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GUEST EDITORS' INTRODUCTION

Physics-based approaches to computer vision employ physical principles—such as mechanics, or the physics of light and its interaction with material surfaces—to tackle an array of challenging vision problems. In recent years, physics-based techniques have evolved into a major theme in the vision field (as they have in related disciplines such as computer graphics). Numerous physics-based computer vision algorithms have been developed and shown to be effective for image segmentation, shape recovery, motion analysis, object representation, object recognition, etc. Many have proven valuable in application areas such as medical imaging.

Early models for vision based on physical metaphors include Julesz' spring-dipole model of stereopis [1], Fischler's spring-loaded templates [2], and Widrow's rubber mask technique [3]. The currently popular notion of *physics-based modeling* for vision has its roots in research in MIT in the early 1980s into visual surface reconstruction using generalized splines with physical interpretations in elasticity theory [4]. This formalism spawned at Schlumberger in the mid-1980s the idea of deformable models, particularly the development by Terzopoulos, Witkin, and Kass of deformable curves ("snakes") and surfaces based on the dynamics of nonrigid bodies [5]. Deformable models are now widely applied in segmentation, shape reconstruction, nonrigid motion analysis, tracking, and numerous other vision applications. Pioneering work in the application of physics-based techniques to medical image analysis was carried out at the University of Pennsylvania by Bajcsy and Broit, who employed 3D elastic grids to match brain CT images against computerized brain atlases [6]. A different research thread was initiated by Horn's groundbreaking work in the early 1970s on shape-from-shading, which ingrained the computer vision community with an appreciation for the physics underlying image formation, including illumination, the interaction of light with surfaces, and imaging optics [7]. This thread has led to current interest in the subject of *physics-based vision,* which attempts to loosen some of the earlier restrictive (e.g., Lambertian) assumptions, allowing the treatment of mutual illumination, color highlights, and glossiness in the image [8].

The *IEEE Workshop on Physics-Based Modeling in Computer Vision* organized in 1995 by Huang and Metaxas [9] was the first attempt to bring together researchers covering all aspects of physics-based techniques in vision. The workshop reinforced our conviction that the existing corpus of research forms a solid foundation upon which to address ever more challenging problems in the hope of developing increasingly potent computer vision algorithms. The purpose of this *Computer Vision and Image Understanding* Special Issue on Physics-Based Modeling and Reasoning is to showcase new physics-based methodologies for the analysis of complex scenes. Of particular interest were papers on the integration of physics-based modeling and reasoning techniques to improve the results of shape and motion estimation and object recognition in scenes with multiple objects and significant occlusion. We received significantly more submissions than anticipated and have included in this issue 17 high-quality papers that have passed a rigorous refereeing process. The papers are organized into the two aforementioned broad categories of physics-based modeling and physics-based vision.

The first group of papers focuses on estimation and reasoning about shape and motion. Mann, Jepson, and Siskind present a Newtonian mechanics approach for interpreting the interactions of moving objects in image sequences. Kakadiaris,

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Metaxas, and Bajcsy present a dynamic automated approach to the two-dimensional part segmentation, shape, and motion estimation of moving multipart objects. Fua and Brechbühler present a computationally efficient method for imposing hard (exact) constraints on snake-like deformable models. Luettin and Thacker present a method for detection, tracking, and parameterization of visual speech features using probabilistic deformable models. Nastar, Moghaddam, and Pentland combine dynamic modal analysis and statistical modes of variation observed in an actual training set to develop a facial matching and recognition method. Brand presents a computationally efficient method for recovering the interaction and response of scene elements to forces and proceeds to build a scene model through interleaved sensing and analysis. Haag, Frank, Kollnig, and Nagel present a Kalman filtering method for the dynamic tracking of partially occluded vehicles. Williams and Wolff present a method for analyzing the pulmonary vascular tree based on the differential geometry of vector fields. Neuenschwander, Fua, Székely, and Kübler develop a new method for the automatic initialization and optimal fitting of a deformable model which uses as input the given data, a small number of 3D seed points, and the corresponding surface normals. Tek and Kimia present a reaction–diffusion method which employs three-dimensional evolving "bubbles" to segment volumetric medical images. Niessen *et al.* present a multiscale approach to estimating the 2D velocity field from image sequences and apply it to cardiac motion analysis.

The second group of papers focuses on reflectance and color models. Maxwell and Shafer present a method for segmenting complex static scenes based on general hypotheses about object shape, illumination, and material properties. Shimshoni and Ponce present a method for recovering the shape of polyhedra through line-drawing analysis and the use of complex reflectance models. Barnard, Finlayson, and Funt present an algorithm for computing color constancy which uses information from both surface reflectance and illumination variation. Langer and Zucker present a computational model of light sources and illumination in which light is represented as a four-dimensional manifold of rays in space for surface shape recovery. Lin and Lee develop a specularity detection method based on a synergistic integration of color and polarization information from multiple views. Finally, Fan and Wolff present a surface curvature and shape reconstruction method from unknown multiple illumination by enforcing an integrability constraint.

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