

3D INTRINSIC SCENE CHARACTERISTICS EXTRACTION FRAMEWORK FOR A SINGLE IMAGE

HABIBULLAH AKBAR

DOCTOR OF PHILOSOPHY

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HABIBULLAH AKBAR

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

Faculty of Information and Communication Technology

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

DECLARATION

I declare that this thesis entitled "3D Intrinsic Scene Characteristics Extraction Framework for a Single Image" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have read this thesis and, in my opinion, this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.

Signature	:	
Supervisor Name	:	Prof. Dr. Nanna Suryana Herman
Date	:	



DEDICATION

To my beloved mother, father, wife, daughter and sons



ABSTRACT

Three-Dimensional (3D) shape reconstruction is an important area of computer vision research because it has numerous potential applications from entertainment production to industrial inspection and clinical analysis. Existing 3D Intrinsic Scene Characteristics (3D-ISCs) extraction methods for a single image have focused solely on estimating diffuse characteristics, i.e. 3D shape, illumination, and reflectance models, of an object. As a result, they have neglected the specular characteristic, the shiny areas of a glossy surface. In reality, many real-world objects emit both specular and diffuse reflections, and thus the specular component may decrease the performance of the 3D-ISCs methods. This study has developed a framework to extract all of these characteristics. The framework combines a Specular Removal (SR) method and a Shape, Illumination, and Reflectance From Shading (SIRFS) method under a Bidirectional Reflectance Distribution Function (BRDF) model. Since the previous SR methods suffered from hue-saturation ambiguity, they are not suitable for this framework. To solve this problem, two SR methods were developed, evaluated, and compared with the standard SR methods. The proposed SR methods are referred as Chaotic Segmentation (CS) and Sparse Coding (SC) methods. To combine the SR and SIRFS methods, two BRDF models were also developed, evaluated, and compared. These models are referred as Modified Dichromatic Reflectance (MDR) and Modified Blinn-Phong (MBP) models. The performances of the proposed SR methods and the BRDF models for extracting 3D-ISCs were evaluated based on public datasets. The results showed that the SC method was more satisfactory compared to the CS and the benchmark method (iterative method). The accuracies of the diffuse and specular characteristics were improved by 7.6% and 53.5% respectively. Moreover, the combination of SC method and MDR model was capable of outperforming the SIRFS method. The computational speed was 19.2% faster. Meanwhile, the average accuracies of depth, surface normal, illumination, shading, and reflectance were improved by 11.4%, 6.5%, 50.5%, 35.2%, and 5.1% respectively. This study indicates that the specular reflection is an important aspect of 3D reconstruction from a single image. The proposed framework has also made considerable improvements in terms of accuracy and computational time of extracting 3D-ISCs.

ABSTRAK

Pembinaan semula bentuk Tiga-Dimensi (3D) merupakan bidang penting dalam penyelidikan visi komputer kerana ia mempunyai banyak aplikasi yang berpotensi daripada pengeluaran hiburan kepada pemeriksaan industri dan analisis klinikal. Kewujudan kaedah-kaedah pengekstrakan Ciri-ciri Paparan Instrinsik 3D (CPI-3D) untuk imej tunggal hanya tertumpu kepada ciri-ciri peresapan seperti model bentuk 3D, pencahayaan dan pembalikan sesuatu objek. Kaedah-kaedah ini mengabaikan ciri spekular (kawasan permukaan objek yang berkilat). Dalam keadaan realiti, kebanyakan objek sebenar memancarkan kedua-dua pantulan spekular dan peresapan, dan ini menjadikan komponen spekular mungkin mengurangkan prestasi kaedah CPI-3D. Kajian ini telah membangunkan kerangka kerja untuk mengekstrak CPI-3D. Kerangka kerja ini menggunakan kaedah Penyingkiran Spekular (PS) dan kaedah Bentuk, Pencahayaan serta Kepantulan dari Pembayangan (BPKP) di bawah model Fungsi Taburan Kepantulan Dwiarah (FTKD). Oleh kerana kaedah-kaedah PS sebelum ini mengalami kesamaran ketepuan warna, ia tidak sesuai untuk kerangka kerja ini. Bagi menyelesaikan masalah tersebut, dua kaedah PS telah dibangunkan, dinilai dan dibandingkan dengan kaedah standard PS. Kedua-duanya merujuk kepada Pensegmenan Camuk (PC) dan Pengkodan Bersela (PB). Bagi menggabungkan kaedah PS dan BPKP, dua model FTKD telah dibangunkan, dinilai dan dibandingkan. Kedua-duanya merujuk kepada Pengubahsuaian Kepantulan Dikromatik (PKD) dan Pengubahsuaian Blinn-Phong (PBP). Prestasi kaedah PS dan model FTKD yang dicadangkan untuk mengekstrak CPI-3D telah dinilai berdasarkan kepada set data awam. Keputusan menunjukkan kaedah PB lebih memuaskan berbanding PC dan kaedah penanda aras (kaedah lelaran). Ketepatan peresapan dan specular telah meningkat masing-masing sebanyak 7.3% dan 53.5%. Gabungan kaedah PB dan model PKD mampu menyaingi kaedah BPKP. Kelajuan pengiraan telah meningkat sebanyak 19.2% manakala ketepatan purata kedalaman, permukaan normal, pencahayaan, pembayangan serta kepantulan telah meningkat masing-masing sebanyak 11.4%, 6.5%, 50.5%, 35.2% dan 5.1%. Kajian ini menandakan bahawa kerangka kerja pengekstrakan CPI-3D cadangan telah menunjukkan kemajuan besar dari segi ketepatan dan masa pengiraan.

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TABLE OF CONTENTS

PAGE

APPROVAL DEDICATION ABSTRACT ABSTRAK ACKNOWLEDGEMENTS TABLE OF CONTENTS LIST OF TABLES LIST OF FIGURES LIST OF ABBREVIATIONS	i ii iii iii v vi vi vi
LIST OF SYMBOLS LIST OF PUBLICATIONS	IX Xİ
	A
CHAPTER	1
I INTRODUCTION 1.1 Research Background	I 1
1.1 Research Background 1.2 Problem Statement	6
1.3 Research Questions	7
1.4 Research Objectives	8
1.5 Research Scope	9
1.6 Thesis Structure	9
2 LITERATURE REVIEW	12
2.1 Overview	12
2.2 Bidirectional Reflectance Distribution Function (BRDF)	12
2.2.1 Lambertian Model	15
2.2.2 Oren-Nayar Model	16
2.2.3 Phong Model	17
2.2.4 Blinn-Phong Model	19
2.2.5 Dichromatic Reflectance Model (DRM)	20
2.3 Shape From Shading (SFS)	21
2.3.1 Analytical Approach	26
2.3.2 Approximation Approach	31
2.5.5 Optimization Approach	32 40
2.4.1 Retinex Approach	40 43
2.4.2 Machine Learning Approach	43
2.5 Specular Removal (SR)	50
2.5.1 Color Space Segmentation Approach	52
2.5.2 Specular-free Approach	53

		2.5.3	Partial D	ifferential Equation Approach	58
		2.5.4	Inpaintin	g Approach	59
			2.5.4.1	Manual Thresholding	60
			2.5.4.2	Automated Thresholding	61
			2.5.4.3	Clonal Selection Algorithm (ClonalG)	64
			2.5.4.4	Particle Swarm Optimization (PSO)	65
	2.6	Resear	ch Metho	ds in Computer Vision	66
	2.7	Resear	rch Gap		68
	2.8	Summ	ary		69
3	RES	SEARC	H METH	ODOLOGY	71
	3.1	Overv	iew		71
	3.2	Quanti	itative Res	earch Methodology	71
	3.3	Resear	ch Phases		72
	3.4	Proble	m Identifi	cation Phase	74
	3.5	Literat	ture Review	w Phase	76
	3.6	Develo	opment Ph	ase of 3D-ISCs Extraction Framework	78
		3.6.1	Framewo	ork Description	79
		3.6.2	Chaotic :	Segmentation Method	81
			3.6.2.1	Formulation of Specular Removal Problem	81
			3.6.2.2	Proposed Specular Removal Method	84
			3.0.2.3	Calorence Consisting Hashing	89
		262	3.0.2.4 Sporae C	Conferency Sensitive Hasning	90
		3.0.3		Formulation of Snooular Domoval Drahlam	9/
			3632	Proposed Specular Removal method	90 101
			3.6.3.2	Specular Free Images	101
			3634	XVZ color space	102
			3635	Dictionary Construction	105
		364	Modified	Blinn-Phong Model	105
		5.0.1	3641	Formulation of Proposed 3D-ISCs Extraction Framework	108
			3642	Proposed MBP Model	108
		3.6.5	Modified	1 Dichromatic Reflectance Model	110
			3.6.5.1	Proposed MDR Model	113
			3.6.5.2	3D Reconstruction	115
			3.6.5.3	Reflectance Image	116
			3.6.5.4	Illumination Estimation	117
			3.6.5.5	Modified Dichromatic Reflectance Model	117
	3.7	Experi	mental Ph	ase	118
		3.7.1	Data Col	lection	118
			3.7.1.1	DECSAI, Berkeley, SIPI and Tennessee Dataset	119
			3.7.1.2	MIT Intrinsic Images Dataset	119
			3.7.1.3	MIT-Berkeley Intrinsic Images Dataset	119
			3.7.1.4	MIT-Berkeley-UTeM Intrinsic Images Dataset	120
		3.7.2	Method	Comparison	120
		3.7.3	Experim	ental Settings	121

		3.7.4	Performance Measures	121
	3.8	Applic	cation Phase	123
	3.9	Summ	lary	123
4	EXF	PERIM	ENTAL RESULTS AND DISCUSSION	125
	4.1	Overv	iew	125
	4.2	Experi	imental Results of Chaotic Segmentation	125
		4.2.1	Results and comparative performance of Segmentation Step	125
			4.2.1.1 Fitness evaluation	126
			4.2.1.2 Stability comparison	126
			4.2.1.3 Efficiency comparison	132
		4.2.2	Result on Images with Significant Specularity	135
		4.2.3	Result on Synthetic Images	143
		4.2.4	Result on Images without Significant Specularity	145
		4.2.5	Discussion	147
	4.3	Experi	imental Results of Sparse Coding	148
		4.3.1	Result on Images with Significant Specularity	148
		4.3.2	Result on Synthetic Images	154
		4.3.3	Result on Images without Specularity	156
		4.3.4	Discussion	156
	4.4	Experi	imental Results of Modified Blinn-Phong Model	159
		4.4.1	Specular from Reflectance Image	159
		4.4.2	Results on Images with Significant Specularity	161
		4.4.3	Discussion	164
	4.5	Experi	imental Results of Modified Dichromatic Reflectance Model	165
		4.5.1	Results on Images with Significant Specularity	165
		4.5.2	Results of Real-World Images	170
		4.5.3	Discussion	172
	4.6	3D Re	ndering Applications of the Proposed Framework	173
		4.6.1	Optimal Linear Direction	174
		4.6.2	Rendering Engine for Highlight image	1/6
		4.6.3	Blinn-Phong Extension	1//
		4.6.4	Dichromatic Editing	1//
	47	4.6.5	Object Recoloring based on Intrinsic Image Estimation	1//
	4./	Summ	lary	1/8
5	CON	NCLUS	IONS	180
	5.1	Overv	iew	180
	5.2	Review	w of Research Objectives	180
	5.3	Conclu	usions	181
		5.3.1	Conclusion related to RO 1.	181
		5.3.2	Conclusion related to $RO 2$.	182
		5.3.3	Conclusion related to <i>RO 3</i> .	183
		5.3.4	Conclusion related to <i>RO</i> 4.	185
	~ •	5.3.5	Conclusion related to <i>RO</i> 5.	185
	5.4	Kesear	rch Contributions	186

5.5	Recommendation for Future Research	187
5.6	Summary	188
REFER	ENCES	189

LIST OF TABLES

TABLE	TITLE PA	AGE
2.1	List of Constraints to Modify the Functional	34
2.2	Different Types of Specular-free Images	57
2.3	A Comparison of Computer Vision Methods with regard to Different Types	
	of Characteristics	69
4.1	Ground Truth Value by an Exhaustive search (Otsu Method) for the Test	
	Images	130
4.2	Mean Values and Standard Deviation of the Objective Function for 50 Runs	133
4.3	Thresholds Value of the Algorithms	134
4.4	Mean Values of the Computational Time and Iteration (it) for 50 Runs	136
4.5	Accuracy Performance of PSO, ClonalG, CS Methods on Images with Signi-	
	ficant Specularity	139
4.6	Speed Performance of PSO, ClonalG, CS on Images with Significant Specularity	y141
4.7	Accuracy Performance of PSO, ClonalG, CS on Synthetic Images	143
4.8	Speed Performance of PSO, ClonalG, CS on Synthetic Images	144
4.9	Accuracy Performance of PSO, ClonalG, CS on Images without Significant	
	Specularity	146

4.10	Speed Performance of PSO, ClonalG, CS on Images without Significant	
	Specularity	146
4.11	Accuracy Performance of MZK06, YCK06, YWA10, SC09 on Images with	
	Significant Specularity	150
4.12	Speed Performance of MZK06, YCK06, SC09 on Images with Significant	
	Specularity	150
4.13	Accuracy Performance of SF1, SF2, Both SF on Images with Significant	
	Specularity	153
4.14	Speed Performance of SF1, SF2, Both SF methods on Images with Significant	
	Specularity	153
4.15	Accuracy Performance of SF1, SF2, Both SF on Synthetic Images	154
4.16	Speed Performance of SF1, SF2, Both SF on Synthetic Images	155
4.17	Accuracy Performance of SF1, SF2, Both SF on Images without Significant	
	Specularity	157
4.18	Speed Performance of SF1, SF2, Both SF on Images without Significant	
	Specularity	157
4.19	Accuracy Performance of SIRFS, SIRFS-MZK06, SIRFS-YCK06, SIRFS-	
	MBP on Images with Significant Specularity	162
4.20	Speed Performance of MZK06, YCK06, MBP Both SF on Images without	
	Significant Specularity	162
4.21	Accuracy Performance of SIRFS, MZK06-SIRFS, YCK06-SIRFS, MDR-	
	SIRFS on MIT-Berkeley Intrinsic Images Dataset	166

4.22 Speed Performance of SIRFS, MZK06-SIRFS, YCK06-SIRFS, MBP-SIRFS on MIT-Berkeley Intrinsic Images Dataset

LIST OF FIGURES

FIGURI	E TITLE P	PAGE
1.1	An Example of a Commercial 3D Scanner, Manufactured by Breuckmann	
	Opto-TOP HE	2
1.2	The Best Method in (Zhang et al., 1999) Review: (left) (Zheng and Chellappa,	
	1991) Method and (right) (Lee and Kuo, 1993) Method	3
1.3	The Best Method in (Durou et al., 2008) Review: (left) (Falcone and Sagona,	
	1997) Method and (right) (Daniel and Durou, 2000) Method	4
1.4	The original Pepper image (Petitcolas, 2014)	5
1.5	(a) input image, (b) orientation of surface normals, (c) illumination, and (d)	
	reflectance	5
1.6	Thesis Structure	10
2.1	Bidirectional Reflectance Distribution Functions: adopted from (Kurihara	
	and Takaki, 2001)	15
2.2	Phong model	19
2.3	a) An ideal of a shading image and (b) the corresponding 3D model.	22
2.4	(Weiss, 2001) Intrinsic-images: (a) an input image, (b) reflectance image, (c)	
	shading image	42

2.5	(a) Input image. (b) Kim et al. (2013) result. (c) Dark channel. (d) Result of	
	(Tan and Ikeuchi, 2005)	57
3.1	Overview of Research Phases	73
3.2	A visualization of 3D-ISCs extraction problem in this study. Given a single	
	input image, the task is to derive the object into these characteristics: (b)	
	diffuse, (c) reflectance, (d) illumination, (e) specular, (f) shading, and (g) 3D	
	shape characteristics.	75
3.3	3D Intrinsic Scene Characteristics Extraction Framework	79
3.4	The Extraction process of diffuse and specular characteristics using CS	
	method. Initially, the input image is segmented into diffuse and specular	
	pixels using the proposed SR method. Then, the specular pixel is replaced	
	based on the information from the neighbors using inpainting method.	85
3.5	The curve of mutation rate is affected by the value of parameter ρ	88
3.6	Diagram of logistic map bifurcation (Bresten and Jung, 2009)	91
3.7	Distribution of logistic map	92
3.8	Comparison of histogram of logistic map distribution and Matlab pseudo-	
	random number distribution. (a) Logistic Map with uniform distribution, (b)	
	Matlab random generator with uniform distribution	92
3.9	The Extraction process of diffuse and specular characteristics using SC	
	method. Initially, the input image is processed using specular-free meth-	
	ods. The output is the n specular-free images. These images then are used to	
	reconstruct a dictionary. From the dictionary, the SC method generates the	
	diffuse and specular images.	101

- 3.10 The Extraction Process of 3D-ISCs using MBP Model. Initially, the input image is processed using SIRFS method. The output is the shading and reflectance image. The shading is rendered using a shader from the 3D shape and illumination model. The SR method then process reflectance image to extract specular and diffuse characteristics.
- 3.11 The extraction process of 3D-ISCs using MDR Model. Initially, the input image is processed using SR method. The output is the diffuse image. The SIRFS then extract the reflectance and shading image. From the shading image is rendered using a shader from the 3D shape and illumination model. 111
- 3.12 Pixel histograms of filter output from diffuse (left) and from specular (right). It is clearly that the filter output histograms have distinctly noticeable difference shape between diffuse and specular reflection.
- 4.1 Original image and their histogram 127 4.2 Original image and their histogram (continued) 128 4.3 Original image and their histogram (continued) 129 4.4 Thresholded image obtained by CS (a) represents K = 3, (b) represents K = 4, (c) represents K = 5137 4.5 Thresholded image obtained by CS (a) represents K = 3, (b) represents K = 4, (c) represents K = 5 (continued) 138 The Ground Truth Images. (top) Input images, (middle) Diffuse Images, 4.6 (bottom) Specular Images. From left to right: Apple, Pear, Potato, Teabag1,

Teabag2

4.7	Thresholded image obtained by CS (a) represents $K = 1$, (b) represents $K = 2$,	
	(c) represents $K = 3$	140
4.8	Thresholded image obtained by CS (a) represents $K = 1$, (b) represents $K = 2$,	
	(c) represents $K = 3$ (continued)	141
4.9	PSO: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	142
4.10	ClonalG: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	142
4.11	CS: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	142
4.12	PSO: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	144
4.13	ClonalG: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	144
4.14	CS: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	145
4.15	PSO: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	146
4.16	ClonalG: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	147
4.17	CS: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	147

4.18	The Ground Truth Images. (top) Input images, (middle) Diffuse Images,	
	(bottom) Specular Images. From left to right: Apple, Pear, Potato, Teabag1,	
	Teabag2	149
4.19	MZK06: (left) Original, (middle) Diffuse, and (right) Specular	151
4.20	YCK06: (left) Original, (middle) Diffuse, and (right) Specular	151
4.21	YWA10: (left) Original, (middle) Diffuse, and (right) Specular	152
4.22	SC09: (left) Original, (middle) Diffuse, and (right) Specular component	152
4.23	Proposed Method: (top) Diffuse Results, (bottom) Specular Results. From	
	left to right: Apple, Pear, Potato, Teabag1, Teabag2	153
4.24	Proposed Method: (top) Diffuse Results, (bottom) Specular Results. From	
	left to right: Apple, Pear, Potato, Teabag1, Teabag2	155
4.25	MZK06: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	155
4.26	YCK06: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	156
4.27	Proposed Method: (top) Diffuse Results, (bottom) Specular Results. From	
	left to right: Apple, Pear, Potato, Teabag1, Teabag2	157
4.28	MZK06: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	158
4.29	YCK06: (top) Diffuse Results, (bottom) Specular Results. From left to right:	
	Apple, Pear, Potato, Teabag1, Teabag2	158
4.30	Intrinsic Scene Characteristics from SIRFS for pear	160
4.31	Intrinsic Scene Characteristics from SIRFS for potato	161

4.32	Intrinsic Scene Characteristics from SIRFS for teabag1	161
4.33	MZK06: From top-left to top-right is the diffuse images of pear, potato, and	
	teabag1 while from bottom-left to bottom-right is the specular images of pear,	
	potato, and teabag1	163
4.34	YCK06: From top-left to top-right is the diffuse images of pear, potato, and	
	teabag1 while from bottom-left to bottom-right is the specular images of pear,	
	potato, and teabag1	163
4.35	MDR: From top-left to top-right is the diffuse images of pear, potato, and	
	teabag1 while from bottom-left to bottom-right is the specular images of pear,	
	potato, and teabag1	164
4.36	MZK06-SIRFS on Pear: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	167
4.37	MZK06-SIRFS on Potato: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	168
4.38	MZK06-SIRFS on Teabag1: (left to right) diffuse, reflectance, shading,	
	surface normals, and illumination images	168
4.39	YCK06-SIRFS on Pear: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	168
4.40	YCK06-SIRFS on Potato: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	169
4.41	YCK06-SIRFS on Teabag1: (left to right) diffuse, reflectance, shading, sur-	
	face normals, and illumination images	169

4.42	MDR-SIRFS on Pear: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	169
4.43	MDR-SIRFS on Potato: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	170
4.44	MDR-SIRFS on Teabag1: (left to right) diffuse, reflectance, shading, surface	
	normals, and illumination images	170
4.45	Results of ISC estimation using the proposed model on real-world Pebbles	
	image, manually cropped color images of objects.	171
4.46	Results of ISC estimation using the proposed model on real-world Toy image,	
	manually cropped color images of objects.	171
4.47	Results of ISC estimation using the proposed model on real-world Fruits	
	image, manually cropped color images of objects.	172
4.48	Results of ISC estimation using the proposed model on real-world Toothpaste	
	image, manually cropped color images of objects.	172
4.49	Specular highlight on sphere for different type of light source	174
4.50	Dichromatic Editing of Pear	178
4.51	Reflectance Editing of Pear	178

xvii