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Introduction. Computer vision systems are becoming ubiquitous in everyday life. From autonomous cars driving on our streets, to robots taking care of our homes, factories, and farms, computer vision systems have started to leave laboratories. One of the key catalysts behind this paradigm change have been computational imaging/photography systems. The field of computational imaging (CI) seeks to develop imaging systems with additional capabilities and/or improved performance over traditional photography. Through the co-design of software (image processing) and hardware (illumination, optics, sensors), CI systems have enabled novel imaging capabilities such as HDR imaging [14, 7], micro-motion tracking [18], 3D reconstruction [22], and seeing-around-corners [20]. Next-generation applications such as autonomous vehicles and VR/AR, will depend on these systems and their ability to perform reliably in a wide variety of challenging imaging settings. Therefore, despite the progress in the field, there are still many interesting challenges (e.g. low-light, high noise, strong global/indirect illumination, scattering media) that need to be addressed before these applications become mainstream.

AI in computational imaging. Recently, there has been growing interest in leveraging deep learning for the design of the software and hardware components of a CI system [8, 21, 19, 12].

1. **Hardware design example:** The employed hardware determines the type of image acquired. For instance, a structured light 3D imaging system acquires images of a scene illuminated by a projector. Selecting the optimal projector illumination patterns for a particular imaging setting is a fundamental question in structured light systems [13, 5]. Recent work, leveraged a simple neural network architecture to minimize the expected depth error of the system [13].

2. **Software design example:** At the core of CI systems lies a specialized algorithm that processes the captured image(s). For instance, in a time-of-flight (ToF) camera (e.g. Kinect) multiple images are acquired and an algorithm is used to solve for scene depths, albedo, and ambient illumination [10]. In some cases, to simplify the algorithmic design and/or make the problem tractable, unrealistic assumptions (e.g. no global illumination) are made. Recent work, showed that a neural network can be trained with synthetic ToF data to solve for depths without having to make strong assumptions on the measured data [4, 12, 19].

Deep learning methods have also been successfully applied to design other CI systems for HDR imaging [9], high-quality 3D reconstruction [11], sensor multiplexing [2], non-line of sight imaging [3], optics optimization for extended depth-of-field [17], lensless imaging [16], etc. There are still many interesting imaging scenarios where deep learning could be applied for end to end (software and hardware) optimization of the system.

Personal statement and research expertise. Overall, it is an exciting time to work in imaging. Personally, I currently work on 3D imaging with continuous-wave ToF (CW-ToF) cameras. During my graduate studies, I have worked on improving the depth precision of CW-ToF cameras by designing high-performance light intensity modulation and sensor exposure functions (hardware design). Previous solutions to this problem, although theoretically interesting, can not be easily implemented in hardware [1, 6]. My work, re-visited this problem as a constrained optimization task, and we demonstrated new high-performance functions that could be easily implemented in current hardware. To demonstrate our ideas, I coded simulations and built a CW-ToF camera prototype from off-the-shelf optics and electronics. The results of this project have been submitted for a patent and are also under review at a top computer vision venue. The manuscript is available upon request. Interesting future work could leverage machine learning methods to design high-performance functions for CW-ToF cameras using similar ideas to [13, 1, 15].

In addition to my research, my graduate studies have allowed me to attain solid foundations in the fields of computer vision, image/signal processing, and machine learning (see website for course projects). Helping teach computer vision and signal processing courses made me experience firsthand the commonly known fact ”while we teach, we learn”. Furthermore, before starting to look for full-time opportunities I was planning on doing my Ph.D. in Computer Vision. To this end, I prepared, presented, and passed the Ph.D. Qualifying Exam in Machine Learning and Computer Vision fundamentals.

I am excited to continue working on a career developing computational imaging systems with unprecedented capabilities that perform reliably ”in the wild”. I believe that these systems will play a key role in enabling novel applications across a wide variety of disciplines including transportation, user interfaces, basic science, and security. In the near future, I anticipate that deep learning methods powered-by realistic synthetic data will be increasingly applied to the co-design of imaging software and hardware. Researchers and engineers working on developing these new systems will need to have solid foundations in the fields of computational imaging, optimization, and machine learning.

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