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WHITE PAPER ON COMPUTATIONAL IMAGING

Based on presentations and discussions during the respective workshop at the ZEISS Symposium on 23 June 2016 in Oberkochen, Germany

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Computational imaging (CI) is the systematic enhancement of computer-aided imaging by dealing with algorithms, sensors, and optics as a single entity and optimizing them.

Computational imaging is an emerging interdisciplinary field of research. Unlike optics, which is a traditional branch of physics, computational imaging is rooted at the intersection between the STEM fields (science, technology, engineering and mathematics). The goal is to bring together the 'best' elements from optics, image processing, physics, mathematics and computer science to break new ground in imaging.

This goal implies both circumventing classical limitations, e.g., Abbe's resolution limit, as well as enabling completely new imaging modalities such as hyperspectral imaging or super-resolution. The large number of application fields and the variety of methods make computational imaging a very heterogeneous field of research which requires experts from extremely different disciplines to collaborate.

Based on presentations and discussions during the Computational Imaging workshop at the ZEISS Symposium on 23 June 2016 in Oberkochen, Germany, you'll find below:

i) A summary of the current state of the field,
ii) A clear picture of current trends and opportunities,
iii) Potential blockers for commercial application and
iv) The needs of a growing community in terms of educational resources, research data sets and standards.

Current state of computational imaging (CI)

While many ideas behind modern computational imaging methods date back to the pioneers of optical imaging, CI in its current form has been made possible by the rapid development of digital image sensors and the tremendous growth in computational and storage capabilities offered by modern electronics.

Hardware: One of the main driving factors of CI in recent years has been the development of high-performance digital imaging sensors and the miniaturization of the surrounding optics and electronics. Hardware developments have been pushing and enabling computational-optical imaging applications that had previously been considered out of reach, such as quantitative phase imaging with partially coherent light, 4D light field imaging or real-time OCT.

A practical benefit of CI techniques is an increase in robustness and repeatability to the mechanical stability of measurement equipment due to acquisition speed and digital post-processing . Another domain of application is the simplification of optical systems, e.g.

leveraging the capability to compensate for geometric distortions digitally. In summary, digital compensation techniques enable less expensive hardware.

Software: CI is not only relying solely on hardware. Software components, in particular, optimization algorithms and the ability for sophisticated system simulation have pushed the size of the data that can be handled as well as the quality of the results to a practically applicable level. We have reached the point where CI techniques are obtaining a sophistication that enables entry into the market. The necessary computational resources are becoming affordable (multi-core, GPU, cloud computing) and enable product integration.

At the core of many CI methods are novel algorithms which reflect i) the physical model of the imaging process, ii) prior knowledge about the data and iii) a coding strategy introduced by the optical hardware setup.

Open issues, challenges and opportunities

While CI is a well-established field of research with its own academic community, its advanced forms (going beyond the normal digital optic processing chain (demosaicing, denoising, gamma correction, distortion correction…)) have had only moderate success in commercialization. It is still an open question how CI can contribute to consumer/industrial optics and what the expected benefits are. In other areas, like medical imaging or microscopy, the benefits of CI are much clearer (for example: in applications like phase contrast imaging, 3D reconstruction or multispectral imaging), but there is still a gap between industrial needs and the current state of research.

A current challenge is the holistic design of CI systems which incorporates the whole imaging chain starting from illumination, incorporating the optical system(s), modeling the sensor, and ending with the post-processing and analysis of the data. The current tools are not yet adequate to address an end-to-end design of CI systems. Tools equaling classical optical design, i.e. quality criteria, merit functions, optimization of system parameters, etc. need to be developed. In addition, performance metrics need to be elaborated. A particular challenge in this respect is the stabilization of CI optimization algorithms by means of prior information about the data to be recorded. While key to the success of state-of-the-art methods, their use in critical scenarios such as medical applications may lead to the suppression of information that is of diagnostic relevance. As an example, tumors may be missed in a brain scan simply because the relevant data does not follow the standard structures found in human brains.

Another issue is that the choice of optimization algorithm typically affects the result of the measurement. The algorithms can be based on either standard optimization methods like gradient descent or customized algorithms that adapt to the optimization at hand, like proximal splitting methods. The choice between these options is still an open issue which lacks clear guidelines. A common choice is that between methods that model the right image formation but only find a local optimum. Alternatively, a globally optimal solution to an approximate image formation model can be found. The trade-offs involved need to be better understood.

A simple suggestion for approaching this problem is to record larger and larger datasets for evaluation and testing. A practical problem associated with this strategy, that is also affecting

CI methods generally, is the problem of handling and processing these huge amounts of data. Storage, transfer and safeguarding of the relevant information is of importance in that respect. Best practices still have to be developed.

One of the main limitations for the short-term future of CI are bandwidth limitations in data transfer. Many modern sensors can record data at high speed. The current bottleneck is often the transfer of the data from the sensor to the processing unit. Optimized hardware that can directly stream into the memory of the processing unit is currently becoming available and should improve the situation. Medium-term developments should include moving processing power closer to the sensor, e.g. using 3D chip designs where upper layers form sensor elements, whereas lower layers would be performing early pre-processing stages of the data.

Community Actions

The interdisciplinary nature of CI implies a diversity of backgrounds in the practitioners of this developing field. The three main issues are i) standard benchmark data sets and open implementations for individual problems, ii) standardized data exchange formats and best practices, and iii) educational and community resources. All three topics only exist in a scattered and basic form.

Data Sets and Open Implementations: Concerning standardized test-sets, many other communities such as the computer vision community have progressed much further, e.g. with the well-known Middlebury benchmark data sets used to compare optical flow methods. Also, it is common practice in computer vision to include standard algorithm comparisons in papers and to publish data and code. Our community should develop similar standards and enforce them in the review process. The reproducible research resulting from this action will strengthen the field, enable competition for best results, and lead to improved industrial transfer by offering a simple way for evaluating the suitability of particular (often complex) solutions for solving application problems. It is important to recognize that code, data, and hardware play an equally important role. Industry can trigger and foster this process by providing “challenges”. Examples for this in other fields are the DARPA challenge for autonomous vehicles, the Amazon Warehouse Stocking Challenge in service robotics, or machine learning challenges such as those listed on kaggle.com.

Standardized Data Formats: The need for standardized data formats and specifications was clearly recognized. However, the field is very diverse with many application domains. Currently, there are no recognizable tendencies for standardization. The field is still open to individual parties/industries to set first-on-market standards.

Educational and Community Resources: It was clearly recognized that informational resources are still scattered. The community would benefit from an information collection website, e.g. computationalimaging.org, possibly organized in a Wiki manner. The web-resource would collect information on research groups, literature, links to lectures, open data sets and challenges, code, etc. In the medium-term, it is important to start developing interdisciplinary curricula. As an example, the Institut d’Optique Graduate School (Bordeaux) is offering a curriculum joining optical and computer science. Key to such curricula are a strong (applied) mathematical and physics education, coupled with key information processing concepts such as signal processing, algorithms and data structures, parallelization, hardware architecture, etc. A link to industry could be explored through more industry-offered or supported PhD opportunities.