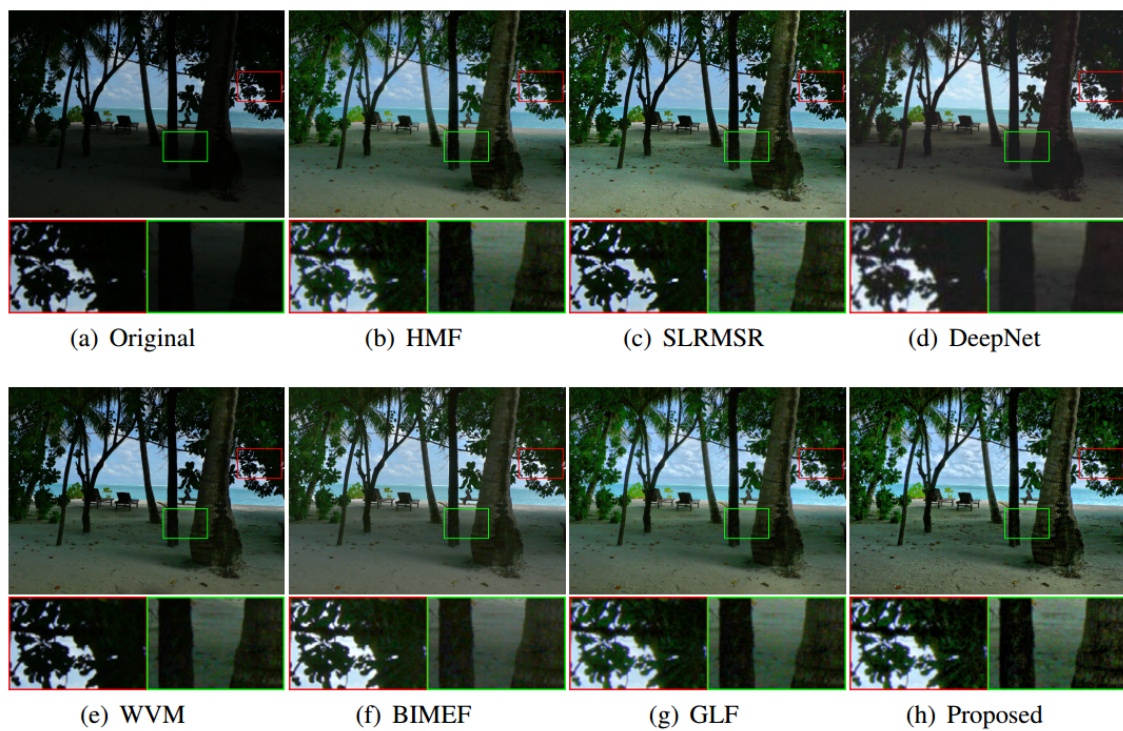


Fig. 7.9 Enhanced results of the image Beach. (a). Original image; (b)-(h). Results enhanced respectively by HMF [10], SLRMSR [11], DeepNet [54], WVM [37], BIMEF [147], GLF [127], and the proposed method.



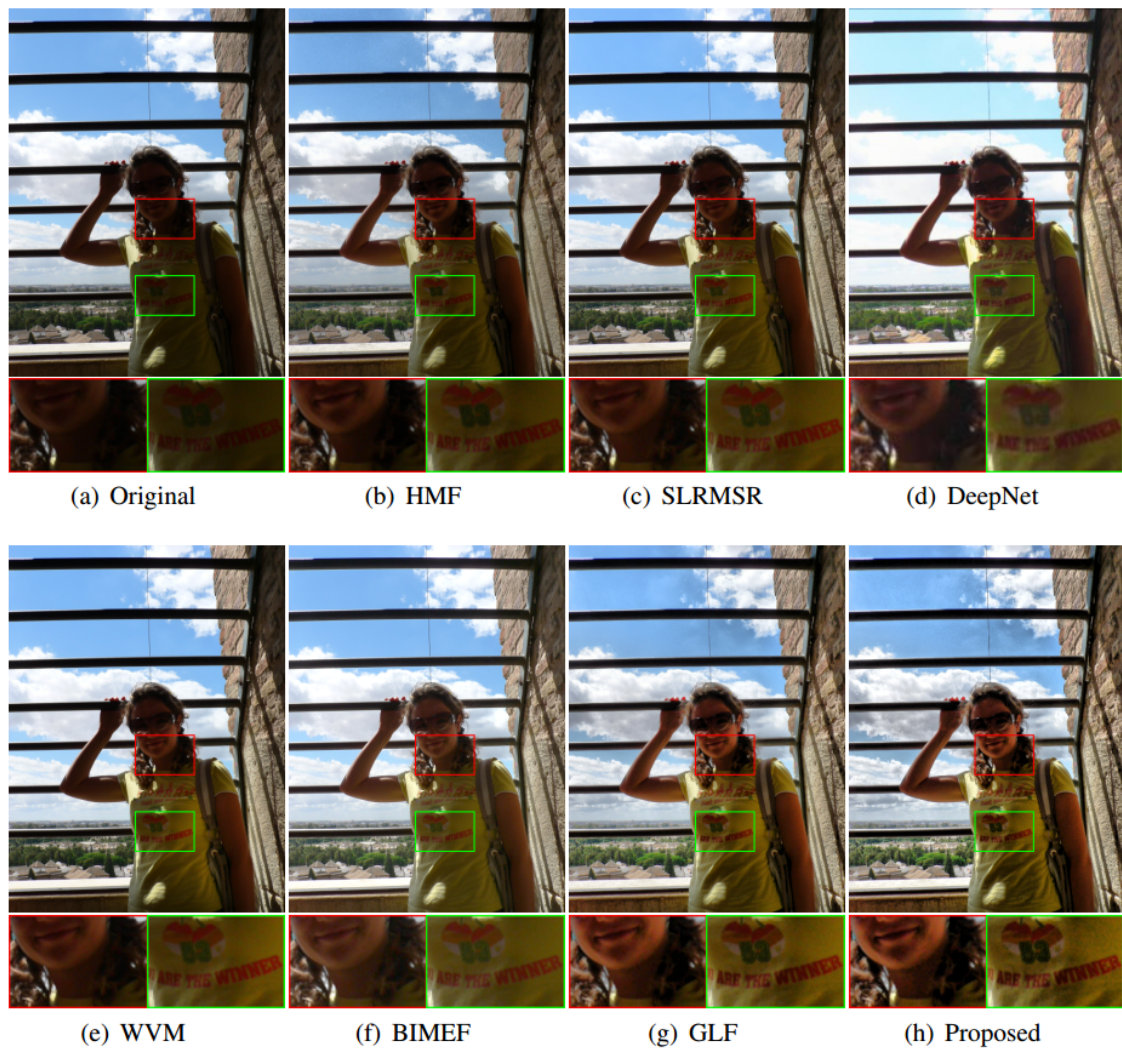


Fig. 7.10 Enhanced results of the image Woman2. (a). Original image; (b)-(h). Results enhanced respectively by HMF [10], SLRMSR [11], DeepNet [54], WVM [37], BIMEF [147], GLF [127] and the proposed method.

### 7.4.2 Quantitative Comparisons

For the quantitative evaluation of our method, two widely adopted image quality assessment metrics are considered below. Hautière et al. [48] proposed a contrast evaluation method via Visible Edges Assessment (VEA). This metric evaluates the contrast improvement with three indicators. The first indicator  $e$  evaluates the ability for restoring edges. The second indicator  $\bar{r}$  is the mean ratio of gradients in visible edges. The third indicator  $\Sigma$  represents the percentage of pixels becoming saturated after the enhancement. The higher values of  $e$  and  $\bar{r}$  present the better contrast improvement. The lower value of  $\Sigma$  indicates the better ability of pixel value range preservation. The evaluation results are shown in Table (7.2), which demonstrates the proposed method outperforms other algorithms in terms of contrast improvement (higher  $e$  and  $\bar{r}$ ). The contrast optimization of the proposed method can generate more visible edges. For the pixel value range preservation (lower  $\Sigma$ ), DeepNet obtains the best result. The proposed method does not obtain desirable performance  $\Sigma$ , since the simple clipping projection for pixels falling outside  $[0, 255]$  is adopted in the variational iteration. However, the performance  $\Sigma$  gives little effect on the image visual quality improvement. As shown in Fig. (7.6), Fig. (7.7), Fig. (7.8) and Fig. (7.9), the proposed method obtains the best results even though the performance  $\Sigma$  is not the best.

	HMF [10]	SLRMSR [11]	DeepNet [54]	WVM [37]	BIMEF [147]	GLF [127]	Proposed
$e$	0.1858	0.2064	-0.0497	0.1965	0.1494	0.2482	<b>0.3597</b>
$\bar{r}$	1.9781	2.3539	1.4993	2.0218	1.9950	2.4277	<b>3.0483</b>
$\Sigma(\%)$	0.0046	0.0336	<b>0</b>	0.0513	0.0077	0.0137	0.2116

Table 7.2 Average VEA of enhancement algorithms on the test dataset

Panetta et al. [91] proposed a color image quality measurement (CQE) combining the contrast, sharpness and colorfulness metrics. CQE is the weighted sum of the three metrics. The contrast is represented by the Michelson-Law measure of enhancement AME [4] of the intensity component. The sharpness is represented by the Weber contrast based measure of enhancement EME [3] of each gray edge map. The colorfulness is represented with the statistical information

## A Variational-based Fusion Model for Non-Uniform Illumination Image Enhancement

[47] of the opponent color components. The higher value of CQE means the better quality of the considered color image. We use these metrics to evaluate our method and several compared algorithms on the test dataset. The results are shown in Table (7.3), which indicates that the proposed method outperforms other algorithms in terms of the image quality. The contrast optimization in the variational-based fusion model can ensure our method obtain better results with higher contrast and sharpness. The hue preservation considered in enhancements and the color correction considered in the variational-based fusion make our method to obtain desirable colorfulness.

	HMF [10]	SLRMSR [11]	DeepNet [54]	WVM [37]	BIMEF [147]	GLF [127]	Proposed
<i>CQE</i>	0.4601	0.4926	0.3970	0.4629	0.4504	0.5052	<b>0.5755</b>
<i>Contrast</i>	0.3510	0.3826	0.2326	0.3757	0.3234	0.3595	<b>0.5304</b>
<i>Sharpness</i>	0.5981	0.6373	0.5589	0.5909	0.6231	0.6776	<b>0.7009</b>
<i>Colorfulness</i>	0.4290	0.4547	0.4049	0.4170	0.4001	0.4779	<b>0.4819</b>

Table 7.3 Average CQE of the enhanced images

## 7.5 Conclusions

In this chapter, we have proposed a variational-based fusion method for non-uniform illumination image enhancement via contrast optimization and color correction. There are three main contributions of our method. Firstly, a global contrast adaptive enhancement method is introduced to improve the global contrast. Secondly, a hue preservation framework is considered in the global enhancement and the local enhancement. Thirdly, a variational-based image fusion method is developed for obtaining final enhanced images. Experiments demonstrate the proposed method outperforms other enhancement methods in terms of subject visual comparisons and objective performance evaluations.

Since there are undesirable noises in the dark regions of some non-uniform illumination images, noise reductions [20] will be considered in the contrast enhancement framework in the future work. The numerical method used to solve the minimization problem has high

## 7.5 Conclusions

---

complexity, which needs more time to obtain final enhanced results. We will consider some other approximate minimization method to finish this task in the future.



# Chapter 8

## Temporally Consistent Contrast

### Enhancement for Videos

#### Contents

---

<b>8.1</b>	<b>Introduction</b>	<b>143</b>
<b>8.2</b>	<b>Related Work</b>	<b>144</b>
8.2.1	Histogram-based Image Enhancement	144
8.2.2	Fusion-based Image Enhancement	144
8.2.3	Temporally Consistency Video Enhancement	146
<b>8.3</b>	<b>The Proposed Method</b>	<b>146</b>
8.3.1	Temporally Consistent Global Contrast Adaptive Enhancement	147
8.3.2	Local Contrast Adaptive Enhancement	150
8.3.3	Contrast-Brightness-based Fusion	150
<b>8.4</b>	<b>Experiments</b>	<b>151</b>
8.4.1	Subjective Comparisons	151
8.4.2	Objective Comparisons	154
8.4.3	Flickering-artifact Comparisons	155

**Temporally Consistent Contrast Enhancement for Videos**

---

**8.5 Conclusion . . . . . 156**

---

### Abstract

Video enhancement is a very challenging work, which is a much more difficult task than image enhancement. Video enhancement is aimed to not only improve the visual quality of videos but also do not produce some side problems. It is not a good solution to directly apply the existing image enhancement method to processing video frames one by one. Because this kind of operation may result in flickering among the frames in the considered video. In order to obtain better-enhanced results for videos, we proposed a temporally consistent contrast enhancement method. This method is extended from the fusion-based enhancement model in chapter 7. Firstly, the video frames are converted from the RGB color space to the HSV color space. Then, luminance channel of each frame is enhanced by both global adaptive enhancement method and local adaptive enhancement method. The key technique is that temporally consistency is considered in the global method since global enhancement methods often produce flickering when they are used to enhance each frame independently. After that, a fusion enhanced luminance channel is obtained with the global results and the local results. Finally, the enhanced color image is produced via HSV-RGB color space conversion. Experiments demonstrate the proposed method outperforms other algorithms in terms of contrast improvement, color image visual quality, and flickering suppression.

### 8.1 Introduction

With the development of digital imaging devices, it is very convenient to capture videos. However, the obtained videos are usually not desirable in terms of visual quality. Specifically, we should apply some relevant enhancement method to improve the visual quality of the considered videos. There are lots of existing image enhancement methods, including histogram-based method, reninex-based methods, fusion-based methods, and learning-based method. One solution for video enhancement is to directly conduct image enhancement algorithms on each video frame. This kind of processing usually results in flickering artifacts [25]. In order to



obtain high contrast videos without producing flickering artifacts, we proposed a flickering-free temporally consistent enhancement method for improving video contrast.

## 8.2 Related Work

### 8.2.1 Histogram-based Image Enhancement

One of the most popular histogram-based enhancement methods is histogram equalization [41], which modifies the original histogram to a uniform histogram for obtaining higher contrasts. This method may produce undesirable artifacts, such as over-enhancement. Various related methods [63, 138] have been proposed to avoid these disadvantages. Arici et al. [10] presented a general histogram equalization framework for contrast enhancement via optimizing cost functions. Rivera et al. [113] applied adaptive mapping functions to obtain well-enhanced images, which spread the dynamic range of the dark intensities and maintain the shapes of their histograms. Lee et al. [69] proposed an enhancement algorithm based on the layered difference reproduction of histograms. Contrast-limited adaptive histogram equalization [100] is another popular histogram-based enhancement method, in which the histogram equalization is considered locally. This kind of local methods [83, 21] can improve more details in the considered image, and preserve the image naturalness. Stark [122] proposed an adaptive image contrast enhancement method based on a generalization of histogram equalization. By setting different forms of mapping functions, this algorithm can obtain corresponding different degrees of contrast enhancement.

### 8.2.2 Fusion-based Image Enhancement

Image fusion is a technique of combining useful information from different images, which describe the same scene. The fusion result contains better visibility than any input images. The fusion can be conducted on various levels, such as signal-level, pixel-level, feature-level, symbol-level [15]. No matter which level is selected, the fusion results should meet the

following two conditions: (1) the fusion image preserves as much as possible information of the input images; (2) the fusion image does not contain new artifacts or noisy. Mertens et al. [80] proposed a practical pixel-level exposure fusion method for generating high dynamic range images. The results can maintain the useful information in each image sequence using weighted blending. Ma et al. [75] proposed a feature-level robust exposure fusion model for avoiding ghosting effect. Wang et al. [137] proposed a variational method for fusing multi-focus images. A family of weight functions using the local average modulus of gradients and the power transform is adopted in Wang et al.'s method. Fu et al. [36] proposed a fusion method for combining three illumination components. This method can obtain good results for weakly-illuminated images. Inspired by the human visual system, Ying et al. [147] proposed a multi-exposure fusion method for low-light image enhancement, which can produce enhanced results with small lightness distortion. The framework of Ying et al.'s enhancement method is shown in Fig. 8.1.

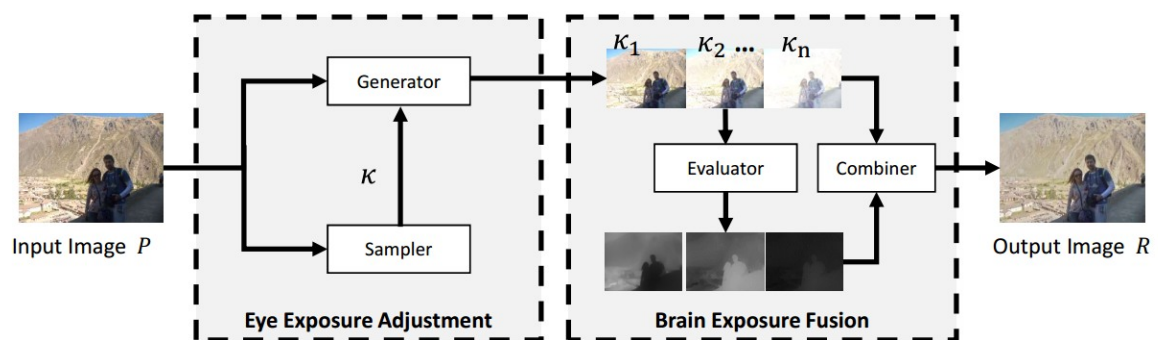


Fig. 8.1 The overall framework of Ying et al.'s multi-exposure fusion method

### 8.2.3 Temporally Consistency Video Enhancement

Video enhancement is not the same as image enhancement. The problem of flickering artifacts may be raised when we treat a video as a lot of images and enhance every frame independently. In order to avoid this problem, temporally consistency should be considered in video enhancement. Bhat et al. [14] proposed a gradient-domain optimization method for video filtering. This method needs to solve a linear optimization problem on each frame. Dong et al. [29] presented a region-based temporally consistent video post-processing method, which depends on region segmentation and spatially consistent enhancement prior. Zhang et al. [150] proposed an efficient perception-driven progressive fusion framework for underexposed video enhancement. An effective texture-preserving spatio-temporal filtering is performed to obtained temporally consistent results. Bonneel et al. [16] proposed a general approach to extending image filters to videos. They formulated it in the gradient domain and proposed an energy function that amounts to a spatial screened Poisson equation with temporal constraints. Fig. 8.2 shown an example of temporally consistency enhancement.

## 8.3 The Proposed Method

Let  $\mathbf{I}(\mathbf{t}) = (I_r(\mathbf{t}), I_g(\mathbf{t}), I_b(\mathbf{t})) : \Omega \rightarrow [0, 255]^3$  be a considered RGB color image,  $\mathbf{t}$  is the frame index in the considered video, where  $\Omega \subset \mathbb{R}^2$  is the image domain.  $\mathbf{x} = (x_1, x_2)$  denotes the position in the image domain  $\Omega$ . Our goal is to obtain the enhanced color image  $\mathbf{F}(\mathbf{t}) = (F_r(\mathbf{t}), F_g(\mathbf{t}), F_b(\mathbf{t}))$ . The overall framework of the proposed temporally consistent video contrast enhancement method is illustrated in Fig. (8.3). The luminance channel  $Y(\mathbf{t})$  is processed by a temporally consistent global contrast enhancement method and a local contrast enhancement method, respectively. Then the globally enhanced gray image  $G_{Y(\mathbf{t})}$  and the locally enhanced gray image  $L_{Y(\mathbf{t})}$  are fused to produce a well-enhanced gray image  $F_{Y(\mathbf{t})}$ . Finally, the enhanced color image  $\mathbf{F}(\mathbf{t})$  is obtained with the HSV2RGB color space conversion. The detailed description of the proposed method is presented below.

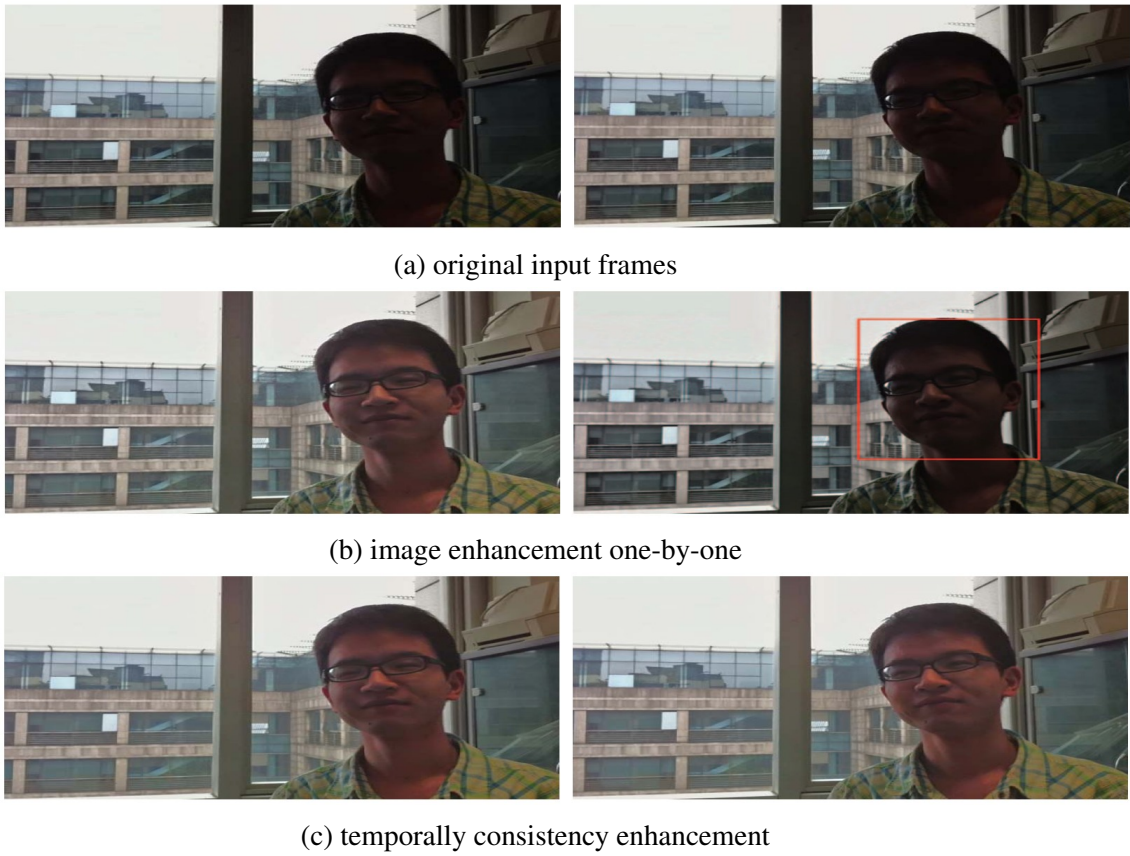


Fig. 8.2 An example of temporally consistency video enhancement [29].

### 8.3.1 Temporally Consistent Global Contrast Adaptive Enhancement

We consider a gray image  $Y(\mathbf{t})$ , which is the luminance channel of the original low contrast color image. The normalized histogram of the image  $Y(\mathbf{t})$  is  $h_{Y(\mathbf{t})}$ .

Histogram-based contrast enhancement methods use the image histogram to obtain the corresponding mapping function for modifying the pixel values and enhancing the contrast of the considered image. Traditional histogram equalization algorithm uses the original histogram of the considered image to obtain the mapping function. The mapping function  $T$  for the image  $Y(\mathbf{t})$  is given by Eq. (8.1)

$$T(i) = \left\lfloor (L-1) \sum_{j=0}^i h_{Y(\mathbf{t})}(j) + 0.5 \right\rfloor, \quad (8.1)$$

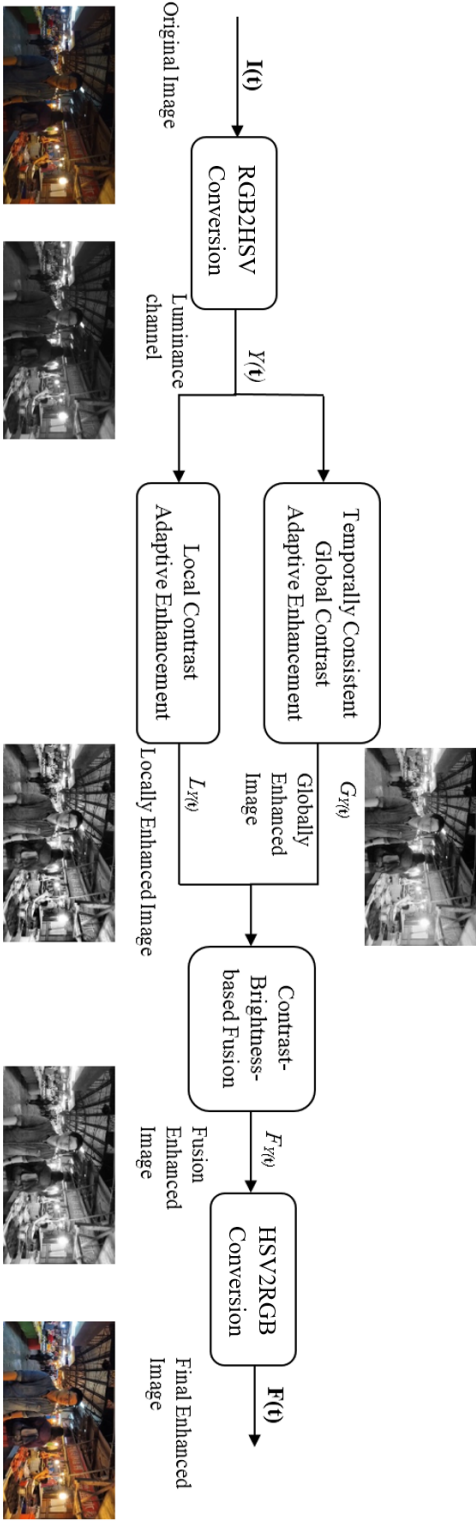


Fig. 8.3 The overall framework of the proposed temporally consistent video contrast enhancement method. The original image  $I(t)$  has low contrast. The final enhanced image  $F(t)$  represents a trade-off between the global contrast and the local contrast.

where  $i \in [0, L - 1]$  is the input integer for the mapping function, and  $\lfloor \cdot \rfloor$  computes the nearest integer of the considered value towards minus infinity.  $L = 256$  for 8 bits images.

Traditional histogram equalization methods try to create a uniform histogram for the enhanced image via considering a cumulative histogram as the corresponding mapping function. This kind of histogram equalization algorithm often produces unnatural looking images with visual artifacts. To deal with this problem, a general histogram modification framework is proposed in [10]. Using the mapping function obtained from the optimal modified histogram, the contrast-enhanced image can avoid unnatural artifacts. The modified histogram  $h_{Y(\mathbf{t})}$  should be closer to the normalized uniform histogram  $h_U$  and the value of the residual  $h - h_{Y(\mathbf{t})}$  should be also small. The problem of obtaining the optimal modified histogram  $\tilde{h}$  can be regarded as a solution of a bi-criteria optimization problem. The detail analysis of this problem is given Section 7.3.1. The optimal modified histogram  $\tilde{h}$  can be formulated as a weighted sum of two terms shown in

$$\min_h (\|h - h_{Y(\mathbf{t})}\| + \lambda \|h - h_U\|), \quad (8.2)$$

where  $\|h - h_{Y(\mathbf{t})}\|$  is a norm of  $h - h_{Y(\mathbf{t})}$ ,  $\|h - h_U\|$  is a norm of  $h - h_U$ , and the parameter  $\lambda > 0$  adjusts the trade-off between the contrast enhancement and the data fidelity.

The optimal modified histogram  $\tilde{h}$  is a weighted sum of  $h_{Y(\mathbf{t})}$  and  $h_U$ . This is a simple and efficient solution to obtain the modified histogram. In Section 7.3.1, an adaptive decision of the optimal modified histogram is given. The method in Section 7.3 is designed for enhancing non-uniform illumination color image. The flicker problem may be raised when we directly apply this method for processing videos. So we consider the neighboring frames of the current video frame to produce the mapping function.

Using the method in Section 7.3.1, we can obtain the mapping function  $T(\mathbf{t})$  of the image  $Y(\mathbf{t})$ , and the the mapping function  $T(\mathbf{t} - \mathbf{1})$  of the image  $Y(\mathbf{t} - \mathbf{1})$ . Then we compute the average between  $T(\mathbf{t})$  and  $T(\mathbf{t} - \mathbf{1})$ . The updated result is considered as the new mapping function of the image  $Y(\mathbf{t})$ . This strategy can avoid or decrease the flicker problem. Eq. 8.3 gives the updated computation of  $T(\mathbf{t})$ .

$$T(\mathbf{t}) = 0.5T(\mathbf{t}) + 0.5T(\mathbf{t} - \mathbf{1}) \quad (8.3)$$

### 8.3.2 Local Contrast Adaptive Enhancement

The proposed global contrast adaptive enhancement method can improve the global contrast and brightness of the whole image. However, it is essentially a global method, which may reduce the local contrast or the detail information in the original image. So we consider a local contrast adaptive enhancement to improve the local contrast and preserve the detail information. In our implement, we directly applied the tradition Contrast-Limited Adaptive Histogram Equalization method (CLAHE) [100]. Since this kind of local contrast enhancement method does not result in the problem of flickering, the temporally consistent is not used in this step.

### 8.3.3 Contrast-Brightness-based Fusion

Inspired by the idea of exposure fusion [80], we develop a contrast-brightness-based fusion framework to obtain the final enhanced image  $F_{Y(\mathbf{t})}$  with the globally enhanced image  $G_{Y(\mathbf{t})}$  and the locally enhanced image  $L_{Y(\mathbf{t})}$ . This fusion framework can keep the better contrast and brightness for each pixel, since we adopt contrast-brightness-based pixel-level weights to fuse every pixel. Firstly, the the weight maps of the globally enhanced image and the locally enhanced image are computed by Eq. (8.4).

$$W_d = \min\{C_d, B_d\}, \quad d \in \{G, L\}, \quad (8.4)$$

where  $W_d$  is the weight map,  $C_d$  is the contrast measure,  $B_d$  is the brightness measure, and the operation  $\min$  can efficiently penalize the corresponding low-contrast, low brightness (under-exposure) or high brightness (over-exposure).  $C_d$  is obtained by a Laplacian filter, which can assign high weights to edges and textures in the corresponding image.  $B_d$  is computed by a

Gaussian curve  $\exp\left(-\frac{(i-0.5)^2}{2\sigma^2}\right)$  and  $\sigma = 0.2$  in our experiments, which can assign high weights to pixel values close to 0.5 and define low weights to pixel values near 0 (under-exposure) or near 1 (over-exposure). Secondly, the two weight maps are normalized by Eq.(8.5) to ensure a consistent fusion result.

$$\hat{W}_d = \frac{W_d}{W_G + W_L}, \quad d \in \{G, L\}, \quad (8.5)$$

Finally, the fusion result is obtained by Eq. (8.6).

$$F_{Y(t)}(\mathbf{x}) = \hat{W}_G(\mathbf{x}) \cdot G_{Y(t)}(\mathbf{x}) + \hat{W}_L(\mathbf{x}) \cdot L_{Y(t)}(\mathbf{x}), \quad (8.6)$$

where  $\mathbf{x}$  is the pixel positions in images.

## 8.4 Experiments

We ran the proposed method and several image enhancement methods on some video clips from the website Youtube. The comparison algorithms include Arici et al.’s histogram-modification-based global contrast enhancement (Arici’09) [10], Rivera et al.’s content-aware enhancement via channel division (Rivera’12) [113], and Ying et al.’s Bio-Inspired Multi-Exposure Fusion framework for image enhancement (Ying’17) [148, 147]. The source codes of Rivera’12 and Ying’17 are available on the authors’ homepages. We reproduced the method of Arici’09 (For all experiments, the parameter  $\lambda = 1$ ).

To evaluate the performance of the proposed adaptive enhancement method, both qualitative comparisons and quantitative assessments are considered in the following parts.

### 8.4.1 Subjective Comparisons

In this part, we show some original test images in videos and the corresponding enhanced images to subjectively compare the performances of these enhancement algorithms. The contrast enhancement, naturalness preservation are considered in the comparisons.



## Temporally Consistent Contrast Enhancement for Videos

---

Fig. (8.4) shows the enhanced results by several methods. Arici'09 enhances the global contrast very well, however the local contrast is not desirable. Rivera'12 slightly enhances the dark region and over-enhances the bright region (the color of the glass and the sky are saturated). Ying'17 obtains the highest bright which makes the image color to be seemingly washed-out. Our method generates good results both in the dark regions and in the bright regions, resulting from combining the globally enhanced image and the locally enhanced image.

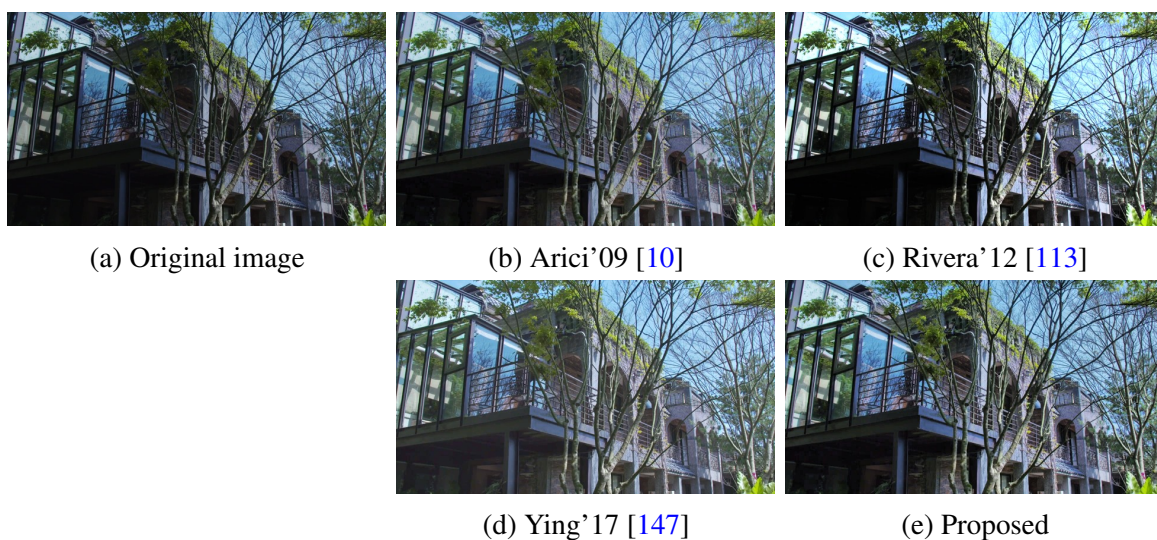


Fig. 8.4 Comparative results

Some other results are shown in Fig. (8.5), Fig. (8.6) and Fig. (8.7), which demonstrate the proposed method can obtain good results both in the dark regions and the bright regions. The other algorithms either slightly enhance the dark regions or over-enhance the bright areas, which produce undesirable enhanced results.

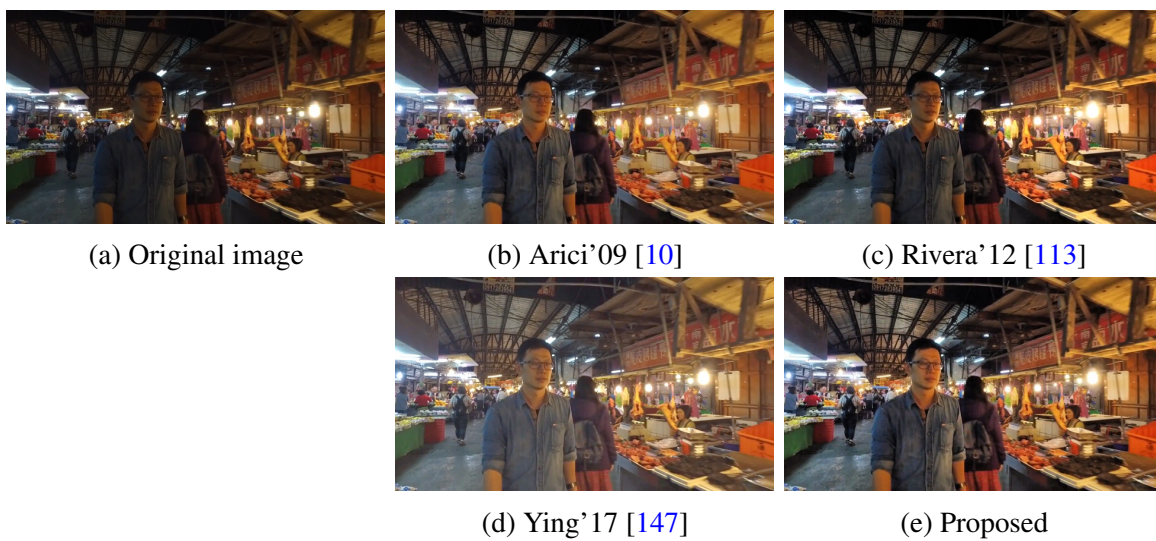


Fig. 8.5 Comparative results

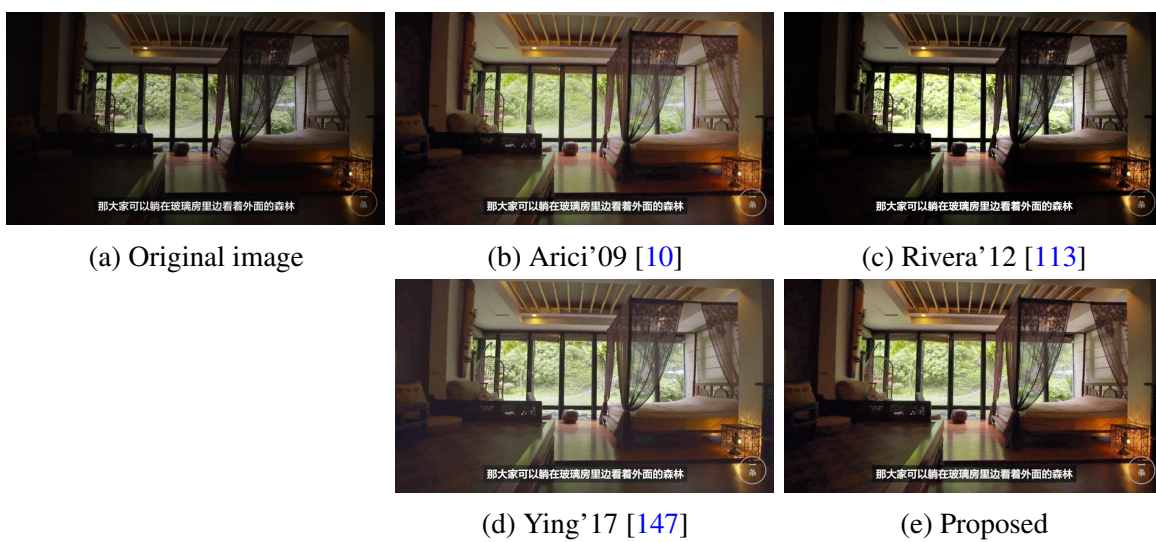


Fig. 8.6 Comparative results

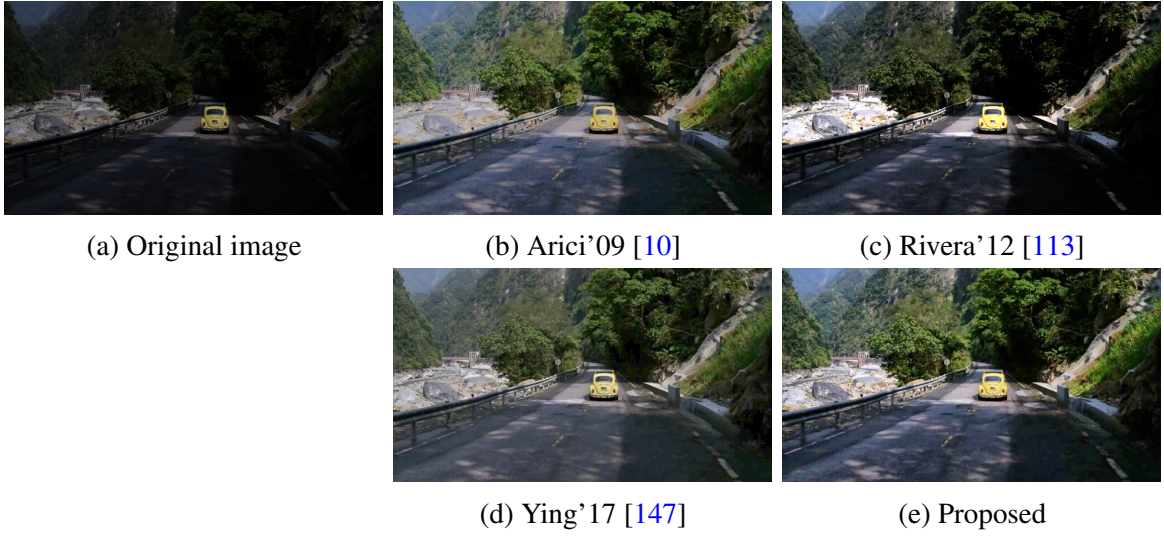


Fig. 8.7 Comparative results

### 8.4.2 Objective Comparisons

For the objective comparisons of the above mentioned methods, two widely adopted image quality assessment metrics are considered below. Hautière et al. [48] proposed a contrast evaluation method via Visible Edges Assessment (VEA). This metric evaluates the contrast improvement with three indicators:  $e$  evaluates the ability for restoring edges,  $\bar{r}$  is the mean ratio of gradients in visible edges,  $\Sigma$  represents the percentage of pixels becoming saturated after the enhancement. The higher values of  $e$  and  $\bar{r}$  present the better contrast improvement. The lower value of  $\Sigma$  indicates the better ability of pixel value range preservation. The evaluation results are shown in Table (8.1), which demonstrates the proposed method outperforms other algorithms in terms of contrast improvement (higher  $e$  and  $\bar{r}$ ).

	Arici'09 [10]	Rivera'12 [113]	Ying'17 [147]	Proposed
$e$	-0.0126	-0.0213	-0.0371	<b>0.0060</b>
$\bar{r}$	2.0449	1.6985	1.9347	<b>2.5614</b>
$\Sigma(\%)$	0.0937	1.9886	0.3362	<b>0.0217</b>

Table 8.1 Average VEA of enhancement algorithms on the test dataset

Panetta et al. [91] proposed a color image quality measurement (CQE) combining the contrast, sharpness and colorfulness metrics. The higher value of CQE means the better quality of the considered color image. We use this metric to evaluate our method and several compared algorithms on the test dataset. The results are shown in Table (8.2), which indicates that the proposed method outperforms other algorithms in terms of the image quality.

	Original	Arici'09 [10]	Rivera'12 [113]	Ying'17 [147]	Proposed
<i>CQE</i>	0.4190	0.4770	0.5145	0.4500	<b>0.5197</b>

Table 8.2 Average CQE of the enhanced images

### 8.4.3 Flickering-artifact Comparisons

In this subsection, we discuss the flickering – artifact problem of the enhancement methods in processing videos. We collected four clips from the above mention videos. To compare the flickering-artifact raised by these methods, we evaluated the variation of the mean brightness values of the original video and the enhanced videos, which is shown in Fig. 8.8. We can easily observe that Ying et al.'s Bio-Inspired Multi-Exposure Fusion framework for image enhancement (Ying'17) produces unstable results. The variation of the mean brightness values of Ying'17 is not relevant to the original video. This is able to raise the flickering-artifact. The variation of the mean brightness values of other methods are all relevant to the original video. This means Arici'09, Rivera'12 and the proposed method do not produce flickering-artifacts. In Fig. 8.8, we can also know that the mean brightness by the proposed method is better than the results by Arici'09 and Rivera'12. This will produce better visible enhanced results. The results of Ying'17 obtain the highest mean brightness. However, this highest value makes the enhanced image to be seemingly washed-out. In short, the proposed method obtained desirable enhanced results and does not produce flickering-artifacts. A direct comparison of flicker-artifacts can be easily observed from the corresponding enhanced videos. Some video demos are shown in the project homepage <sup>1</sup>.

<sup>1</sup>[www.ceremade.dauphine.fr/~tian/video-enhancement.html](http://www.ceremade.dauphine.fr/~tian/video-enhancement.html)

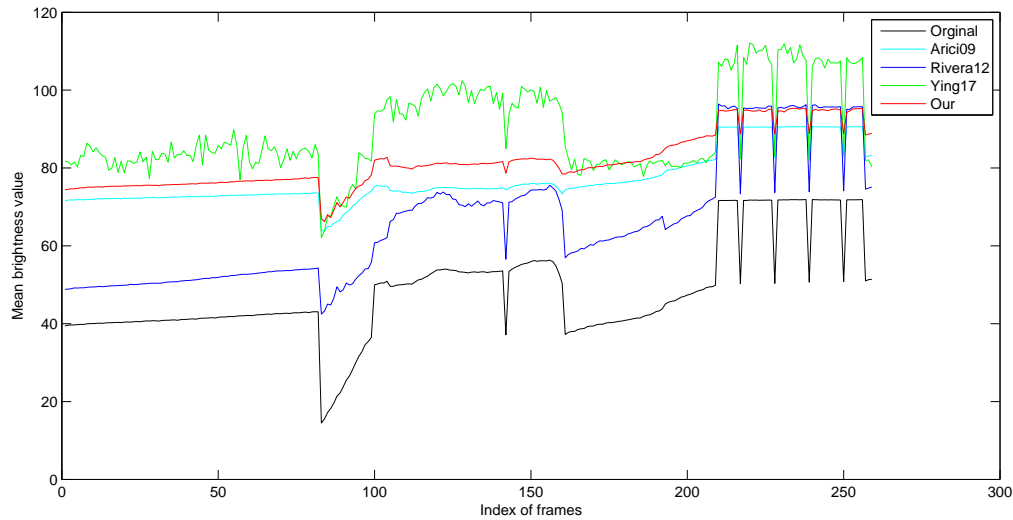


Fig. 8.8 Mean Brightness values of the original low contrast frames and enhanced results.

## 8.5 Conclusion

In this chapter, we have proposed a temporally consistent contrast adaptive enhancement method for videos. There are two main contributions of our method. Firstly, a temporally consistent enhancement method is proposed to improve the global contrast adaptively. Secondly, a contrast-brightness-based image fusion method is developed for obtaining final enhanced images. Experiments demonstrate the proposed method outperforms other enhancement methods in terms of subject visual comparisons, objective evaluations, and the flickering problem.

The proposed method is developed from the algorithm in Chapter 7, which based on histogram modification and fusion framework. Histogram modification maybe produce unnatural results. The fusion framework is time-consuming. In the future, we will consider some other model to avoid these problems.

# Chapter 9

## Conclusion

### Contents

---

9.1 Summary of the Thesis . . . . .	158
9.2 Future Work . . . . .	160

---

### 9.1 Summary of the Thesis

In this thesis, we have addressed two challenging issues in image processing, including color correction and contrast enhancement. The two problems and the corresponding solvers are described in Part I and Part II, respectively.

In Part I, we firstly review the related work on color correction of natural images. Then, two individual problems received corresponding attentions.

Image stitching is the technique for producing a panorama large-size image from multiple small-size images. Due to the differences in imaging devices, camera settings or illumination conditions, these multiple images are usually color inconsistent. This will affect visual results of image stitching. So color correction plays an important role in image stitching. It can reduce the color inconsistencies and make the panorama be more natural. We combine the ideas of histogram specification and global mapping to produce a color transfer function, which can extend well the color mapping from the overlapping region to the entire image. Generally speaking, there are four steps in this algorithm. Firstly, there are two given images to be stitched. The image having good visual quality is defined as the reference image and the other is defined as the test image. Overlapping regions between these two images are obtained using a feature-based matching method. Secondly, histogram specification is conducted for the overlapping regions. Thirdly, using corresponding pixels in the overlapping region which are original pixels and the pixels after histogram specification, the mapping function is computed with an iterative method for minimizing color differences. At last, the whole color corrected image is produced by applying the mapping function to the entire test image. The main contribution of the proposed method is to produce a global mapping function with an iteration method, which can effectively minimize color differences between a reference image and a test image. Another advantage of our method is the color correction ability for two images having small overlapping regions.

Color correction for photo collections is another problem in Part I. The most simple color correction method is the auto color adjustment technique, which is implemented in most

commercial photo editing tools. However, this kind of method makes the color correction for each image independently, not considering the color distribution relations among all images in the same collection. Another kind of method is manually adjusting all images by professional photographers, which requires a significant amount of processing time for a large number of photos. Some existing automatic color correction methods for image collections eighth highly depend on accurate correspondences or result in saturated problems. To avoid gamut problems and reduce the effects from bad quality images, we present an automatic color consistency algorithm for photo collections based on image quality assessment and range-preserving histogram specification. In our method, input images are divided into two sets, namely high-quality image set and low-quality image set. And then the images having high quality will be used to produce corresponding color balanced images. At last, the images classified in the low-quality image set will be color transferred with the corrected high-quality images as the reference. These three stages can obtain color consistency among the whole set of images and not cause the disadvantages of some existing methods.

In Part II, we firstly summarize the relevant methods of image contrast enhancement. Then, three different contrast enhancement methods are described in corresponding chapters.

Since many existing contrast enhancement algorithms usually produce over-enhanced results, the naturalness preservation is needed to be considered in the framework of image contrast enhancement. Some existing contrast enhancement methods need to manually tuning the parameters, which is time-consuming. In order to deal with this problem, we propose an automatic global image contrast enhancement method based on histogram modification and quality assessment. The proposed method adopts the histogram matching to improve the contrast and uses the image quality assessment to automatically select the optimal target histogram. The contrast improvement and the naturalness preservation are both considered in the target histogram, so this method can avoid the over-enhancement problem.

Images captured in uniform illumination environment can be enhanced well in terms of contrast improvement. However, most of the enhancement algorithms fail to process non-



## Conclusion

---

uniform illumination images. Some existing methods either under-enhance dark regions or over-enhance bright regions of images. Inspired by the idea of exposure fusion and variational model, we proposed an enhancement method combining globally enhanced images and locally enhanced images. The fusion is conducted with a variational model via optimizing image contrast and minimizing color inconsistency. This method improves the contrast both in dark regions and bright regions of images.

Video enhancement is slightly different from image enhancement. Some undesirable disadvantages may be produced after directly applying the image enhancement method to process each frame of videos. For example, image contrast enhancement methods maybe improve the contrast with varying degrees for neighboring frames of videos. This could result in the problem of video shake or flicker. In order to avoid this disadvantage, a temporally consistent video enhancement method is proposed. This method can both improve contrast and maintain temporally consistent among neighboring frames.

## 9.2 Future Work

This thesis is based on the peer-reviewed conference papers and journal papers authored by us. After having discussions with relevant researchers in the international conferences and obtaining the constructive suggestions from the anonymous reviewers, some new research topics are raised. These work could be finished in the following years after defending this thesis.

- **Patch-based Color Correction**

The two color correction methods proposed in chapter 3 and chapter 4 are both based on pixel-level to produce correction functions. These algorithms do not consider the neighbors of each pixel. In future work, we will consider the information of local patches to construct the color mapping functions, which may be more accurate to transfer colors.

- **Region-based Contrast Enhancement**

The contrast enhancement methods proposed in this thesis adopt a global enhancement model, a block-based local enhancement strategy, or a combination of both. Region-based local enhancement framework maybe produce better results with adaptive enhancement degrees in different regions. This kind of method may be avoid the problems of over-enhancement and under-enhancement.

- **Learning-based Contrast Enhancement**

Machine learning is a very popular and powerful technique in the domains of computer vision and image processing. It achieves better performance than traditional algorithms in lots of research topics. We will try to apply the contrast enhancement methods in this thesis to a machine learning framework. We expect better results will be obtained with this kind of learning-based model.



# References

- [1] The Berkeley segmentation dataset and benchmark. Available online: <https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/>. Accessed on 02-September-2017.
- [2] Color correction image dataset. Available online: [https://www.researchgate.net/publication/282652076\\_color\\_correction\\_images](https://www.researchgate.net/publication/282652076_color_correction_images). Accessed on 02-September-2017.
- [3] Aghaian, S. S., Panetta, K., and Grigoryan, A. M. (2000). A new measure of image enhancement. In *IASTED International Conference on Signal Processing & Communication*, pages 19–22.
- [4] Aghaian, S. S., Silver, B., and Panetta, K. A. (2007). Transform coefficient histogram-based image enhancement algorithms using contrast entropy. *IEEE Transactions on Image Processing*, 16(3):741–758.
- [5] Aguerrebere, C., Almansa, A., Delon, J., Gousseau, Y., and Musé, P. (2017). A bayesian hyperprior approach for joint image denoising and interpolation, with an application to HDR imaging. *IEEE Transactions on Computational Imaging*, 3(4):633–646.
- [6] Aguerrebere, C., Almansa, A., Gousseau, Y., Delon, J., and Muse, P. (2014a). Single shot high dynamic range imaging using piecewise linear estimators. In *2014 IEEE International Conference on Computational Photography (ICCP)*, pages 1–10. IEEE.
- [7] Aguerrebere, C., Delon, J., Gousseau, Y., and Musé, P. (2014b). Best algorithms for hdr image generation. a study of performance bounds. *SIAM Journal on Imaging Sciences*, 7(1):1–34.
- [8] Anbarjafari, G. (2015). An objective no-reference measure of illumination assessment. *Measurement Science Review*, 15(6):319–322.
- [9] Ancuti, C. O., Ancuti, C., and Bekaert, P. (2011). Enhancing by saliency-guided decolorization. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'11)*, pages 257–264. IEEE.
- [10] Arici, T., Dikbas, S., and Altunbasak, Y. (2009). A histogram modification framework and its application for image contrast enhancement. *IEEE Transactions on Image Processing*, 18(9):1921–1935.
- [11] Banić, N. and Lončarić, S. (2015). Smart light random memory sprays retinex: a fast retinex implementation for high-quality brightness adjustment and color correction. *JOSA A*, 32(11):2136–2147.

## References

---

- [12] Bay, H., Ess, A., Tuytelaars, T., and Van Gool, L. (2008). Speeded-up robust features SURF. *Computer Vision and Image Understanding*, 110(3):346–359.
- [13] Bertalmío, M., Caselles, V., Provenzi, E., and Rizzi, A. (2007). Perceptual color correction through variational techniques. *IEEE Transactions on Image Processing*, 16(4):1058–1072.
- [14] Bhat, P., Zitnick, C. L., Cohen, M., and Curless, B. (2010). Gradientshop: A gradient-domain optimization framework for image and video filtering. *ACM Transactions on Graphics (TOG)*, 29(2):10.
- [15] Blum, R. S. and Liu, Z. (2005). *Multi-sensor image fusion and its applications*. CRC press.
- [16] Bonneel, N., Tompkin, J., Sunkavalli, K., Sun, D., Paris, S., and Pfister, H. (2015). Blind video temporal consistency. *ACM Transactions on Graphics (TOG)*, 34(6):196.
- [17] Bringier, B., Richard, N., Larabi, M.-C., and Fernandez-Maloigne, C. (2006). No-reference perceptual quality assessment of colour image. In *14th European Signal Processing Conference*, pages 1–5. IEEE.
- [18] Brown, M. and Lowe, D. G. (2007). Automatic panoramic image stitching using invariant features. *International Journal of Computer Vision*, 74(1):59–73.
- [19] Bychkovsky, V., Paris, S., Chan, E., and Durand, F. (2011). Learning photographic global tonal adjustment with a database of input/output image pairs. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'11)*, pages 97–104. IEEE.
- [20] Carre, P. and Helbert, D. (2005). Ridgelet decomposition: Discrete implementation and color denoising. In *Wavelet Applications in Industrial Processing III*, volume 6001, page 60010F. International Society for Optics and Photonics.
- [21] Caselles, V., Lisani, J.-L., Morel, J.-M., and Sapiro, G. (1999). Shape preserving local histogram modification. *IEEE Transactions on Image Processing*, 8(2):220–230.
- [22] Chen, S.-D. and Ramli, A. R. (2003). Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation. *IEEE Transactions on Consumer Electronics*, 49(4):1301–1309.
- [23] Cheng, D., Price, B., Cohen, S., and Brown, M. S. (2015). Beyond white: Ground truth colors for color constancy correction. In *Proceedings of the IEEE International Conference on Computer Vision (CVPR'15)*, pages 298–306.
- [24] Delon, J. (2004). Midway image equalization. *Journal of Mathematical Imaging and Vision*, 21(2):119–134.
- [25] Delon, J. and Desolneux, A. (2010). Stabilization of flicker-like effects in image sequences through local contrast correction. *SIAM Journal on Imaging Sciences*, 3(4):703–734.
- [26] Delon, J. and Desolneux, A. (2013). A patch-based approach for removing impulse or mixed gaussian-impulse noise. *SIAM Journal on Imaging Sciences*, 6(2):1140–1174.
- [27] Deng, H., Deng, W., Sun, X., Ye, C., and Zhou, X. (2016). Adaptive intuitionistic fuzzy enhancement of brain tumor MR images. *Scientific Reports*, 6:35760.

- 
- [28] Dix, A. (2009). Human-computer interaction. In *Encyclopedia of Database Systems*, pages 1327–1331. Springer.
- [29] Dong, X., Bonev, B., Zhu, Y., and Yuille, A. L. (2015). Region-based temporally consistent video post-processing. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR'15)*, pages 714–722.
- [30] Faridul, H., Stauder, J., Kervec, J., and Trémeau, A. (Dec. 2013). Approximate cross channel color mapping from sparse color correspondences. In *IEEE International Conference on Computer Vision (ICCV'13) – Workshop in Color and Photometry in Computer Vision (CPCV'13)*, pages 860–867.
- [31] Faridul, H. S., Pouli, T., Chamaret, C., Stauder, J., Reinhard, E., Kuzovkin, D., and Tremeau, A. (2016). Colour mapping: A review of recent methods, extensions and applications. *Computer Graphics Forum*, 35(1):59–88.
- [32] Faridul, H. S., Stauder, J., and Trémeau, A. (2014). Illumination and device invariant image stitching. In *IEEE International Conference on Image Processing (ICIP'14)*, pages 56–60. IEEE.
- [33] Fecker, U., Barkowsky, M., and Kaup, A. (2008). Histogram-based prefiltering for luminance and chrominance compensation of multiview video. *IEEE Transactions on Circuits and Systems for Video Technology*, 18(9):1258–1267.
- [34] Fitschen, J. H., Nikolova, M., Pierre, F., and Steidl, G. (May 2015). A variational model for color assignment. In *International Conference on Scale Space and Variational Methods in Computer Vision (SSVM'15)*, volume LNCS9087, pages 437–448. Springer.
- [35] Frigo, O., Sabater, N., Demoulin, V., and Hellier, P. (2014). Optimal transportation for example-guided color transfer. In *Asian Conference on Computer Vision*, pages 655–670. Springer.
- [36] Fu, X., Zeng, D., Huang, Y., Liao, Y., Ding, X., and Paisley, J. (2016a). A fusion-based enhancing method for weakly illuminated images. *Signal Processing*, 129:82–96.
- [37] Fu, X., Zeng, D., Huang, Y., Zhang, X.-P., and Ding, X. (2016b). A weighted variational model for simultaneous reflectance and illumination estimation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'16)*, pages 2782–2790.
- [38] Gevers, T., Gijzenij, A., Van de Weijer, J., and Geusebroek, J.-M. (2012). *Color in computer vision: fundamentals and applications*, volume 23. John Wiley & Sons.
- [39] Gevers, T. and Smeulders, A. W. (2000). Pictoseek: Combining color and shape invariant features for image retrieval. *IEEE Transactions on Image Processing*, 9(1):102–119.
- [40] Gevers, T. and Stokman, H. (2004). Robust histogram construction from color invariants for object recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(1):113–118.
- [41] Gonzalez, R. C. and Woods, R. E. (2007). *Digital image processing (Third Edition)*.

## References

---

- [42] Grementieri, L. and Provenzi, E. (2016). A computational model for the selection of achromatic and non-neutral colors to fill lacunae in frescoes. In *International Conference on Graphic and Image Processing (ICGIP'16)*.
- [43] Guettari, N., Capelle-Laizé, A. S., and Carré, P. (2014). Fusion of imprecise data applied to image quality assessment. In *2014 IEEE International Conference on Image Processing (ICIP'14)*, pages 521–525. IEEE.
- [44] HaCohen, Y., Shechtman, E., Goldman, D. B., and Lischinski, D. (2011). Non-rigid dense correspondence with applications for image enhancement. *ACM transactions on graphics (TOG)*, 30(4):70.
- [45] HaCohen, Y., Shechtman, E., Goldman, D. B., and Lischinski, D. (2013). Optimizing color consistency in photo collections. *ACM Transactions on Graphics (TOG)*, 32(4):38.
- [46] Hao, Q., Cai, R., Li, Z., Zhang, L., Pang, Y., and Wu, F. (2012). 3d visual phrases for landmark recognition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'12)*, pages 3594–3601. IEEE.
- [47] Hasler, D. and Suesstrunk, S. E. (2003). Measuring colorfulness in natural images. In *Human vision and electronic imaging VIII*, volume 5007, pages 87–96. International Society for Optics and Photonics.
- [48] Hautière, N., Tarel, J.-P., Aubert, D., and Dumont, E. (2011). Blind contrast enhancement assessment by gradient ratioing at visible edges. *Image Analysis & Stereology*, 27(2):87–95.
- [49] Hays, J. and Efros, A. A. (2007). Scene completion using millions of photographs. In *ACM Transactions on Graphics (TOG)*, volume 26, page 4. ACM.
- [50] Hristova, H., Le Meur, O., Cozot, R., and Bouatouch, K. (2015). Style-aware robust color transfer. In *Proceedings of the workshop on Computational Aesthetics*, pages 67–77. Eurographics Association.
- [51] Hsu, W.-Y. and Chou, C.-Y. (2015). Medical image enhancement using modified color histogram equalization. *Journal of Medical and Biological Engineering*, 35(5):580–584.
- [52] Hurtut, T., Gousseau, Y., and Schmitt, F. (2008). Adaptive image retrieval based on the spatial organization of colors. *Computer Vision and Image Understanding*, 112(2):101–113.
- [53] Hwang, Y., Lee, J.-Y., Kweon, I. S., and Kim, S. J. (June 2014). Color transfer using probabilistic moving least squares. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'14)*, pages 3342–3349.
- [54] Ignatov, A., Kobyshev, N., Timofte, R., Vanhoey, K., and Van Gool, L. (2017). DSLR-Quality photos on mobile devices with deep convolutional networks. In *IEEE International Conference on Computer Vision (ICCV'17)*, pages 3277–3285.
- [55] Ikeuchi, K. (2014). *Computer vision: A reference guide*. Springer Publishing Company, Incorporated.

- [56] Jiang, G., Lin, S., Wong, C., Rahman, M., Ren, T., Kwok, N., Shi, H., Yu, Y.-H., and Wu, T. (2015). Color image enhancement with brightness preservation using a histogram specification approach. *Optik-International Journal for Light and Electron Optics*, 126(24):5656–5664.
- [57] Jobson, D. J., Rahman, Z.-u., and Woodell, G. A. (1997a). A multiscale retinex for bridging the gap between color images and the human observation of scenes. *IEEE Transactions on Image Processing*, 6(7):965–976.
- [58] Jobson, D. J., Rahman, Z.-u., and Woodell, G. A. (1997b). Properties and performance of a center/surround retinex. *IEEE Transactions on Image Processing*, 6(3):451–462.
- [59] Jung, C. and Sun, T. (2016). Optimized perceptual tone mapping for contrast enhancement of images. *IEEE Transactions on Circuits and Systems for Video Technology*.
- [60] Kaufman, L., Lischinski, D., and Werman, M. (2012). Content-aware automatic photo enhancement. In *Computer Graphics Forum*, volume 31, pages 2528–2540. Wiley Online Library.
- [61] Kim, J.-Y., Kim, L.-S., and Hwang, S.-H. (2001). An advanced contrast enhancement using partially overlapped sub-block histogram equalization. *IEEE Transactions on Circuits and Systems for Video Technology*, 11(4):475–484.
- [62] Kim, S.-W., Jung, J.-Y., Yoo, C.-H., and Ko, S.-J. (2016). Retinex-based illumination normalization using class-based illumination subspace for robust face recognition. *Signal Processing*, 120:348–358.
- [63] Kim, Y.-T. (1997). Contrast enhancement using brightness preserving bi-histogram equalization. *IEEE Transactions on Consumer Electronics*, 43(1):1–8.
- [64] Kimmel, R., Elad, M., Shaked, D., Keshet, R., and Sobel, I. (2003). A variational framework for retinex. *International Journal of Computer Vision*, 52(1):7–23.
- [65] Kolb, H., Fernandez, E., and Nelson, R. (1995). Bipolar cell pathways in the vertebrate retina—webvision: The organization of the retina and visual system.
- [66] Land, E. H. (1986). An alternative technique for the computation of the designator in the retinex theory of color vision. *Proceedings of the National Academy of Sciences (PNAS)*, 83(10):3078–3080.
- [67] Land, E. H. and McCann, J. J. (1971). Lightness and retinex theory. *Journal of the Optical Society of America*, 61(1):1–11.
- [68] Larson, E. C. and Chandler, D. M. (2010). Most apparent distortion: full-reference image quality assessment and the role of strategy. *Journal of Electronic Imaging*, 19(1):011006.
- [69] Lee, C., Lee, C., and Kim, C.-S. (2013). Contrast enhancement based on layered difference representation of 2D histograms. *IEEE Transactions on Image Processing*, 22(12):5372–5384.
- [70] Lew, M. S., Sebe, N., Djeraba, C., and Jain, R. (2006). Content-based multimedia information retrieval: State of the art and challenges. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 2(1):1–19.



## References

---

- [71] Lin, C.-C., Pankanti, S. U., Natesan Ramamurthy, K., and Aravkin, A. Y. (2015). Adaptive as-natural-as-possible image stitching. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR'15)*, pages 1155–1163.
- [72] Lisani, J.-L., Michel, J., Morel, J.-M., Petro, A. B., and Sbert, C. (2016). An inquiry on contrast enhancement methods for satellite images. *IEEE Transactions on Geoscience and Remote Sensing*, 54(12):7044–7054.
- [73] Liu, H.-D., Yang, M., Gao, Y., and Cao, L. (2014). Fast local histogram specification. *IEEE Transactions on Circuits and Systems for Video Technology*, 24(11):1833–1843.
- [74] Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110.
- [75] Ma, K., Li, H., Yong, H., Wang, Z., Meng, D., and Zhang, L. (2017). Robust multi-exposure image fusion: A structural patch decomposition approach. *IEEE Transactions on Image Processing*, 26(5):2519–2532.
- [76] Maitre, H. (2015). *From Photon to Pixel: The Digital Camera Handbook*. Wiley Online Library.
- [77] Martin, D., Fowlkes, C., Tal, D., and Malik, J. (2001). A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In *Proceedings of Eighth IEEE International Conference on Computer Vision (ICCV'01)*, volume 2, pages 416–423. IEEE.
- [78] Martin-Brualla, R., Gallup, D., and Seitz, S. M. (2015). Time-lapse mining from internet photos. *ACM Transactions on Graphics (TOG)*, 34(4):62.
- [79] McCann, J. J. (1989). The role of simple nonlinear operations in modeling human lightness and color sensations. In *Human Vision, Visual Processing, and Digital Display*, volume 1077, pages 355–364. International Society for Optics and Photonics.
- [80] Mertens, T., Kautz, J., and Van Reeth, F. (2009). Exposure fusion: A simple and practical alternative to high dynamic range photography. *Computer Graphics Forum*, 28(1):161–171.
- [81] Misaki, M., Savitz, J., Zotev, V., Phillips, R., Yuan, H., Young, K. D., Drevets, W. C., and Bodurka, J. (2015). Contrast enhancement by combining T1- and T2- weighted structural brain MR images. *Magnetic Resonance in Medicine*, 74(6):1609–1620.
- [82] Morel, J.-M., Petro, A. B., and Sbert, C. (2014). What is the right center/surround for retinex? In *IEEE International Conference on Image Processing (ICIP'14)*, pages 4552–4556. IEEE.
- [83] Morrow, W. M., Paranjape, R. B., Rangayyan, R. M., and Desautels, J. L. (1992). Region-based contrast enhancement of mammograms. *IEEE Transactions on Medical Imaging*, 11(3):392–406.
- [84] Moulon, P., Duisit, B., and Monasse, P. (2013). Global multiple-view color consistency. In *European Conference on Visual Media Production (CVMP'13)*.

- [85] Naik, S. K. and Murthy, C. (2003). Hue-preserving color image enhancement without gamut problem. *IEEE Transactions on Image Processing*, 12(12):1591–1598.
- [86] Nikolova, M. and Steidl, G. (2014a). Fast hue and range preserving histogram specification: Theory and new algorithms for color image enhancement. *IEEE Transactions on Image Processing*, 23(9):4087–4100.
- [87] Nikolova, M. and Steidl, G. (2014b). Fast ordering algorithm for exact histogram specification. *IEEE Transactions on Image Processing*, 23(12):5274–5283.
- [88] Nikolova, M., Wen, Y.-W., and Chan, R. (2013). Exact histogram specification for digital images using a variational approach. *Journal of Mathematical Imaging and Vision*, 46(3):309–325.
- [89] Ocampo-Blandon, C. and Gousseau, Y. (2016). Non-local exposure fusion. In *Iberoamerican Congress on Pattern Recognition*, pages 484–492. Springer.
- [90] Palma-Amestoy, R., Provenzi, E., Bertalmío, M., and Caselles, V. (2009). A perceptually inspired variational framework for color enhancement. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(3):458–474.
- [91] Panetta, K., Gao, C., and Agaian, S. (2013). No reference color image contrast and quality measures. *IEEE Transactions on Consumer Electronics*, 59(3):643–651.
- [92] Papadakis, N., Provenzi, E., and Caselles, V. (2011). A variational model for histogram transfer of color images. *IEEE Transactions on Image Processing*, 20(6):1682–1695.
- [93] Park, J., Tai, Y.-W., Sinha, S. N., and So Kweon, I. (2016). Efficient and robust color consistency for community photo collections. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR'16)*, pages 430–438.
- [94] Petit, F., Capelle-Laize, A.-S., and Carre, P. (2009). Underwater image enhancement by attenuation inversion with quaternions. In *2009 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP'09)*, pages 1177–1180. IEEE.
- [95] Petro, A. B., Sbert, C., and Morel, J.-M. (2014). Multiscale retinex. *Image Processing On Line*, pages 71–88.
- [96] Pierre, F., Aujol, J.-F., Bugeau, A., Steidl, G., and Ta, V.-T. (2017). Variational contrast enhancement of gray-scale and RGB images. *Journal of Mathematical Imaging and Vision*, 57(1):99–116.
- [97] Pierre, F., Aujol, J.-F., Bugeau, A., and Ta, V.-T. (2015). Luminance-hue specification in the RGB space. In *International Conference on Scale Space and Variational Methods in Computer Vision (SSVM'15)*, pages 413–424. Springer.
- [98] Pitié, F., Kokaram, A. C., and Dahyot, R. (2007). Automated colour grading using colour distribution transfer. *Computer Vision and Image Understanding*, 107(1):123–137.
- [99] Pitie, F., Kokaram, A. C., and Dahyot, R. (Oct. 2005). N-dimensional probability density function transfer and its application to color transfer. In *IEEE International Conference on Computer Vision (ICCV'05)*, volume 2, pages 1434–1439.

## References

---

- [100] Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., ter Haar Romeny, B., Zimmerman, J. B., and Zuiderveld, K. (1987). Adaptive histogram equalization and its variations. *Computer Vision, Graphics, and Image Processing*, 39(3):355–368.
- [101] Ponomarenko, N., Jin, L., Ieremeiev, O., Lukin, V., Egiazarian, K., Astola, J., Vozel, B., Chehdi, K., Carli, M., Battisti, F., et al. (2015). Image database TID2013: Peculiarities, results and perspectives. *Signal Processing: Image Communication*, 30:57–77.
- [102] Provenzi, E. (2009). Perceptual color correction: A variational perspective. In *International Workshop on Computational Color Imaging (CCIW'09)*, pages 109–119. Springer.
- [103] Provenzi, E. (2016). *Variational models for color image processing in the RGB space inspired by human vision*. Habilitation à Diriger des Recherches, ED 386 : École doctorale de sciences mathématiques de Paris centre, UPMC.
- [104] Provenzi, E. (2017). *Computational Color Science: Variational Retinex-like Methods*. John Wiley & Sons.
- [105] Provenzi, E. (2018). *Color Image Processing* (<http://www.mdpi.com/books/pdfview/book/640>). Multidisciplinary Digital Publishing Institute.
- [106] Provenzi, E., Fierro, M., Rizzi, A., De Carli, L., Gadia, D., and Marini, D. (2007). Random spray retinex: a new retinex implementation to investigate the local properties of the model. *IEEE Transactions on Image Processing*, 16(1):162–171.
- [107] Provenzi, E., Gatta, C., Fierro, M., and Rizzi, A. (2008). A spatially variant white-patch and gray-world method for color image enhancement driven by local contrast. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(10):1757–1770.
- [108] Rabin, J., Delon, J., and Gousseau, Y. (2009). A statistical approach to the matching of local features. *SIAM Journal on Imaging Sciences*, 2(3):931–958.
- [109] Rabin, J. and Papadakis, N. (2015). Convex color image segmentation with optimal transport distances. In *International Conference on Scale Space and Variational Methods in Computer Vision (SSVM'15)*, pages 256–269. Springer.
- [110] Reinhard, E., Adhikhmin, M., Gooch, B., and Shirley, P. (2001). Color transfer between images. *IEEE Computer Graphics and Applications*, 21(5):34–41.
- [111] Reinhard, E., Heidrich, W., Debevec, P., Pattanaik, S., Ward, G., and Myszkowski, K. (2010). *High dynamic range imaging: acquisition, display, and image-based lighting*. Morgan Kaufmann.
- [112] Reinhard, E., Khan, E. A., Akyuz, A. O., and Johnson, G. (2008). *Color imaging: fundamentals and applications*. AK Peters/CRC Press.
- [113] Rivera, A. R., Ryu, B., and Chae, O. (2012). Content-aware dark image enhancement through channel division. *IEEE Transactions on Image Processing*, 21(9):3967–3980.
- [114] Rizzi, A., Gatta, C., and Marini, D. (2003). A new algorithm for unsupervised global and local color correction. *Pattern Recognition Letters*, 24(11):1663–1677.

- [115] Ross, L. and Russ, J. C. (2011). The image processing handbook. *Microscopy and Microanalysis*, 17(5):843.
- [116] Sapiro, G. and Caselles, V. (1997). Histogram modification via differential equations. *Journal of Differential Equations*, 135(2):238–268.
- [117] Schaefer, G., Rajab, M. I., Celebi, M. E., and Iyatomi, H. (2011). Colour and contrast enhancement for improved skin lesion segmentation. *Computerized Medical Imaging and Graphics*, 35(2):99–104.
- [118] Shan, Q., Curless, B., Furukawa, Y., Hernandez, C., and Seitz, S. M. (2014). Photo uncrop. In *European Conference on Computer Vision (ECCV'14)*, pages 16–31. Springer.
- [119] Sim, K., Tso, C., and Tan, Y. (2007). Recursive sub-image histogram equalization applied to gray scale images. *Pattern Recognition Letters*, 28(10):1209–1221.
- [120] Snavely, N., Seitz, S. M., and Szeliski, R. (2006). Photo tourism: exploring photo collections in 3D. In *ACM transactions on graphics (TOG)*, volume 25, pages 835–846. ACM.
- [121] Solomon, C. and Breckon, T. (2011). *Fundamentals of Digital Image Processing: A practical approach with examples in Matlab*. John Wiley & Sons.
- [122] Stark, J. A. (2000). Adaptive image contrast enhancement using generalizations of histogram equalization. *IEEE Transactions on Image Processing*, 9(5):889–896.
- [123] Szeliski, R. (2006). Image alignment and stitching: A tutorial. *Foundations and Trends® in Computer Graphics and Vision*, 2(1):1–104.
- [124] Tai, Y.-W., Jia, J., and Tang, C.-K. (June 2005). Local color transfer via probabilistic segmentation by expectation-maximization. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 1, pages 747–754.
- [125] Tian, Q.-C. and Cohen, L. D. (2016). Color correction in image stitching using histogram specification and global mapping. In *6th International Conference on Image Processing Theory Tools and Applications (IPTA'16)*, pages 1–6. IEEE.
- [126] Tian, Q.-C. and Cohen, L. D. (2017a). Color consistency for photo collections without gamut problems. In *International Conference on Multimedia Modeling (MMM'17)*, pages 90–101. Springer.
- [127] Tian, Q.-C. and Cohen, L. D. (2017b). Global and local contrast adaptive enhancement for non-uniform illumination color images. In *IEEE International Conference on Computer Vision Workshops (ICCV'17 Color and Photometry in Computer Vision Workshop)*, pages 3023–3030. IEEE.
- [128] Tian, Q.-C. and Cohen, L. D. (2017c). Histogram-based color transfer for image stitching. *Journal of Imaging*, 3(3):Article 38.
- [129] Tian, Q.-C. and Cohen, L. D. (2018a). Naturalness preservation image contrast enhancement via histogram modification. In *Ninth International Conference on Graphic and Image Processing (ICGIP 2017)*, volume 10615, page 106152U. International Society for Optics and Photonics.

## References

---

- [130] Tian, Q.-C. and Cohen, L. D. (2018b). A variational-based fusion model for non-uniform illumination image enhancement via contrast optimization and color correction. *Signal Processing*, 153:210–220.
- [131] Trémeau, A., Tominaga, S., and Plataniotis, K. N. (2008). Color in image and video processing: most recent trends and future research directions. *Journal on Image and Video Processing*, 2008:7.
- [132] Trussell, H. J., Saber, E., and Vrhel, M. (2005). Color image processing [basics and special issue overview]. *IEEE Signal Processing Magazine*, 22(1):14–22.
- [133] Vonikakis, V. (Accessed on 02-January-2018). A collection of the most challenging cases for image enhancement. <https://sites.google.com/site/vonikakis/datasets/challenging-dataset-for-enhancement>.
- [134] Vonikakis, V., Andreadis, I., and Gasteratos, A. (2008). Fast centre-surround contrast modification. *IET Image processing*, 2(1):19–34.
- [135] Wang, Q., Sun, X., and Wang, Z. (2009). A robust algorithm for color correction between two stereo images. In *Asian Conference on Computer Vision (ACCV'09)*, pages 405–416. Springer.
- [136] Wang, W. and Ng, M. K. (2012). A variational method for multiple-image blending. *IEEE Transactions on Image Processing*, 21(4):1809–1822.
- [137] Wang, W.-W., Shui, P.-L., and Feng, X.-C. (2008). Variational models for fusion and denoising of multifocus images. *IEEE Signal Processing Letters*, 15:65–68.
- [138] Wang, Y., Chen, Q., and Zhang, B. (1999). Image enhancement based on equal area dualistic sub-image histogram equalization method. *IEEE Transactions on Consumer Electronics*, 45(1):68–75.
- [139] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P. (2004). Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612.
- [140] Welsh, T., Ashikhmin, M., and Mueller, K. (2002). Transferring color to greyscale images. In *ACM Transactions on Graphics (TOG)*, volume 21, pages 277–280. ACM.
- [141] Wen, C.-L., Hsieh, C.-H., Chen, B.-Y., and Ouhyoung, M. (2008). Example-based multiple local color transfer by strokes. In *Computer Graphics Forum*, volume 27, pages 1765–1772. Wiley Online Library.
- [142] Wu, X. (2011). A linear programming approach for optimal contrast-tone mapping. *IEEE Transactions on Image Processing*, 20(5):1262–1272.
- [143] Xiong, Y. and Pulli, K. (2010). Fast panorama stitching for high-quality panoramic images on mobile phones. *IEEE Transactions on Consumer Electronics*, 56(2).
- [144] Xu, H., Zhai, G., Wu, X., and Yang, X. (2014). Generalized equalization model for image enhancement. *IEEE Transactions on Multimedia*, 16(1):68–82.

- [145] Xu, W. and Mulligan, J. (June 2010). Performance evaluation of color correction approaches for automatic multi-view image and video stitching. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'10)*, pages 263–270.
- [146] Yeganeh, H. and Wang, Z. (2013). Objective quality assessment of tone-mapped images. *IEEE Transactions on Image Processing*, 22(2):657–667.
- [147] Ying, Z., Li, G., and Gao, W. (2017a). A bio-inspired multi-exposure fusion framework for low-light image enhancement. *arXiv preprint arXiv:1711.00591*.
- [148] Ying, Z., Li, G., Ren, Y., Wang, R., and Wang, W. (2017b). A new image contrast enhancement algorithm using exposure fusion framework. In *17th International Conference on Computer Analysis of Images and Patterns (CAIP'17)*, pages 36–46. Springer.
- [149] Yuan, L. and Sun, J. (2012). Automatic exposure correction of consumer photographs. In *European Conference on Computer Vision (ECCV'12)*, pages 771–785. Springer.
- [150] Zhang, Q., Nie, Y., Zhang, L., and Xiao, C. (2016). Underexposed video enhancement via perception-driven progressive fusion. *IEEE Transactions on Visualization and Computer Graphics*, 22(6):1773–1785.
- [151] Zuiderveld, K. (1994). Contrast limited adaptive histogram equalization. In *Graphics Gems IV*, pages 474–485. Academic Press Professional, Inc., San Diego, CA, USA.









## Résumé

L'amélioration d'image vise à améliorer la qualité visuelle d'une image. Elle joue un rôle très important dans les domaines du traitement de l'image et la vision par ordinateur. En particulier, nous considérons la correction de couleur et l'amélioration du contraste pour améliorer la qualité d'image.

Dans la première partie de cette thèse, nous nous concentrons sur la correction des couleurs pour les images naturelles. Tout d'abord, nous donnons un bref état de l'art de la correction des couleurs. Deuxièmement, nous proposons une méthode efficace de correction des couleurs pour la combinaison d'images via la spécification d'histogramme et une transformation globale. Troisièmement, nous présentons une approche cohérente des couleurs pour les collections d'images, basée sur la spécification d'histogramme conservant la gamme.

Dans la deuxième partie, nous prêtons attention à l'amélioration du contraste pour les images et les vidéos naturelles. Tout d'abord, nous donnons un bref aperçu des méthodes d'amélioration du contraste. Deuxièmement, nous proposons une méthode d'amélioration globale du contraste de préservant l'aspect naturel des images, évitant un surplus d'amélioration. Troisièmement, nous présentons une méthode variationnelle de fusion pour l'amélioration d'images d'illumination non uniforme, qui peut éviter la suramplification ou la sous-amélioration. Enfin, nous étendons le cadre basé sur la fusion pour améliorer les vidéos avec une stratégie temporellement cohérente, qui n'entraîne pas d'artéfacts de scintillement.

## Mots Clés

Amélioration d'image, correction de couleur, amélioration de contraste, fusion d'image

## Abstract

Image enhancement aims to improve the image visual quality, and plays a very important role in the domains of image processing and computer vision. Specifically, we consider color correction and contrast enhancement to improve the image quality.

In the first part of this thesis, we focus on color correction for natural images. Firstly, we give a simple review of color correction. Secondly, we propose an efficient color correction method for image stitching via histogram specification and global mapping. Thirdly, We present a color consistency approach for image collections, based on range preserving histogram specification.

In the second part, we pay attention to contrast enhancement for natural images and videos. Firstly, we give a simple review of contrast enhancement. Secondly, we propose a naturalness preservation global contrast enhancement method, which can avoid over-enhancement. Thirdly, we present a variational-based fusion method for non-uniform illumination image enhancement, which can avoid over-enhancement or under-enhancement. Finally, we extend the fusion-based framework to enhance videos with a temporally consistent strategy, which does not result in flickering artifacts.

## Keywords

Image enhancement, color correction, contrast enhancement, image fusion