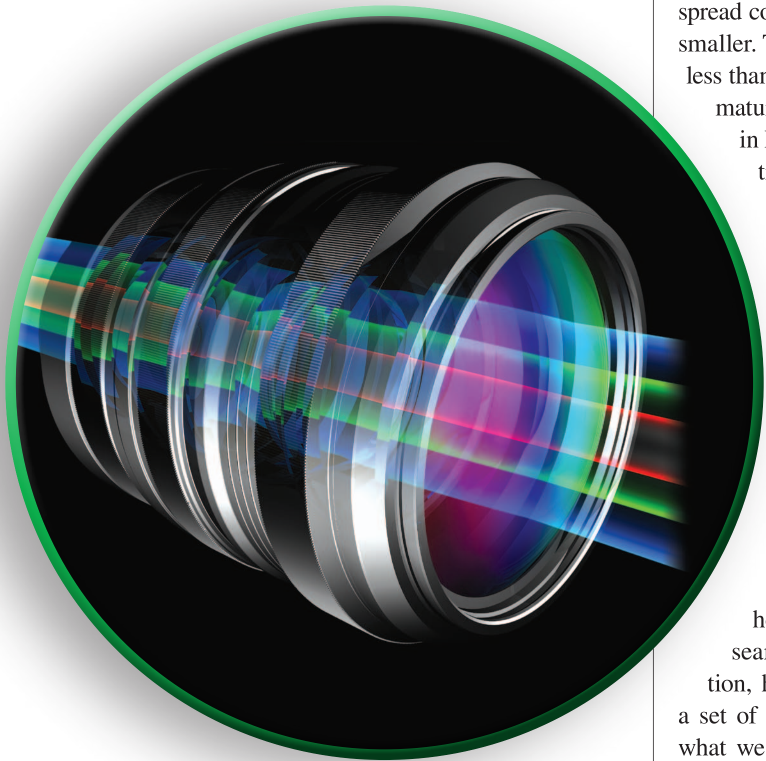
Sanjeev J. Koppal

A Survey of Computational Photography in the Small

Creating intelligent cameras for the next wave of miniature devices



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The sheer ubiquity of smartphones and other mobile vision systems has begun to transform the way that humans and machines interact with each other and the way that they interact with the world. Even so, a new wave of widespread computing is on the horizon, with devices that are even smaller. These are micro and nano platforms, with feature sizes less than one millimeter. These types of platforms are quickly maturing out of research labs, with some examples shown in Figure 1. These devices can potentially induce futuristic applications; for example, swarms of robotic flapping insects [29] could have applications in agriculture and security, while medical devices such as those described in [5] and [8] would enable body area networks and minimally invasive procedures. Devices such as those described in [1] are commercially available and could allow the creation of far-flung sensor networks.

Anticipating vision and imaging capabilities on these smaller platforms is a long-term prospect since, currently, none of the devices in Figure 1 even have cameras let alone full sensing systems. However, the possible impact is large since equipping tiny devices with computational cameras could help realize a new wave of applications in security, search and rescue, environmental monitoring, exploration, health, energy, and more. In this article, we outline a set of technologies that are currently converging to allow what we term computational photography *in the small*; i.e., across the millimeter, micro, and nano scales. This survey covers ongoing research that may break through existing barriers by combining ideas across computational photography, compressive sensing, micro/nano optics, sensor fabrication, and embedded computer vision. We map out the next research challenges whose solutions can propel us toward making miniature sensing systems a reality.

The broad architecture of miniature computational cameras is illustrated in Figure 1(b), where an array of (possibly heterogeneous) sensors are placed on a miniature low-power

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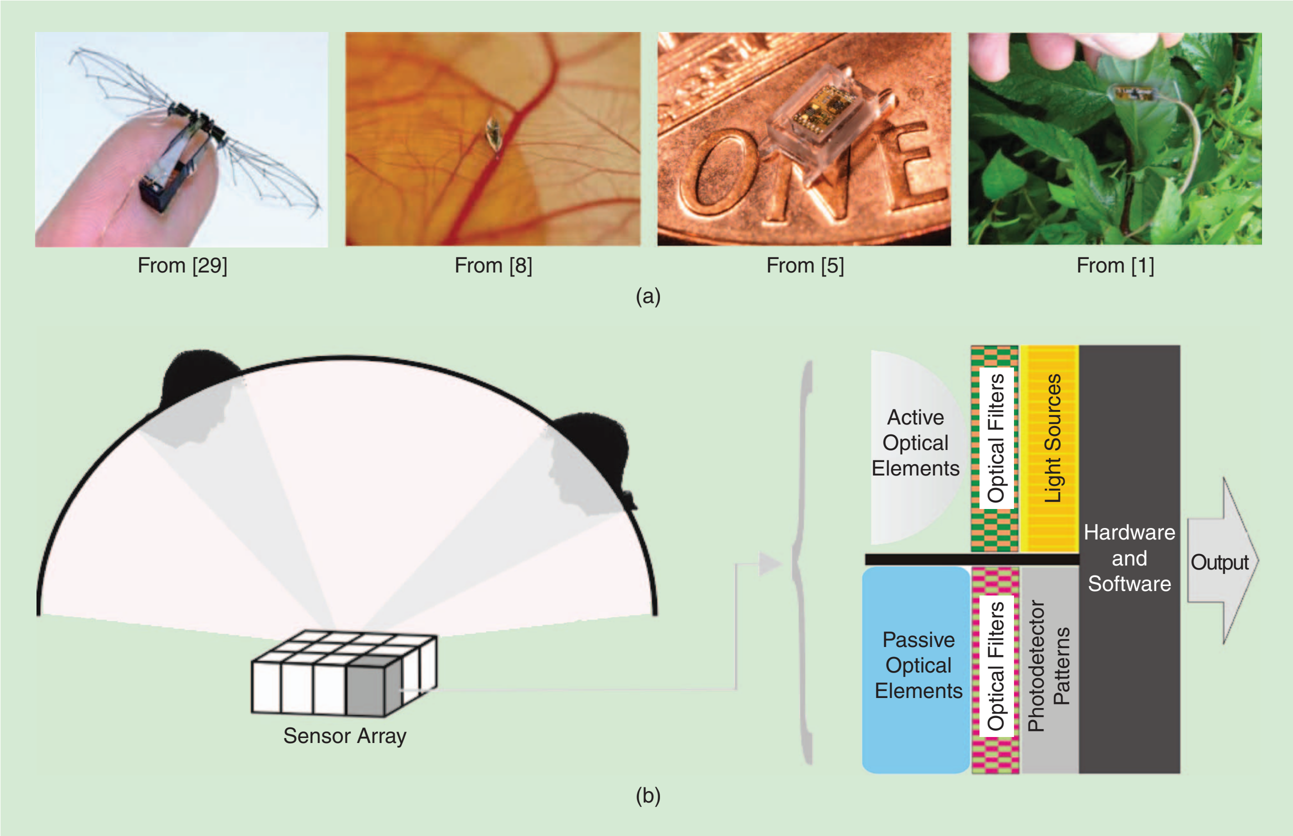

FIGURE 1. Miniature sensors: a new frontier for computational photography. In (a), a few motivating examples (images used courtesy of [1], [5], [8], and [29]) illustrate the coming, new wave of small machines that are transforming surveillance, medicine, sensor networks, agriculture, and other fields. Some, such as [1], are commercially available. However, due to restrictive power/mass budgets, none of these systems have cameras, let alone computational photography capability. If these devices could visually sense their environment, their impact would greatly increase. In this survey article, we cover relevant work in computational photography, compressive sensing, micro/nano optics, sensor fabrication, miniature displays, and embedded computer vision that together are defining the subdiscipline of computational photography in the small. In (b) we show the overall framework of such a miniature computational camera, where every sensor aspect, from optics to computing, is influenced by the visual task at hand.

platform. The design of each sensor can be optimized so that the computation is distributed across all aspects of the device, including passive optics to modulate the incoming light, active optics to project patterns onto the scene, optical filters for either polarization or wavelength as well as accompanying embedded hardware and optimized software. This comprehensive strategy can address the problem of achieving computational photography on compact devices.

Converging miniature sensor technologies: A brief history

In the last two decades, a few billion cameras became available to a large portion of humanity. This created a surge of interest and accompanying progress in a variety of imaging related technologies including, to name just a few, efficient hardware, small optical designs, miniature light-field sensors, and compact active illumination and displays.

We focus here on a brief history of three technologies in particular that have built the foundation for computational photography in the small. The first is the maturing of embedded vision sensing technologies, which includes both mass-produced low-power computing platforms from the mobile revolution as well as specialized systems that intentionally blur the lines between computing hardware and sensing. The second is the impact of miniature optics for visual sensing, where display and imaging optics that were previously only created in research labs are now widely available. The third is the recent application of plenoptic designs to consumer cameras to allow for increased postprocessing control of photography.

Taken together, these fields have created the opportunity to make a new type of camera, as illustrated in Figure 2. This is a camera in which the visual task at hand can influence every aspect of the sensor, from the scene illumination and imaging optics to the sensing electronics and on-board processing. This allows for truly task-specific sensors that can extract every possible size, power, and mass efficiency from the system and can enable miniature computational cameras.

Embedded vision sensing and the mobile revolution

Processing images and video in real time on hand-held devices over the last two decades has resulted in a mature infrastructure for low-power vision and imaging. Dedicated imaging application-specific integrated circuits (ASICs), consisting of digital signal processors (DSPs), field-programmable gate arrays (FPGAs)

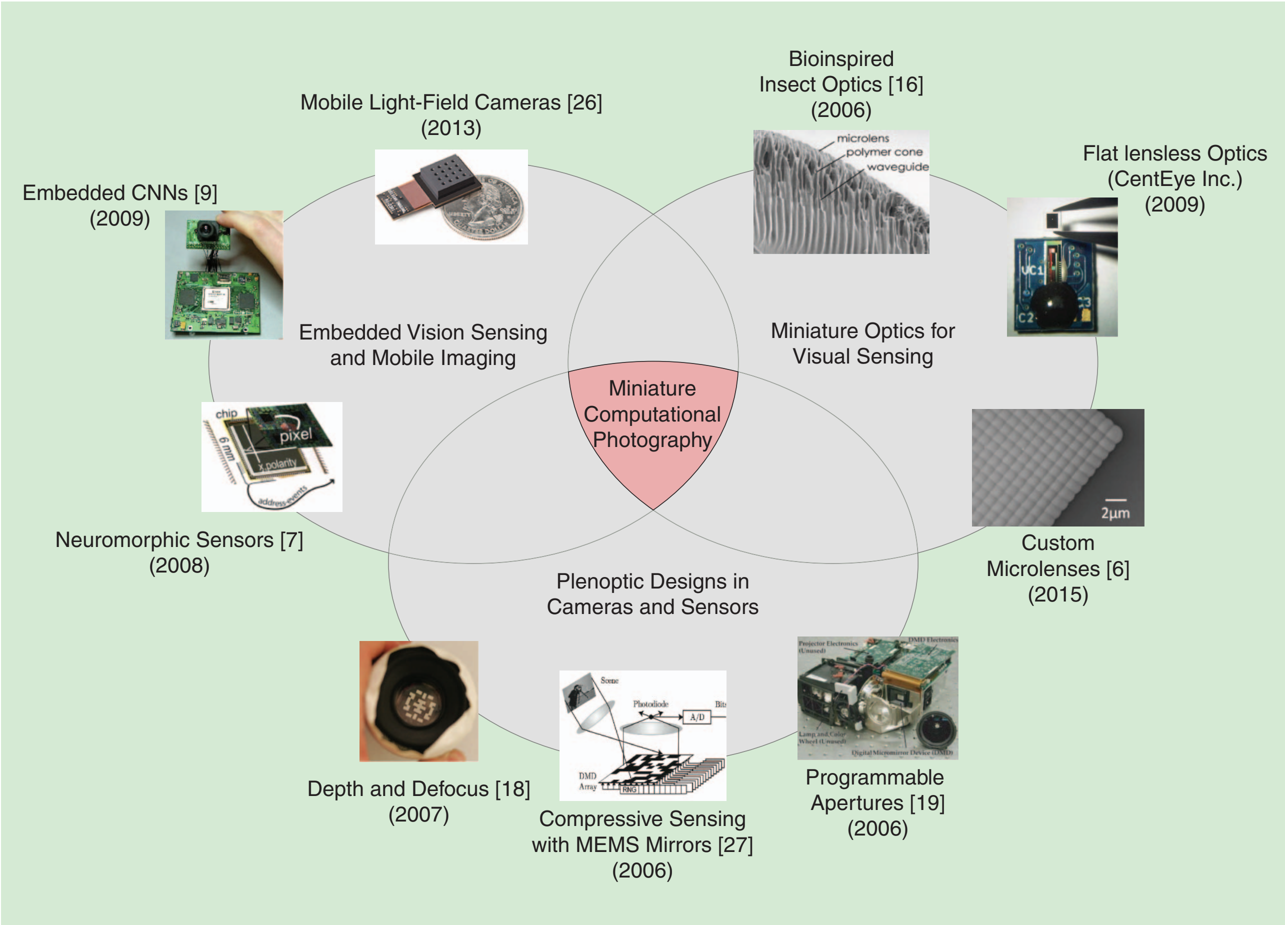

FIGURE 2. A convergence of miniature sensor technologies. We discuss the brief history of three sensor technology areas; embedded vision, miniature optics and plenoptic designs. Efforts in each area has built a library of mature techniques that allow us to build a type of camera where the energy cost of performing a visual task can influence every component in the camera architecture. [All images used with permission: [7], [9], and [27] courtesy of the IEEE; [18] and [26] courtesy of ACM; [16] courtesy of AAAC (Science); [6] courtesy of AIP; and [19] courtesy of Springer.]

and other processors are now standard in mobile devices, and much work exists in the embedded systems research community on low-power hardware support for vision [4]. For example, convolutional neural networks (CNNs) that have gained widespread use with their ability to exploit large data sets, were recently implemented on FPGA hardware with a peak power consumption of only 15 W [9]. In addition, many entrepreneurs are building mobile-scale light-field sensors [26].

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The impact of vision and imaging on the mobile revolution cannot be overstated. However, as the anxiety about Moore's law suggests, such a strategy may not work for the type of extremely small devices shown in Figure 1. For such future applications, even a few watts is likely to be larger than what micro platforms are likely to support. For example, recent microscale body area networks have a per-node average power consumption of only 140 μW [14], and far-flung sensor networks have similar per-node requirements. For such scenarios, the paradigm of capture and postprocessing of images simply cannot offer enough power and mass savings.

Luckily, in addition to traditional embedded sensing research, there has been work done over the last few decades to build analogs to biological and neural architectures in vision systems. These devices perform computations at the sensor level, while photons are being converted into voltages and digitized into pixels. For example, [7] created sensors that automatically adjusted exposure pixel-wise. In this sense, these devices blur the line between sensing and computation since the sampling of voltages itself is part of the imaging algorithm. Many of these sensors have reached a mature level of development and some, such as those from Inilabs, are available commercially.

Miniature optics for visual sensing

Miniaturized optics has a long-standing impact in traditional fields such as microscopy. Micro and nano optics benefits the rise of miniature computational photography since there now exists useful fabrication strategies [3]. However, most of the previous efforts in this area have been to create optics for generating sharp, high-quality imagery. For example, a variety of techniques exist to create microlenses by taking advantage of surface tension properties of PDMS and other materials that are heated and form lens shapes when in liquid form. Microlenses now form an integral part of many smartphone cameras, as they collect light within each pixel on the sensor. In research, a goal has been to create miniature optics that mimic insect eyes [16] or that offer shape control of microlenses [6].

Computational photography is about more than just capturing images but is also about exploiting the image-formation process to extract even more information from the world.

While these previous efforts focus on the extremely useful goal of creating high-quality images, they cannot provide the full story. Computational photography is about more than just capturing images but is also about exploiting the image formation process to extract even more information from the world. It includes sampling the light-field, encoding the incoming light-rays and even analysis of the scene itself through filtering and optical convolutions. The fabrication technologies for creating micro-optics are useful for making computational cameras at small scales, but the design tools available require updating. For example, ray tracing softwares that model aberrations and image blurring and that assume a plano-parallel scene model are still the norm. However, geometric distortions reduce for small optics, and, instead, diffraction becomes important, posing both a challenge and an opportunity, as we will see in the next section.

Wide-angle fields of view (FOV) become important since narrow FOV miniature platforms must move to capture the surrounding visual field, which has power costs. However, wide-angle optics, while well understood at large scales, are not easily manufactured at the miniature scale. For example, miniature fish-eye lenses consist of multiple optical elements at cm scales with only 120° FOV being demonstrated. Curved mirrors allow panoramic imaging for computer vision applications and have no dispersion related problems; unfortunately, to the best of our knowledge, the state of the art for miniature mirrors does not appear to have a greater FOV than 45° [11].

Plenoptic designs in computational photography

Fourier optics [12] involves building optical systems to implement computations like Fourier transforms by, among other things, designing point spread functions (PSFs). For decades, such optical processing research resulted in the use of both coherent light and partially coherent light to build computing platforms that were meant to compete with silicon-based computers. Ten years ago, controllable PSFs began to appear in computer vision and computer graphics communities, where attenuating templates, assorted pixels and plenoptic designs created by standard photolithographic techniques, filtered scene radiance before measurement. For consumer cameras, this allows image deblurring, refocusing [20], and depth sensing [18].

The key lesson learned by these early computational photography researchers was that important scientific questions involved the coded aperture patterns and the related decoding algorithms for images captured under these apertures. Making the coded aperture itself enjoyed the support of relatively established approaches, especially if the coded aperture in question was binary. At the millimeter scale, laser printing provided the required resolution. For smaller and more complex systems, photolithography techniques such as the 1 μm Heidelberg photomask writer could easily do the job. Therefore, many computational photography researchers became the new customers of the existing national nanotechnology infrastructure built during the 1990s and 2000s.

The plenoptic designs created by the aforementioned photolithography techniques were static and could not be changed over time. To create programmable optics, researchers took advantage of the wide availability of display related technologies for manipulating light, such as liquid crystal displays or digital micromirror devices that allow either controlled sampling of the light-field or processing of information for computer vision and image processing. Initially, these efforts required systems engineering; for example, in [19], the researchers hacked a Texas Instruments DLP projector, using it as a camera instead of a projector and whose “projected” patterns became the camera’s coded aperture. Today, almost ten years later, the Texas Instruments developer kit is affordable enough that such hacking is no longer common. In fact, this availability has resulted in some of the most visible successes of compressive sensing [27] and continues to impact vision and imaging. This is a past example of the evolution and commodification of key technologies that we believe will happen in the future for many of the related areas summarized in Figure 2.

A first wave of computational photography in the small

There has been a recent surge of miniature computational cameras, and some of these are illustrated in Figure 3. The previous efforts we discuss here may lack integration, but they represent a new line of thinking that seeks to merge the intertwined technologies of plenoptic designs, miniature optics, and computational sensing in hardware and algorithms to create new types of cameras. Figure 3 depicts these on an axis of optical size and power consumption. Each of the authors cited reported their sensors’ optical size, but, calculating the power footprint was more challenging since it is subject to interpretation and can change depending on the task at hand. For example, the raw images from a sensor could be used for optical flow directly, without much power consumption. However, the same sensor might require

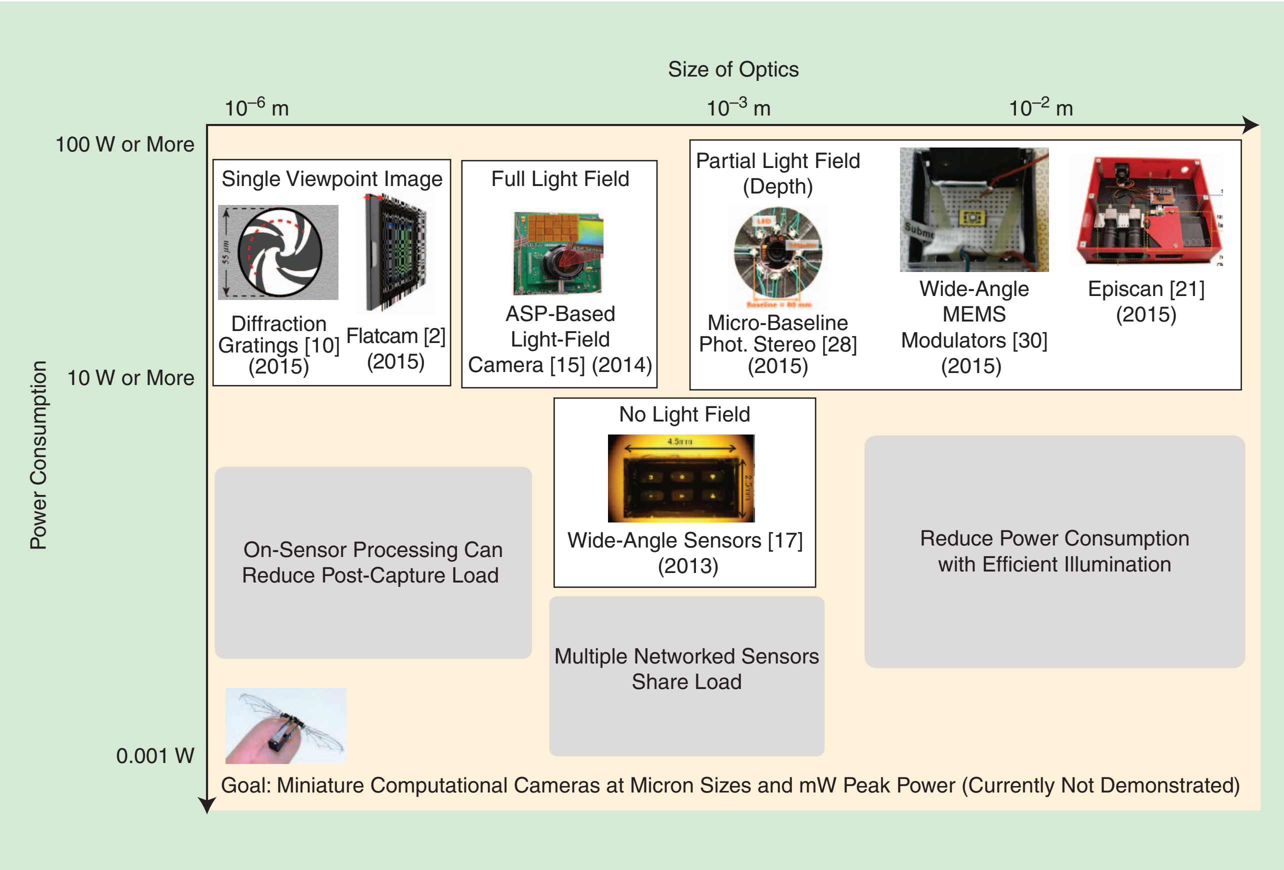

FIGURE 3. The first wave of miniature computational cameras. We organize the new wave of small computational cameras according to optical size and power consumption of the full system. Light-field cameras require powerful on-board computations, but the size of the optics and coded apertures has reached micron scales. On-board computation at millimeter scales has been proposed for vision sensors, but these do not capture the entire light-field. We illustrate the new broad steps such as applying sensor-based processing to reduce footprints, applying optical processing to share in the computational load and exploiting efficient active lighting to reduce on-board power consumption. [All images used with permission: [15], [17], [28], and [30] courtesy of the IEEE; [10] courtesy of Rambus/OSA; and [21] courtesy of ACM.]

multiple hours of PC-grade processing of the measurements to allow full light-field analysis. We picked the full power footprint required to generate the key result in each research paper.

A significant portion of this first wave of miniature computational photography has been in the realm of lensless imaging, which has long been valued due its simplicity, throughput, and potential for miniaturization. Recent novel image sensor designs recover angular information for light-field analysis [15]. Reference [10] also used lensless diffraction patterns to capture angular variations in the light field. Lensless imaging has played an important role in new types of compressive imagers [2]. Reference [17] demonstrated an angular theory of wide-angle optical processing and showed results for fiducial detection on small, autonomous robots, without needing to capture the entire light field.

Certain common ideas are shared among these first few forays into computational photography in the small. First, diffraction is embraced, unlike much of conventional computational photography, which relies on a ray geometric model of light, albeit partially augmented with color and polarization. For example, [13] have shown the promise of adding micron-scale fabricated polarizing filters to CMOS/CCD cameras. Exploiting diffraction does not happen as in the optical processing community, where coherent or partially coherent models are used to obtain closed form solutions. Instead, to handle fully incoherent light from the real world, the relative effects of diffraction are used to infer scene properties. For example, in [15], angle sensitivity is obtained from the relative effects of a double decker layer of diffraction patterns. Another idea among these pioneering designs is the use of nonconventional optics and coded apertures fused together as one unit. For example, in [17], optical templates for detecting targets are embedded in a refractive slab, enabling the Snell's window effect, and allowing an extremely wide FOV without using fish-eye lenses.

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The devices discussed above lie in the micro to millimeter scales and are passive in the sense that the coded apertures do not change over time and there is no controlled illumination projected onto the scene. This is in contrast to vision and graphics methods that use designed lighting to decode scene information and create new displays. Researchers have recently began to ask how these methods could work on miniature platforms. For example, a challenge on small devices is the inherent reduction in baseline. Reference [28] has shown how a circular setup can address some of these challenges for photometric stereo. Another direction to address the baseline issue is to move from triangulation to time-of-flight using active illumination. On the macro-scale, time-of-flight research has allowed the extraction of novel scene properties [25]. For miniature systems, trading off the modulated source's's power consumption versus the depth sensing becomes important.

One way to balance these needs and enable illumination-based sensing on small devices would be to extract a signal out of low wattage illumination. A new generation of computational illumination methods take advantage of low-power microelectromechanical systems (MEMS) mirrors that have been created for mobile hand-held projectors, such as those manufactured by Microvision, Syndiant, and Cremotech. For example, using a 5-W hand-held projector from Microvision, the authors of [21] have enabled computational illumination techniques in outdoor scenes, in the face of full sunlight. For miniature computational photography, the converse is clear; if there is no strong ambient illumination, then the same system can be made to work at orders of magnitude lower power budgets, since similar techniques of exposure synchronization and epipolar rectification can be harnessed to decrease power consumption.

Miniature computational photography has great potential for applications in a variety of fields where small, networked platforms are already making an appearance, such as agriculture, security, health, and the Internet of Things.

While these methods prove promising, an interesting direction put forth by [30] is to engineer a wide-angle MEMS mirror modulator for enabling futuristic applications such as micro light detection and ranging (LIDAR) by demonstrating an electrothermal MEMS working in liquid for the first time. By submerging the MEMS mirror into a mineral oil whose refractive index is 1.47, a wide-angle optical scan ($>120^\circ$) was achieved at small driving voltage ($<$ 10 V), and the scan frequency reached up to 30 Hz. The power consumption shown was 11.7 mW per degree in the mineral oil.

The next opportunities

Figure 3 depicts shaded gray regions that show the potential for further advances in efficiency and performance. For example, very few existing techniques take advantage of, say, computing in ASICs at the sensor level and many rely on conventional PC-based postimage capture processing. Task specific sampling may also reduce on-board processing; for example, a low-power face detector may have an optimal combination of thermal pixels, polarized pixels and skin filter pixels to do the job. This requires exploiting the latest efforts in nano-optics, such as from [22], to use spectrally selective filters at the desired scales. Another goal is to find ways to exploit low-power programmable optical templates that use technologies such as eInk, which powers many e-readers and which remains static until sufficient energy is available for a pattern change.

Another potential opportunity is the integration of computational photography techniques with existing robotics and SLAM techniques for flying microrobots [24], floating sensors and surveillance drones. These tools could allow, for example, photometric stereo of large tourism sites or disaster zones by using varying illumination from multiple drones.

Temporal visual information at small scales can enable navigation, obstacle avoidance and optical flow; yet processing video on low-power platforms is prohibitive. CentEye (http://www.centeye.com/) has shown embedded computing based optical flow at high rates and at low resolution using embedded vision cameras. Integrating data from multiple sensors has enabled optical flow at real-time rates. For extremely fast sampling, it may be possible to exploit graded index lenses or optical fibers that can bend light in curves. Such optical elements can introduce time delay by guiding incoming scene radiance into optical loops, which can be tightly wound in a small volume, enabling, perhaps, fast capture of near simultaneous photographs without clocking at extremely high rates.

Finally, since true efficiency is only possible by having the sensing task at hand influence every part of the sensor, a fascinating question is how to distribute the work load over these different components. Should we sample and process with the optics, in such a way as to minimize the computational load? Or should we use a neuromorphic sensor to process the measurements as they are made? This suggests that design tools in the form of a compiler, to allow automatic partitioning of the computing problem into components that can be performed best by optics, coded sampling, on-board processing, or general-purpose signal processing and vision algorithms.

Toward full systems: Societal, legal, and cultural impact

We anticipate a future with trillions of networked miniature cameras. These computational cameras will be small, cheap, numerous, and capable of recovering more information about the world around them than today's conventional point-and-shoot cameras. The hypothetical impact of such devices has been discussed in many contexts, such as within the camera sensor network research community, and not all impacts may be desirable. For example, if these tiny sensors are not biodegradable, then the potential environmental impact may dwarf current concerns on e-waste. Another issue is privacy, as miniature cameras may be discretely placed where their presence is unwanted. Blunt legal and societal restrictions to these types of small sensors may unintentionally harm the huge potential upside in terms of new applications and new platforms. Computational photography can provide answers to some of these challenges. For example, [23] proposes a new layer of optical privacy for small sensors, where optics filter or block sensitive information directly from the incident lightfield before sensor measurements are made.

To conclude, we have shown that there is a confluence of technologies over the past few decades that has made the tools for enabling miniature computational photography possible. This has resulted in a recent surge of activity to build computational cameras, displays, and sensors that push the limits of size, power, weight, and mass. Miniature computational photography has great potential for applications in a variety of fields where small, networked platforms are already making an appearance, such as agriculture, security, health, and the Internet of Things. There are dangers regarding social acceptance of a trillion networked eyes around us, which can and should also be solved by computational photography research.

Author

Sanjeev J. Koppal (sjkoppal@ece.ufl.edu) received his B.S. degree from the University of Southern California in 2003. He obtained his master's and Ph.D. degrees from the Robotics Institute at Carnegie Mellon University (CMU). After CMU, he was a postdoctoral research associate in the School of Engineering and Applied Sciences at Harvard University. He is an assistant professor in the Electrical and Computer Engineering Department at the University of Florida (UF). Prior to joining UF, he was a researcher at Texas Instruments' Imaging R&D lab. His interests span computer vision, computational photography, and optics and include novel cameras and sensors, three-dimensional reconstruction, physics-based vision, and active illumination.

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