UNIVERSITY OF TECHNOLOGY SYDNEY Faculty of Engineering and Information Technology

IMAGE SUPER-RESOLUTION BASED ON FRACTAL ANALYSIS

by

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE

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Certificate of Authorship/Originality

I, Xunxiang Yao, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

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List of Publications

Journal Papers

- J-1. X. Yao, Q. Wu, P. Zhang and F. Bao, "Weighted Adaptive Image Super-Resolution Scheme based on Local Fractal Feature and Image Roughness," *IEEE Transactions on Multimedia*, vol. 23, pp. 1426-1441, 2021.
- J-2. X. Yao, Q. Wu, P. Zhang and F. Bao, "Adaptive rational fractal interpolation function for image super-resolution via local fractal analysis," *Image and Vision Computing*, vol. 82, pp. 39-49, 2019.
- J-3. F. Bao, X. Yao, Q. Sun, Y. Zhang, C. Zhang, "Smooth fractal surfaces derived from bicubic rational fractal interpolation functions," *Science China Information Sciences*, vol. 61, pp. 1-3, 2018.
- J-4. Y. Zhang, P. Wang, F. Bao, X. Yao, C.Zhang, H. Lin, "A Single-Image Super-Resolution Method Based on Progressive-Iterative Approximation," *IEEE Transactions on Multimedia*, vol. 22, pp. 1407-1422, 2019.
- J-5. Y. Zhang, P. Wang, Q. Fan, F. Bao, X. Yao, C.Zhang, "Single Image Numerical Iterative Dehazing Method Based on Local Physical Features," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 30, pp. 3544-3557,2019.
- J-6. P. Zhang, Q. Wu, X. Yao J. Xu, "Beyond modality alignment: Learning partlevel representation for visible-infrared person re-identification", *Image and Vision Computing*, vol. 108, 104118, 2021.

Submitted Papers

J-1. X. Yao, Q. Wu, P. Zhang and F. Bao, "Image super-resolution based on multifractals in transfer domain," *Signal Processing: Image Communication*, Under review, 2021.

Contents

	Certificate	ii
	Acknowledgments	iii
	List of Publications	iv
	List of Figures	viii
	List of Tables	xi
	Abstract	xiii
1	Introduction	1
	1.1 Background	1
	1.2 Research Problems	4
	1.2.1 Detail preservation in complex texture region	4
	1.2.2 Non-decreasing image roughness in image super-resolution process	5
	1.2.3 High-frequency information increase in through multifractal in NSCT domain	5
	1.3 Thesis Contribution	6
	1.4 Thesis Structure	7
2	Literature Review and Related Works	9
	2.1 Image super-resolution methods	9
	2.1.1 Interpolation-based methods	9
	2.1.2 Reconstruction-based methods	11

		2.1.3	Learning-based methods	12
		2.1.4	Fractal-based super-resolution method	15
	2.2	Fractal	theory	16
		2.2.1	Fractal function	17
		2.2.2	Fractal dimension	18
	2.3	NSCT		21
3	Re	egion-ł	based image super-resolution via single fracta	1
	int	erpola	ation function and fractal analysis	25
	3.1	Motiva	tion \ldots	25
	3.2	Related	l work	26
	3.3	Propos	ed Method	28
		3.3.1	Image Patches Classification	30
		3.3.2	Single Image Super-Resolution	31
		3.3.3	Optimization for vertical scaling factor	34
	3.4	Experin	ments	36
		3.4.1	Running Time Analysis	37
		3.4.2	Comparison with State-of-the-Art Methods	38
4	Piz	xel-wi	se Image Super-Resolution based on Local Frac	-
	tal	Featu	are and Image Roughness	50
	4.1	Motiva	tion \ldots	50
	4.2	Related	l Work	52
	4.3	Propos	ed Method	54
		4.3.1	Image Pixel Labeling	54
		4.3.2	Adaptive Fractal Interpolation	58

vi

	4.3.3	Optimization for Maintaining Image Roughness	. 61
	4.3.4	Weighted Blended Model in Local Area	. 64
4.4	Experir	ment	. 65
	4.4.1	Running Time Analysis	. 66
	4.4.2	Simulation	. 66
	4.4.3	Quantitative Analysis	. 69
	4.4.4	Qualitative analysis	. 78
Im	age si	per-resolution based on multifractals and im	-
age	e roug	hness in NSCT domain	89
5.1	Motivat	tion	. 89
5.2	Related	l Work	. 89
5.3	Propose	ed Method	. 93
	5.3.1	Image decomposition through NSCT	. 94
	5.3.2	Individual image pixels classification	. 94
	5.3.3	Adaptive fractal interpolation in different sub-band image .	. 96
	5.3.4	Optimization for increasing image roughness	. 101
5.4	Experir	nents and discussions	. 102
	5.4.1	Running Time Analysis	. 104
	5.4.2	Quantitative comparison	. 104
	5.4.3	Qualitative comparison	. 105
Co	onclusi	ons and Future Work	112
6.1	Conclus	sions	. 112
6.2	Future	Work	. 113
	 4.4 Image 5.1 5.2 5.3 5.4 Control 6.1 6.2 	4.3.3 4.3.4 4.3.4 4.3.4 4.4.1 4.4.2 4.4.3 4.4.3 4.4.4 IIIIIIIIIIIIIIIIIIIIIIIIIIIIIII	 4.3.3 Optimization for Maintaining Image Roughness

List of Figures

2.1	The illustration of Nonsubsampled contourlet transform. First, NSP	
	is applied for multi-scale decomposition, the first layer is	
	decomposed to obtain lowpass subband image (y_1) and bandpass	
	subband images $(y_2, y_3 \text{ and } y_4)$. Second, the NSDFB is applied to	
	get the corresponding bandpass directional subband images. $\ . \ . \ .$	22
2.2	The NSP in decomposition at level 3. NSP decomposes the input	
	image in a tower filter bank and decomposes it into two parts:	
	highpass image (H_Z) and lowpass image $(H_0(Z))$. The lowpass	
	image $(H_0(Z))$ can be further decomposition into $H_0(Z^{21})$ and	
	$H_1(Z^{21})$. The $H_0(Z^{41})$ and $H_1(Z^{41})$ can be obtained after 3^{th} level	
	decomposition. \ldots	23
2.3	The illustration of NSDFB. The NSDFB consists of fan filter and	
	quadrant filter: first, the image is divided into four directional	
	sub-bands by using the fan filter; second, quadrant filter bank is	

- utilized to obtain different directions bandpass images. $\dots \dots \dots 24$
- 3.1 Illustration of super-resolution process. For the given low-resolution image, it is divided into patches and the fractal dimension of patches is calculated. Then, the patches are classified to different categorizes and different interpolation models are selected in different regions. Finally, the optimization process is conducted. . . . 29
 3.2 Image regions classified into texture area and smooth area 32
- 3.3 Comparison results $(\times 2)$ on Wall image. $\ldots \ldots \ldots \ldots \ldots \ldots 42$

3.4	Comparison results $(\times 3)$ on Baby image $\ldots \ldots \ldots \ldots \ldots \ldots$	48
3.5	Comparison results $(\times 4)$ on Head image $\ldots \ldots \ldots \ldots \ldots \ldots$	49
4.1	The distribution of the local fractal dimension. FD represents	
	fractal dimension and P is the value of the probability density function	56
4.2	Result of pixel labeling by local fractal feature	57
4.3	Illustration of pixel mapping and calculation in the super-resolution	
	process. For every sub-region, four points in the same rectangle and	
	four vertices of the larger square are used to calculate the value of	
	the pixel in the high-resolution image	60
4.4	Illustration of blended mode. The unknown pixel (marked in green)	
	belongs to four interpolation units	
	I(i-1:i+1,j-1:j+1), I(i-1:i+1,j:j+2), I(i:i+2,j-1:i+1), I(i-1:i+1,j:j+2), I(i:i+2,j-1:i+1)	
	j + 1, $I(i : i + 2, j : j + 2)$. The value of unknown pixels can be	C 4
	calculated by four adjacent fractal functions.	64
4.5	Fractal interpolating surface with different scaling factors	67
4.6	Interpolation error comparison with different FIF	76
4.7	Comparison results ($\times 2$) on Baby image. The number is the value	
	of PSNR	79
4.8	Comparison results $(\times 2)$ on Matches image. The number is the	
	value of PSNR	80
4.9	Comparison results ($\times 2$) on Matches image. The number is the value	
	of PSNR	82
4.10	Comparison results ($\times 2$) on Wall image. The number is the value of	
	PSNR	83
4.11	Comparison results (×3) on Urban100-088 image. The number is the	
	value of PSNR.	84

4.12	Comparison results ($\times 3$) on River image. The number is the value of	
	PSNR	85
4.13	Comparison results ($\times 4$) on Texture image. The number is the value	
	of PSNR	86
4.14	Comparison results ($\times 4$) on Houses image. The number is the value	
	of PSNR	87

5.1 NSCT decomposition process. For the given image, the NSPFB is applied for multi-scale decomposition to get low frequency subband and high frequency subband. The low-frequency subband can be further decomposition by NSPFB. Then the NSDFB is applied to get the corresponding bandpass directional subband images. 95

5.2	The NSP in decomposition at level 3. NSP decomposes the input
	image in a tower filter bank and decomposes it into two parts:
	highpass image (H_Z) and lowpass image $(H_0(Z))$. The lowpass
	image $(H_0(Z))$ can be further decomposition into $H_0(Z^{21})$ and
	$H_1(Z^{21})$. The $H_0(Z^{41})$ and $H_1(Z^{41})$ can be obtained after 3^{th} level
	decomposition
5.3	Pixel value calculation via fractal interpolation in SR process 99
5.4	Comparison of results ($\times 2$) on head image $\ldots \ldots \ldots$
5.5	Comparison of results ($\times 2$) on Wall image $\ldots \ldots \ldots$

List of Tables

3.1	Comparison of different methods on running time (s) (Set14)	39
3.2	Comparison of different methods on PSNRs, SSIMs, FSIMs (Set5) $$.	40
3.3	Comparison of different methods on PSNRs, SSIMs, FSIMs (Set5) $$	41
3.4	Comparison of different methods on $\operatorname{PSNRs}, \operatorname{SSIMs},$ FSIMs (Set14-1) .	43
3.5	Comparison of different methods on $\operatorname{PSNRs}, \operatorname{SSIMs},$ FSIMs (Set14-1) .	44
3.6	Comparison of different methods on $\operatorname{PSNRs}, \operatorname{SSIMs},$ FSIMs (Set14-2) .	45
3.7	Comparison of different methods on $\operatorname{PSNRs}, \operatorname{SSIMs},$ FSIMs (Set14-2) .	46
4.1	Variation in image roughness (quantified by fractal dimension) with	
	different up-sampling factors in different super-resolution methods $\ . \ .$	51
4.2	Comparison of different methods on running time (s) (Set14)	68
4.3	Set of interpolation data	69
4.4	$2 \times$ Comparison of different methods on PSNRs,SSIMs, FSIMs	
	(Set14-1)	70
4.5	$2\times$ Comparison of different methods on PSNRs, SSIMs, FSIMs	
	$(Set 14-2) \ldots \ldots$	71
4.6	$3\times$ Comparison of different methods on PSNRs, SSIMs, FSIMs	
	$(Set 14-1) \ldots \ldots$	72
4.7	$3\times$ Comparison of different methods on PSNRs, SSIMs, FSIMs	
	$(Set 14-2) \ldots \ldots$	73

4.8	$4\times$ Comparison of different methods on PSNRs, SSIMs, FSIMs
	$(Set 14-1) \ldots 74$
4.9	$4\times$ Comparison of different methods on PSNRs, SSIMs, FSIMs
	(Set 14-2)
4.10	Objective quality assessment of different methods on PSNRs,SSIMs,
	FSIMs
4.11	Objective quality assessment of different methods on PSNRs,SSIMs,
	FSIMs
4.12	Objective quality assessment of different methods on PSNRs,SSIMs,
	FSIMs
۳ 1	
1.6	Comparison of different methods on running time (s) (Set14) 105
5.2	Quantitative comparison of different methods on PSNRs,SSIMs,
-	FSIMIS
5.3	Quantitative comparison of different methods on PSNRs,SSIMs,
- 1	
5.4	Quantitative comparison of different methods on PSNRs,SSIMs, FSIMe
	I DIMO

ABSTRACT

Image super-resolution is an important problem in the computer vision field. Image super-resolution aims to generate high-resolution images with an "ideal" appearance from low-resolution ones. From traditional interpolation methods (bilinear, bicubic et al.) to CNN methods, the quality of reconstructed HR image is highly improved. However, most of these methods are failing to keep texture details and edge structure, especially in highly complicated texture area.

To tackle such problems, fractal geometry is applied to image super-resolution, which demonstrates its advantages when describing the complicated details in an image. The common fractal-based method does not distinguish the complexity difference of texture across all regions of image regardless of smooth regions or texture-rich regions. Due to such strong presumption, it causes artificial errors while recovering smooth area and texture blurring at the regions with rich texture. This thesis firstly proposes a rational fractal interpolation model with various setting in different regions to adapt to the local texture complexity. Secondly, it should keep the degree of image roughness non-decreasing, which reflects various texture features and appearance during the image super-resolution process. However, this point is not well addressed in the current work. This thesis argues that reducing roughness during image super-resolution is the key reason causing various problems such as artificial texture and/or edge blur. Here, keeping the image roughness non-decreasing during super-resolution is being well investigated for the first time to our best knowledge. Thirdly, fine details are more related to the information in the high-frequency spectrum on the Fourier domain. Most of the existing methods do not have specific modules to handle such high-frequency information adaptively. Thus, they cause edge blur or texture disorder. To tackle the problems, this thesis explores image super-resolution on multiple sub-bands of the corresponding image, which are generated by NonSubsampled Contourlet Transform (NSCT). Different sub-bands hold the information of different frequency which is then related to the detailedness of information of the given low-resolution image. Our extensive experimental results demonstrate that the proposed method achieves encouraging performance with state-of-the-art super-resolution algorithms.