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An Industry and Government Perspective on Challenges and Open Problems in Signal Processing

ICASSP Panel

The majority of ICASSP presentations are given by professors and students. Perhaps resulting from its strategic location near a great deal of high-technology activity, the strong economy [the result of a focus on machine learning (ML) and in employment therein] and because of the energetic outreach by the organizing committee, ICASSP 2018 had an especially strong industry presence, both in attendance and sponsorship. Calgary, a cosmopolitan city in the Canadian province of Alberta, was the conference's site and provided the perfect opportunity for a panel focused on industry feedback. What spurs the interests of both industry and government, the entities who are actually making the products and know the competition? How can academia participate (and maybe even help)?

As a natural successor to the panel "Challenges and Open Problems in Signal Processing" (organized by Yonina Eldar and Al Hero) held during ICASSP 2017 in New Orleans, Louisiana, a panel responsible for soliciting industry perspectives was organized at ICASSP 2018. The goal of the panel was to obtain the industry and government perspective on signal processing (SP) research; i.e., from their perspective,

what are open problems where an impact can be made? Our aim was to enable an open discussion within the IEEE Signal Processing Society on what are the key challenges today in industry with high payoff, what areas should potentially be deemphasized, and to identify synergies and possible cross-field contributions. The panel attracted a large audience and touched on many interesting topics and perspectives.

When the panel was organized, an attempt was made to have broad representation from SP fields. The organizers, Yonina Eldar, Martin Haardt,

and Peter Willett, sincerely thank the participants for taking time from their busy work schedules to offer their thoughts. We are also grateful to the ICASSP board for accommodating the panel by working it into the conference's packed schedule. The panelists (Figure 1) who participated in the event and the topics they discussed were

- Tom Baran (cofounder and chief executive officer, Lumii, Inc.): challenges and open problems in tera-scale SP
- Gene Franz (retired Texas Instruments principal fellow, founder and chief technical officer, Octavo Systems):



FIGURE 1. The panelists and organizers of ICASSP 2018 (from left): Peter Willett, Brian Sadler, Bhuvana Ramabhadran, Mariappan Nadar, Fernando Mujica, Gene Franz, Tom Baran, Yonina Eldar, and Martin Haardt. (Photo courtesy of Naim Dahnoun.)

challenges and open problems in hardware

- Fernando Mujica (Apple, Inc.): challenges and open problems in embedded implementations
- Mariappan Nadar (senior director of research, Siemens Healthineers): challenges and open problems in artificial intelligence (AI) for medical imaging
- Bhuvana Ramabhadran (manager at Google): challenges and open problems in speech and language processing
- Brian Sadler (U.S. Army Research Laboratory): challenges and open problems in wireless autonomous systems.

Each panelist was asked to prepare remarks and slides for a short introductory presentation, which was followed by a general forum. The panelists addressed the following:

- 1) What is the most important breakthrough in your field in the past 10 years, and how did this affect your field?
- 2) What, in your view, is the most important challenge in your field that needs to be addressed?
- 3) Outline two or three specific open problems that are steps in that direction and stress what is difficult about these problems.
- 4) What issues do you think academics overemphasize, and what areas do they tend to ignore but shouldn't?

The panelists prepared short statements that addressed these points. Some of the main conclusions that emerged from the panel discussion were the following:

- 1) We should be more impressed by flops per watt than flops per device.
- 2) We should not forget analog computation, which has fallen out of favor but is far better suited to some applications than is digital.
- 3) We should embrace ML breakthroughs; however, to ensure that our solutions are acceptable and more reliable, we need to make more of an effort to render them explainable and interpretable.
- 4) There is tremendous opportunity in biomedical SP. An effective approach to make our research more relevant is

one that demonstrates results based on known benchmarks and uses open source software where appropriate. Biomedical SP is unique because ethical concerns are paramount.

- 5) Large problems often require decentralized and autonomous solutions that are robust and do not need continual maintenance.

Challenges and opportunities in tera-scale SP

Three trends appear to be rapidly converging, collectively pointing to a new set of challenges and opportunities in SP: tera-scale data sets, tera-scale computational performance of individual devices, and tera-scale networks interconnecting the devices. Handheld video game consoles are, e.g., currently capable of teraflop performance, processor manufacturers are preparing for potentially trillions of connected Internet of Things devices, and content such as light-field video for augmented reality (AR) and virtual reality (VR) applications readily requires tera-scale data processing and storage. These trends point to new opportunities for creating scalable, robust algorithms that will take advantage of next-generation computational architectures, including graphics processor units, tensor processing units, and digital-SP (DSP) accelerators that can operate elastically across a heterogeneous collection of such computational nodes.

In thinking about the next generation of tera-scale algorithms, it is wonderful that there is a broad collection of serviceable practical and theoretical concepts resulting from foundational SP work that reaches back to the origins of modern electrical network theory and beyond. As one example, a variety of theorems abound concerning the behavior of complex, heterogeneous, generally nonlinear and stochastic electrical networks that may be derived from the celebrated Tellegen's theorem [1], [2]. In the context of tera-scale SP, a collection of recently developed related theorems [3], [4] enable SP practitioners to readily construct scalable, robust, and dynamically changing systems using heterogeneous components that are inter-

connected without requiring centralized coordination. These principles have, e.g., been used to design decentralized algorithms for regulating intervehicle spacing among a collection of locally communicating vehicles having heterogeneous and changing dynamics [5]. The algorithms have provable stability in the presence of nonlinearities, sensor failures, and changes in the topology, and the underlying principles can be applied to more general resource-allocation problems involving potentially trillions of agents. Related results have also led to highly scalable algorithms for convex and nonconvex optimization, resulting in decentralized algorithms that are inherently robust and, for example, are more resilient in the presence of communication delays and dropped data, while achieving convergence rates comparable to widely used centralized algorithms [6], [7].

As tera-scale data sets become increasingly prevalent, the ability to efficiently process them will become increasingly critical. For example, in AR and VR applications, light-field video content can easily require mass processing of trillions of scalar variables. There is also an emerging application in which printed light fields are being used as a next-generation tool to help prevent product and document counterfeiting [8]. In this application, light fields must be generated at the native resolution of the best commercial presses, which would require a trillion variables to be processed to originate a light field print the size of a letter-sized sheet.

When considering where these challenges and opportunities fit into the future of SP, the idea calls to mind a recent symposium organized, in part, by several of the authors of this article that was held at the Massachusetts Institute of Technology in honor of Prof. Alan Oppenheim [9], as well as a quote of Oppenheim's that became a central theme of the symposium: "There will always be signals, they will always need processing, and there will always be new applications, new mathematics, and new implementation technologies." It would seem that, as a collection of trends, tera-scale SP suggests a new category of

challenges and opportunities underlying the applications, mathematics, and technologies of SP.

The new era of SP hardware

The success of SP has been the result of the advancement of three different aspects: 1) advancements in the theory of SP, 2) the advancements of hardware processing, and 3) the expansive application of theory using hardware processing elements. Today, the pace of advancements in hardware seem to be slowing while applications have continued to accelerate.

State-of-the-art digital processing architectures do not provide enough raw performance to capitalize on many of the new opportunities. Even when we do muster enough raw performance, power dissipation becomes problematic. This is an exciting challenge because it drives researchers and industrialists to explore new areas. One of those interesting areas requires us to look back rather than forward, i.e., revisiting the world of analog SP to make that next advancement (remembering that all advancements are interim until we perfect the next one).

From a historical perspective, analog computing was a casualty of the digital computer. Most recently (circa 1970), it was the casualty of the invention of the microprocessor. We in the world of DSP convinced the industry that there was no longer a need for analog computational elements because they had solved all of the problems, i.e., noise, accuracy, dynamic range, linearity, and reliability. However, it is time to revisit analog computing given the advancements of SP theory and integrated circuit (IC) technology, along with the expanding new applications that beg for an SP solution. For example, the multiply function is what limits both the raw performance and battery life of a DSP. A cursory comparison to an analog multiplier suggests that the raw performance of an analog multiplier could be several orders of magnitude higher in raw performance, while having several orders of magnitude lower power dissipation. To exploit these advantages, we must resolve the aforementioned problems that inspired the movement to DSP to

begin with. Therefore, the challenge, in light of new applications that need higher performance at lower power dissipation, is whether we can resolve the problems inherent to analog SP with today's IC technology. If we can, then we are at the dawn of a new era of explosive growth of SP-enabled applications.

Embedded implementations of SP systems

Wearables, smartphones, Internet-connected appliances, and many more devices that we interact with on a daily basis are all examples of the embedded implementations of SP systems. The ever-increasing computational capabilities of these systems are possible due, in part, to Moore's law, which documents the doubling of transistor density every two years [10]. More recently, the dreaded deceleration of Moore's law [11] has been met with increased innovation in hardware-friendly parallel algorithm implementations as well as in the design of algorithms and hardware. The result is embedded systems with heterogeneous computational platforms, including programmable and specialized energy-efficient hardware accelerators. The cross-disciplinary research collaboration between SP, digital architectures, and circuits areas will continue to drive innovation for the embedded implementation of SP systems for years.

The intersection of traditional SP and modern ML represents one of the biggest opportunities. Advances in learning-based systems have demonstrated impressive results for many tasks as long as adequate training data is available. However, what is the best way to deal with systematic sensor impairments in a real-time system? Most importantly, what is the energy overhead inferred from these types of implementations compared to one that leverages traditional SP to compensate for systematic sensor impairments that normalize the data? More generally, learning-based methods for complex signals are still an open problem worthy of the SP community's attention and could allow us to leverage the vast research in frequency domain SP that heavily relies on complex representations.

Interpretability of learning-based methods is another important open problem. Many applications require extremely high levels of robustness against environmental impairments, failures, and malicious attacks. Progress is being made, but general formalized methods that analyze learning-based systems are not broadly used.

In academia, we often tend to ignore practical implementation issues and the connection of theory to applications. Exposure to applications and implementation issues can drive many important aspects of research. As we explore implementation issues in academia, we will naturally encounter opportunities for combining traditional SP with modern ML. Thankfully, people are adept at one-shot learning, so exposure to a few implementation examples is all many students will need to form generalizations!

AI for advanced medical imaging

SP methods have played a key role in diagnostic imaging since the 1960s when A.M. Cormack, a South African-American physicist and academician who won the 1979 Nobel Prize in Physiology or Medicine (along with G. Hounsfield), described a technique for reconstruction tomography. In the previous decade, the field of compressed sensing emerged, establishing that a signal can be reconstructed from fewer samples than what the Nyquist–Shannon theorem requires. Compressed sensing is significantly impacting the speeding up of acquisitions in various medical imaging domains such as magnetic resonance imaging (MRI).

In the current decade, AI, which has gained acceptance in the field of diagnostic imaging, is a general term often loosely associated with (among others) deep learning (DL), deep reinforcement learning (RL), artificial neural networks (ANNs), and traditional ML methods. AI techniques are used in Internet search engines and speech recognition as well as in the analysis of genetic data, photographic images or financial transactions, humanoid robots, and self-driving cars. In fact, the recent resurgence of ANNs in the form of deep neural

networks [14], [15] started in the speech processing community [16].

ML has been the workhorse in diagnostic imaging, particularly in medical image understanding. The robust extraction of information is a fundamental task in medical image analysis and supports the entire workflow, including screening, diagnosis, patient stratification, therapy planning, intervention, and follow-up. Current state-of-the-art solutions in medical imaging are based on ML [17], and, although ML algorithms have been used for some time in segments of the imaging field, new ML methods, e.g., DL, are much more powerful. In the next five to 10 years, AI is expected to fundamentally transform diagnostic imaging [18]. AI will provide radiologists with all the tools necessary to meet the rising demand for diagnostic imaging and actively shape the transformation of radiology into a

data-driven research discipline. AI algorithms will help speed up clinical workflows and prevent diagnostic errors, thus enabling sustained productivity increases. Above all, AI methods could lead to more precise results and more meaningful prognostic risk scores and integrate diagnostic radiology even further into outcome-oriented clinical decision making. AI could potentially improve the outcomes that truly matter to patients, i.e., avoiding unnecessary interventions, prioritizing complex/acute cases, and so on. From the perspective of its technological impact on health care, the scope of AI techniques covers a broad set of categories, such as

- scanner technologies for acquisitions, reconstructions, and workflow automation
- radiology reading, postprocessing of medical images, and/or guidance
- patient-centric approaches for clinical decision support
- population health management.

However, for AI solutions to deliver on these high expectations and fulfill its potential, understanding its limitations is important. There are a number of challenges that must be overcome by aca-

demia and industry before AI solutions can live up to their promises in diagnostic imaging. Perhaps the most important of these is gaining access to large quantities of high-quality data. DL is a data-hungry ML technique; therefore, a large amount of high-quality data that covers the whole problem space is essential. This also implies that, in medical imaging, DL solutions must be robust enough to class imbalances according to a number of reasons—one being the possibility of rare pathologies.

Bias in the data (whether implicit or explicit) based on demographics, age, gender, and so on must be addressed in an appropriate manner. If bias in the data is not addressed appropriately, the generalizability of AI solutions will be limited.

In medical imaging, variability in the data because of differences in scanner models, acquisition protocols, and reconstruction

protocols could limit the optimality and generalizability of DL solutions. This is especially challenging with MRI data; therefore, DL approaches that can seamlessly accommodate the protocol variations in an optimal manner are desirable. The integration and standardization of heterogeneous data (including imaging and nonimaging data) will be essential in enabling DL-based approaches for heterogeneous data.

In addition to the large quantities of high-quality data required, a number of current DL solutions (i.e., supervised learning methods) require the availability of high-quality and accurate expert annotations/labeling. In many scenarios, however, this may be inaccessible or cost-prohibitive to gather. Algorithms that use weak labeling or other viable proxies for the ground truth as well as supplementary corroborating sources could be a potential avenue of research. Semisupervised/unsupervised learning or one-/few-shot learning solutions could help alleviate the problems associated with a lack of annotations.

Aside from the significant challenges arising from the requirements of high-quality data and annotations, there

are a number of open problems inherent in an AI system. An oft-cited (and debated) topic is the “black box” nature of DL solutions. For DL methods to gain the trust of its consumers, it is important that the system explains its predictions. In addition to explaining its predictions, augmenting them with a confidence level will help the consumer take accurate and appropriate actions. There has been progress in academia along these lines in Bayesian DL. Another important aspect at the system level, especially for AI solutions in diagnostic imaging and health care, are built-in safety checks and fallbacks. The axiom, “first, do not harm,” is appropriate and applicable for AI-based methods. For any AI technique used in diagnostic imaging, we must adopt the axiom “if it does not help, it does not hurt.”

AI-based approaches in medical imaging have shown great empirical success. Unlike the two example technologies cited previously (which are rooted in strong mathematical foundations), DL solutions have further to go in terms of theoretical and mathematical understanding. Hopefully, the recent question raised at NIPS 2017 [19], “Has machine learning become alchemy?” motivates and accelerates scientific progress in the understanding and solving of open problems in AI.

Wireless autonomous systems

Wireless networking and autonomous systems are rapidly converging and drawing upon many aspects of SP, including communications (physical layer to network management), sensing (active, passive, and fusion), perception, mobility (navigation, control), and human-machine interaction. This convergence is leading to distributed intelligent systems that are rich with SP challenges, whose goals include rapid human-machine teaming, robust wireless networking, environmental sensing and perception, and other, more advanced collaborative behaviors. At the core of many of these SP challenges are problems in AI, ML, and RL.

On the one hand, wireless networking, especially mobile ad hoc networks (MANETs), are building on many SP

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advances in cognitive radio; dynamic spectrum access; array processing; and multiple input, multiple output. On the other hand, autonomous systems are building on many SP advances in vision, planning, collaborative control, distributed optimization, and perception. The combination and rich interplay between wireless networking and autonomy will enable both to advance well beyond the respective state of the art in each. Collaborative autonomy requires networking, while mobile ad hoc networking can be dramatically enhanced and enabled by incorporating mobile autonomous agents into the network. Autonomy enables networking, and networking enables autonomy.

Commercial networking is built on a massive, wired worldwide infrastructure that supports the semimobile cellular system, where mobile users have a one-hop wireless link into a nearby fixed site. Commercial wireless has steadily progressed to multiradio diversity (e.g., cellular, Wi-Fi, and Bluetooth), and this multiwavelength approach enables an overall system that is robust, diverse, and responsive. There are many cases in which autonomous agents may not have access to the commercial network, it is not sufficient to support autonomous operations in a challenging environment, or when the commercial infrastructure is damaged or failing, such as during a natural disaster.

The autonomy-network coupling raises many interesting interdisciplinary problems, with SP being at the core. MANET robustness and management can be dramatically enhanced by introducing autonomous agents for topology control and networking healing [20]. Furthermore, an autonomous mobile infrastructure with cognitive radio and array processing may lead to unprecedented MANET performance that pairs with an overall intelligent system objective and autonomously adapts across the physical layer, media access control, and higher layers. To achieve a desired autonomous system behavior in nonstationary and time-varying cases, the overall goal may be robustness and reliability rather than some form of short-term optimality. RL provides the

necessary tools for developing appropriate distributed policies. SP is also needed to provide networked geolocation, distributed sensing, and mapping, and the interplay of these with mobile networking and collaborative processing provides many open problems.

Wireless ad hoc networking will benefit significantly by incorporating hybrid cognitive multiradio approaches that use different wavelengths for different purposes. Traditional microwave frequencies provide high-bandwidth local connectivity. Low frequencies [e.g., lower very high-frequency (VHF) band] provide long wavelength signals that penetrate structures and buildings with relatively little multipath, and new miniaturized antennas enable efficient narrow-band low-VHF communications on small platforms [21]. Optical transceivers

opportunistically provide high-bandwidth line-of-sight communications. SP is necessary for developing hybrid networking approaches that combine all of these approaches for robust wireless autonomy.

Distributed optimization and processing are very active SP research areas that often rely on a nearest-neighbor-based iterated-processing paradigm. However, algorithms such as consensus are not necessarily scalable nor readily applied in a mobile ad hoc setting and require a large communications load for convergence. Consensus typically assumes a particular communications protocol, whereas the adaptive combination of autonomy, mobility, and distributed processing is relatively unexplored. One approach enforces only local consensus [22], although wireless configurations and routing ideas can provide more general techniques [23]. There are many open questions regarding the combination of communications protocols and cognitive radio tools, handling-channel variation, rate, delay, and multiuser interference. General heterogeneous distributed processing

opens questions in information extraction, abstraction, and learning, and resource-constrained SP accounting for networking, power, and computational resources.

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Correction

The "Lecture Notes" article that was published in the January 2019 issue of *IEEE Signal Processing Magazine* [1] contains an error in the last line of the caption of Figure 2, page 157: the word *because* should be *whenever*.

The correct caption of Figure 2 is as follows:

Additionally, if P approaches the corner $(1, 0)$ by the fourth quadrant, i.e., the lower-right triangle that forms the paraconsistent plane, a linear classifier solves the problem whenever, in that region, $\beta = 0$, i.e., no interclass overlap exists.

Subsequently, the text on page 158, left column, fourth row after the equations, is amended as follows:

Therefore, since the smallest among the distances places P closer to $(1, 0)$

than to the other corners and P is in the fourth quadrant with $\beta = 0$, the features are linearly separable, thus providing an accurate classification based on a modest strategy.

Reference

[1] R. C. Guido, "Paraconsistent feature engineering," *IEEE Signal Process. Mag.*, vol. 36, no. 1, pp. 154–158, 2019.

