Marginal Space Learning for Medical Image Analysis

Yefeng Zheng • Dorin Comaniciu

Marginal Space Learning for Medical Image Analysis

Efficient Detection and Segmentation of Anatomical Structures



Yefeng Zheng Imaging and Computer Vision Siemens Corporate Technology Princeton, NJ, USA Dorin Comaniciu Imaging and Computer Vision Siemens Corporate Technology Princeton, NJ, USA

ISBN 978-1-4939-0599-7 ISBN 978-1-4939-0600-0 (eBook) DOI 10.1007/978-1-4939-0600-0 Springer New York Heidelberg Dordrecht London

Library of Congress Control Number: 2014934133

© Springer Science+Business Media New York 2014

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed. Exempted from this legal reservation are brief excerpts in connection with reviews or scholarly analysis or material supplied specifically for the purpose of being entered and executed on a computer system, for exclusive use by the purchaser of the work. Duplication of this publication or parts thereof is permitted only under the provisions of the Copyright Law of the Publisher's location, in its current version, and permission for use must always be obtained from Springer. Permissions for use may be obtained through RightsLink at the Copyright Clearance Center. Violations are liable to prosecution under the respective Copyright Law.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

While the advice and information in this book are believed to be true and accurate at the date of publication, neither the authors nor the editors nor the publisher can accept any legal responsibility for any errors or omissions that may be made. The publisher makes no warranty, express or implied, with respect to the material contained herein.

Printed on acid-free paper

Springer is part of Springer Science+Business Media (www.springer.com)

To Muna, Allen, and Amy - Y. Z.

To my family – D. C.

Preface

Medical imaging is today an integrated part of the healthcare continuum, supporting early disease detection, diagnosis, therapy, monitoring, and follow-up. Images of the human body help in estimating the organ anatomy and function, reveal clues indicating the presence of disease, or help in guiding treatment and interventions. All these benefits are achieved by extracting and quantifying the medical image content, answering questions such as: "Which part of the 3D image represents the heart and what is the ejection fraction?", "What is the volume of the liver", "Which are the axillary lymph nodes with a diameter larger than 10 mm?", "Is the artificial heart valve being positioned at the right location, with the right angulation?"

With the continuous increase in the spatial and temporal resolution, the informational content of images increases, contributing to new clinical benefits. While most of the content extraction, quantification, and decision making are guided and validated by the clinicians, computer-based image systems benefit from efficient algorithms and exponential increase in computational power. Thus, they play an important role in analyzing the image data, performing tasks such as identifying the anatomy or measuring a certain body function.

Systems based on machine learning have recently opened new ways to extract and interpret the informational content of medical images. Such systems learn from data through a process called training, thus developing the capability to identify, classify, and label the image content.

Learning systems have been initially applied to nonmedical images for twodimensional (2D) object detection problems such as face detection, pedestrian or vehicle detection in 2D images, and video sequences. In these methods, object detection or localization is formulated as a classification problem: whether an image block contains the target object or not. The robustness of the methods comes from the exhaustive search with the trained classifier during object detection on an input image. The object pose parameter space is first quantized into a set of discrete hypotheses covering the entire space. Each hypothesis is tested by a trained classifier to get a detection score and the hypotheses with the highest score are taken as the detection output. In a typical setting, only three pose parameters are estimated, the position (X and Y) and isotropic scale (S), resulting in a three-dimensional search space and a search problem of relatively low complexity.

On the other hand, most of the medical imaging data used in clinical practice are volumetric and three-dimensional (3D). Computed tomography, C-Arm X-Ray, magnetic resonance, ultrasound, and nuclear imaging create 3D representations of the human body. To accurately localize a 3D object, one needs to estimate nine pose parameters: three for position, three for orientation, and three for anisotropic scaling. However, a straightforward extension of a 2D object detection method to 3D is not practically possible due to the exponential increase in the computation needs attributed to exhaustive search. How do we solve this problem? What kind of learning strategy would help to perform efficient search in a nine-dimensional pose parameter space?

This book presents a generic learning-based method for efficient 3D object detection called Marginal Space Learning (MSL). Instead of exhaustively searching the original nine-dimensional pose parameter space, only low-dimensional marginal spaces are searched in MSL to improve the detection speed.

We split the estimation into three steps: position estimation, position-orientation estimation, and position-orientation-scale estimation. First, we train a position estimator that can tell us if a position hypothesis is a good estimate of the target object position in an input volume. After exhaustively searching for the position marginal space (three-dimensional), we preserve a small number of position candidates with the largest detection scores. Next, we perform joint position-orientation estimation with a trained classifier that answers if a position-orientation hypothesis is a good estimate. The orientation marginal space is exhaustively searched for each position candidate preserved after position estimation. Similarly, we only preserve a limited number of position-orientation candidates after this step. Finally, the scale parameters are searched in the constrained space in a similar way.

Since after each step we only preserve a small number of candidates, a large portion of search space with low posterior probability is pruned efficiently in the early steps. Complexity analysis shows that MSL can reduce the number of testing hypotheses by six orders of magnitude, compared to the exhaustive full space search. Since the learning and detection are performed in a sequence of marginal spaces, we call the method Marginal Space Learning (MSL).

As it will be shown in this book, the MSL has been applied to detect multiple 2D/3D anatomical structures in the major medical imaging modalities. Several key techniques have later been proposed to further improve its detection speed and accuracy: Constrained MSL to exploit the strong correlation existing among pose parameters in the same marginal spaces; Iterated MSL to detect multiple instances of the same object type in a volume; Hierarchical MSL to improve the robustness by performing learning/detection on a volume pyramid; Joint spatio-temporal MSL to detect the trajectory of a landmark in a volume sequence.

With these improvements, we can reliably detect a 3D anatomical structure with a speed of 0.1–0.5 s/volume on an ordinary personal computer (3.2 GHz duo-core processor and 3 GB memory) without the use of special hardware such as graphics processing units.

The MSL can also be applied to generate accurate shape initialization for the segmentation of a nonrigid anatomical structure. To further improve the initialization accuracy, the MSL has been extended to directly estimate the nonrigid deformation parameters in combination with a learning-based boundary detector that guides the boundary evolution.

Several practical anatomy segmentation systems have been built and evaluated at multiple clinical sites. Examples include four-chamber heart segmentation, liver segmentation, and aorta segmentation. At the time of publication they all outperformed the state of the art in both speed and accuracy.

This book is for students, engineers, and researchers with interest in medical image analysis. It can also be used as a reference or supplementary material for related graduate courses. Preliminary knowledge of machine learning and medical imaging is needed to understand the content of the book.

Princeton, NJ, USA

Yefeng Zheng Dorin Comaniciu

Acknowledgements

We owe our gratitude to all colleagues who have made this work possible.

At the beginning, this was a joint project with a former colleague at Siemens Corporate Research, Adrian Barbu. During the summer of 2006 we were looking for an efficient and robust 3D detection method to automatically identify the heart chambers in cardiac computed tomography volumes. Based on our previous experience, we knew machine learning was the right direction; however, we lacked an efficient search method. After a series of systematic investigations, we jointly proposed a simple and elegant method called marginal space learning (MSL) as presented here. We really appreciated Adrian's enthusiasm during this development.

We would also like to thank many other colleagues at Siemens Corporate Research for applying, tuning, and improving the MSL on various 2D/3D object detection and segmentation problems in medical imaging. Bogdan Georgescu and Kevin Zhou contributed to the early development stages of this technology; Zhuowen Tu provided the implementation of the probabilistic boosting-tree and 3D Haar wavelet features; Haibin Ling helped in performing comparison experiments for Constrained MSL and Nonrigid MSL on liver detection; and Xiaoguang Lu and Gustavo Carneiro contributed to the comparison experiments of full space learning and MSL on 2D left ventricle detection in magnetic resonance images. Furthermore, several important improvements of MSL originated from our colleagues' work, including Hierarchical MSL from Michal Sofka and Jingdan Zhang, Iterated MSL from Michael Kelm, and Joint Spatio-Temporal MSL from Razvan Ionasec and Yang Wang.

We thank our colleagues from Siemens Healthcare, especially Michael Scheuering, Fernando Vega-Higuera, Dominik Bernhardt, and Michael Suehling from Computed Tomography; Matthias John, Jan Boese, and Martin Ostermeier from Angiographic and Interventional X-Ray Systems; Arne Littmann, Edgar Mueller, and Berthold Kiefer from Magnetic Resonance; and Helene Houle and Sara Good from Ultrasound. They provided us challenging medical imaging problems so that we had a chance to develop the MSL. They collected data all over the world for us and coordinated the clinical evaluation of the resulting systems. Most importantly, they asked us to continuously improve the detection/segmentation speed and robustness of the algorithms.

We are thankful to the Springer editors, Courtney Clark and Jennifer Evans, for their enthusiasm and support to the project.

Yefeng owes his deepest thanks to his wife, Muna Tang, for allowing him to work overtime, often during the weekends.

Dorin would like to thank his family for being so inspiring and supportive.

Contents

1	Intro	duction	1	
	1.1	Advances in Medical Imaging		
	1.2	Applications of Automatic Detection and Segmentation		
		in Medical Imaging	3	
	1.3	Previous Work on Automatic Object Detection		
		in Medical Images	6	
	1.4	Previous Work on Medical Image Segmentation	9	
	1.5	Marginal Space Learning	11	
	1.6	Comparison of Marginal Space Learning and Full Space		
		Learning for 2D Problems	12	
	1.7	Constrained Marginal Space Learning	12	
	1.8	Marginal Space Learning for Nonrigid Object Detection	14	
		1.8.1 Optimal Mean Shape	14	
		1.8.2 Direct Estimation of Nonrigid Deformation Parameters	15	
	1.9	Other Extensions of Marginal Space Learning	16	
	1.10	Nonrigid Object Segmentation	17	
	1.11	Applications of Marginal Space Learning	18	
	1.12	Organization of this Book	19	
	Refer	ences	19	
2	Marg	zinal Space Learning	25	
	2.1	Introduction	25	
	2.2	3D Object Detection Using Marginal Space Learning	27	
		2.2.1 Derivation of Object Pose Ground Truth From Mesh	27	
		2.2.2 Principle of Marginal Space Learning	29	
		2.2.3 Training of Position Estimator	32	
		2.2.4 Training of Position-Orientation Estimator	34	
		2.2.5 Training of Position-Orientation-Scale Estimator	35	
		2.2.6 Aggregation of Pose Candidates	36	
		2.2.7 Object Detection in Unseen Volume	36	
		-		

	2.3	3D Imag	e Features	37
		2.3.1	3D Haar Wavelet Features	38
		2.3.2	Steerable Features	41
	2.4	Classifie	rs	43
		2.4.1	Probabilistic Boosting-Tree	44
		2.4.2	Combining Classifier Cascade and Tree	47
	2.5	Experim	ents on Heart Chamber Detection in CT Volumes	49
	2.6	Direct E	stimation of Nonrigid Deformation Parameters	54
		2.6.1	Nonrigid Marginal Space Learning	54
		2.6.2	Experiments on Liver Detection in 3D CT Volumes	56
	2.7	Theoreti	cal Foundations of Marginal Space Learning	58
		2.7.1	Relation to Shortest Path Computation	58
		2.7.2	Relation to Particle Filtering	63
	2.8	Conclusi	ions	63
	Refer	ences		63
	~	_		
3	Com	parison of	f Marginal Space Learning and Full Space	
	Lear	ning in 2L)	67
	3.1	Introduc	tion	67
	3.2	Margina	I Space Learning for 2D Object Detection	68
		3.2.1	Training of Position Estimator	70
		3.2.2	Training of Position-Orientation Estimator	70
		3.2.3	Training of Position-Orientation-Scale Estimator	71
		3.2.4	Object Detection in Unseen Images	72
	3.3	Full Spa	ce Learning for 2D Object Detection	72
	3.4	Performa	ance Comparison Experiment for MSL	
		and FSL	Detection	74
	3.5	Conclusi	ions	76
	Refe	ences		77
4	Cons	trained N	farginal Snace Learning	79
-	4.1	Introduc	tion	79
	4.2	3D Orie	ntation	80
	1.2	4 2 1	Representation with Fuler Angles	81
		422	Representation with Quaternions	83
		423	Uniform Sampling of 3D Orientation Space	85
		424	Mean Orientation	86
	43	Constrai	ned Search Space for MSI	87
	ч.5	4 3 1	Constrained Space for Object Position	87
		432	Constrained Space for Orientation	80
		433	Constrained Space for Scale	01
	44	Fyperim	ents on Constrained Marginal Space Learning	02
	4.4		Liver Detection in CT Volumes	02
		4.4.2	Laft Ventricle Detection in CT Volumes	93 05
		4.4.2 1 1 2	Left Ventricle Detection in Ultrasound Volumes	90
		4.4.3	Left venuticie Detection in Utuasound voluilles	- 70

	4.5 Refei	Conclu rences	isions	100 100			
5	Part-	Based (Direct Detection and Segmentation	103			
•	51	Introdu	iction	103			
	52	Part-B	ased Left Atrium Detection and Segmentation	100			
	0.1	in C-a	m CT.	105			
		5.2.1	Part-Based Left Atrium Model	107			
		522	Constrained Detection of Left Atrium Parts	109			
		523	Experiments on Left Atrium Segmentation	107			
		5.2.5	in C-arm CT	111			
	53	Rankir	ng Based Multi-Detector Aggregation for Left	111			
	5.5	Ventria	the Detection in 2D MRI	115			
		531	Part-Based I eft Ventricle Model	116			
		532	Ranking Features	117			
		533	Ranking Peatures	121			
		534	Experiments on Ranking-Based Aggregation	121			
	54	Part_R	ased Aorta Detection and Segmentation	122			
	5.7	from (Larm CT	124			
		5 4 1	Part-Based Aorta Segmentation	124			
		542	Further and Arta Segmentation	125			
	5 5	Conclu		131			
	J.J Dofor	conces	1310113	131			
	Refer	chees		155			
6	Optin	Optimal Mean Shape for Nonrigid Object Detection and					
	Segn	ientatio	n	13/			
	6.1	Introdu		13/			
	6.2	Heuristic Mean Shape Using a Bounding Box Based Approach					
	6.3	Optim	al Mean Shape for Nonrigid Shape Initialization	139			
		6.3.1	Procrustes Optimization for Mean Shape and				
			Pose Parameters	139			
		6.3.2	Procrustes Analysis Under Isotropic Similarity				
			Transformation	140			
		6.3.3	Procrustes Analysis Under Anisotropic				
			Similarity Transformation	142			
		6.3.4	Generalized Procrustes Analysis to Align				
			a Group of Shapes Under Anisotropic				
			Similarity Transformation	144			
	6.4	Applic	ation to Aortic Valve Landmark Detection	145			
		6.4.1	Aortic Valve Landmark Detection				
			for Transcatheter Aortic Valve Implantation	146			
		6.4.2	Unique Mean Shape for Aortic Valve Landmarks	147			
		6.4.3	Experiments on Aortic Valve Landmark Detection	148			
	6.5	Applic	ation to Whole-Heart Segmentation	150			
		6.5.1	Whole-Heart Segmentation	150			
		6.5.2	Experiments on Whole-Heart Segmentation	153			

	6.6	Conclu	sions	156
	Refe	rences		156
7	Nonr	igid Obj	ject Segmentation: Application	
	to Fo	ur-Chan	nber Heart Segmentation	159
	7.1	Introdu	ction	159
	7.2	Related	Work on Heart Modeling and Segmentation	161
		7.2.1	Heart Modeling	161
		7.2.2	Heart Segmentation	162
	7.3	Four-C	hamber Heart Modeling	162
		7.3.1	Left Ventricle and Left Atrium Models	162
		7.3.2	Right Ventricle and Right Atrium Models	163
		7.3.3	Establishing Point Correspondence	166
		7.3.4	Statistical Shape Model	168
	7.4	Nonrig	id Deformation Estimation for Heart Chambers	173
		7.4.1	Learning Based Boundary Detector	174
		7.4.2	TPS Deformation Model	175
		7.4.3	Boundary Delineation	177
	7.5	Optima	l Smooth Surface for Left Ventricle Endocardium	
		Segmer	ntation	179
		7.5.1	Clinical Requirements	179
		7.5.2	Left Ventricle Blood Pool Extraction	181
		7.5.3	Optimization Based Surface Smoothing	182
		7.5.4	Comparison with Previous Work	185
	7.6	Experir	ments on Four-Chamber Heart Segmentation	186
		7.6.1	Data Sets	186
		7.6.2	Experiments on Boundary Delineation	187
		7.6.3	Heart Chamber Tracking	193
	7.7	Conclu	sions	195
	Refe	rences		196
8	Appl	ications	of Marginal Space Learning in Medical Imaging	199
	8.1	Introdu	ction	199
	8.2	Detecti	on of Devices and Anatomical Structures	200
		8.2.1	Ultrasound Transducer Detection in Fluoroscopy	200
		8.2.2	Balloon Marker Detection in Fluoroscopy	
			for Stent Enhancement	201
		8.2.3	Pigtail Catheter Tip Detection in Fluoroscopy	203
		8.2.4	Catheter Detection and Tracking in Fluoroscopy	204
		8.2.5	Landmark Detection and Scan Range	
			Delimitation in Topogram	205
		8.2.6	Left and Right Ventricle Detection in 2D MRI	207
		8.2.7	Cardiac Measurements from 2D Ultrasound	210
		8.2.8	Mid-Sagittal Plane Detection in 3D MRI	211
		8.2.9	Intervertebral Disk Detection in 3D MRI/CT	212
		8.2.10	Osteolytic Spinal Bone Lesion Detection in CT	214

		8.2.11	Lymph Node Detection in CT	216
		8.2.12	Ileocecal Valve Detection in CT	217
		8.2.13	Aortic Valve Landmark Detection in C-arm CT	218
		8.2.14	Coronary Ostium Detection in CT	220
		8.2.15	Rib Detection in CT	221
		8.2.16	Standard Echocardiographic Plane Detection	
			in 3D Ultrasound	222
		8.2.17	Fetal Brain Anatomical Structure Detection	
			in 3D Ultrasound	224
	8.3	Detecti	on and Segmentation of Anatomical Structures	226
		8.3.1	Heart Chamber Segmentation in CT	226
		8.3.2	Left and Right Ventricle Segmentation	
			and Tracking in 3D MRI	228
		8.3.3	Left Ventricle Segmentation and Tracking	
			in 3D Ultrasound	229
		8.3.4	Whole-Heart Segmentation in CT	231
		8.3.5	Segmentation of Left Atrium, Pulmonary Vein,	
			and Left Atrial Appendage in C-arm CT	233
		8.3.6	Aorta Segmentation in CT/C-arm CT	234
		8.3.7	Heart Valve Segmentation in 3D Ultrasound	
			and CT	236
		8.3.8	Pulmonary Artery Trunk Segmentation in CT	
			and MRI	238
		8.3.9	Esophagus Segmentation in CT	239
		8.3.10	Liver Segmentation in CT	241
		8.3.11	Segmentation of Prostate, Bladder, and Rectum	
			in CT and MRI	242
		8.3.12	Lung Segmentation in CT	243
		8.3.13	Wrist Bone Segmentation in 3D MRI	245
		8.3.14	Ovarian Follicle Detection/Segmentation in 3D	
			Ultrasound	246
		8.3.15	Fetal Face Detection and Segmentation in 3D	
			Ultrasound	247
		8.3.16	Fetal Limb Segmentation in 3D Ultrasound	248
		8.3.17	Multiple Subcortical Brain Structure	
			Segmentation in 3D MRI	249
		8.3.18	Multiple Organ Segmentation in Full Body CT	250
	8.4	Conclu	sions	251
	Refer	ences		252
9	Conc	lusions a	and Future Work	257
	9.1	Summa	rv of Contributions	257
	9.2	Future		259
In	dex			263

Acronyms

A2C	Apical two chamber view
A3C	Apical three chamber view
A4C	Apical four chamber view
AAM	Active appearance model
AF	Atrial fibrillation
ASM	Active shape model
AV	Aortic valve
CPU	Central processing unit
СТ	Computed tomography
CTA	Computed tomography angiography
ED	End-diastole
EF	Ejection fraction
ES	End-systole
FSL	Full space learning
GPU	Graphics processing unit
LA	Left atrium
LAA	Left atrial appendage
LIPV	Left inferior pulmonary vein
LSPV	Left superior pulmonary vein
LV	Left ventricle
LVOT	Left ventricular outflow tract
MRF	Markov random field
MPR	Multi-planar reformatting or multi-planar reconstruction
MRI	Magnetic resonance imaging
MSL	Marginal space learning
MV	Mitral valve
PBT	Probabilistic boosting-tree
PCA	Principal component analysis
PDM	Point distribution model
PV	Pulmonary vein or pulmonary valve
RA	Right atrium

RIPV	Right inferior pulmonary vein
ROI	Region of interest
RSPV	Right superior pulmonary vein
RV	Right ventricle
RVOT	Right ventricular outflow tract
SAX	Short axis view
SNR	Signal-to-noise ratio
SVD	Singular value decomposition
SVM	Support vector machine
TAVI	Transcatheter aortic valve implantation
TAVR	Transcatheter aortic valve replacement
TEE	Transesophageal echocardiography
TPS	Thin-plate spline
TV	Tricuspid valve