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Optical Flow and Trajectory Estimation Methods

Springer

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ISSN 2191-5768 ISSN 2191-5776 (electronic)
SpringerBriefs in Computer Science
ISBN 978-3-319-44940-1 ISBN 978-3-319-44941-8 (eBook)
DOI 10.1007/978-3-319-44941-8

Library of Congress Control Number: 2016948603

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer International Publishing AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

To Andrea

—Joel Gibson

To Ingrid

—Oge Marques

Preface

Optical flow can be thought of as the projection of 3-D motion onto a 2-D image plane. We are generally given the 2-D projections of the objects at different points in time, i.e., the images, and asked to ascertain the motion between these projections. While points of a physical object, considered at different points in time, should indeed have some dense motion vector in 3-D space, the projection of these points onto a 2-D image sacrifices this one-to-one characteristic. Indeed, it is ordinary that the projection of a point on an object is hidden or *occluded* from view or moved outside of the domain of the image. This inverse process is akin to trying to deduce objects from shadows cast on the ground.

Yet understanding the motion within a scene is the key to solving many problems. Within film and video, high-quality motion estimation is fundamental to the restoration of archival footage. Optical flow is used to help interpolate frames for speed changes. Robots use real-time motion approximations to navigate their environment. Combined with stereo depth estimation, optical flow is an intrinsic part of scene flow.

Perhaps the most fundamental concept in optical flow is *color constancy*. It claims that the projection of a given point on any image will produce the same color value. For all but synthetically generated images this will not hold exactly. As the amount or angle of light changes between the captured images, color intensity can vary dramatically. A closely related property which attempts to mitigate this variability is *gradient constancy* or edge matching.

For all but the most simplistic case, matching the color of a pixel between two images yields a one-to-many map. The process might be improved by comparing the neighborhoods around a pixel in order to find a best match. This too fails along the edge of an object where the neighborhoods all look the same in what is called *aperture effect*.

We must add some knowledge about how flow behaves in order to choose which of the many possible color constancy matches is best. In this role, the most successful regularizer has been Total Variation (TV). Roughly speaking, total variation in optical flow sums the total amount of change in the flow field. Then, given ambiguous flows with similar color constancy, it will choose the flow with the least total change.

Since the beginning of modern optical flow estimation methods, multiple frames have been used in an effort to improve the computation of motion. More recently, researchers have stitched together sequences of optical flow fields to create *trajectories*. These trajectories are temporally coherent, a necessary property for virtually every real-world application of optical flow. New methods compute these trajectories directly using variational methods and low-rank constraints.

Optical flow and trajectories are ill-posed, under-constrained, inverse problems. Sparse regularization has enjoyed some success with other problems in computer vision but there has been little application in optical flow. In part this is because of the difficulty of dictionary learning in the absence of an exemplar. Applying sparsity to trajectories as a low-rank constraint has been stifled by the computational complexity.

This book focuses on two main problems in the domain of optical flow and trajectory estimation: (i) The problem of finding convex optimization methods to apply sparsity to optical flow; and (ii) The problem of how to extend sparsity to improve trajectories in a computationally tractable way.

It is targeted at researchers and practitioners in the fields of engineering and computer science. It caters particularly to new researchers looking for cutting-edge topics in optical flow as well as veterans of optical flow wishing to learn of the latest advances in multi-frame methods.

We expect that the book will fulfill its goal of serving as a preliminary reference on the subject. Readers who want to deepen their understanding of specific topics will find more than eighty references to additional sources of related information spread throughout the book.

We would like to thank Courtney Dramis and her staff at Springer for their support throughout this project.

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June 2016

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