Wave Engineering meets Information Science: How to Fully Reap the Potential of Artificial Intelligence for Programmable Metamaterials

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This paper emphasizes the importance of designing wave systems with an end-to-end vision of the information flow for the targeted applications. Focusing for concreteness on programmable-metamaterial hardware which is expected to become a pivotal ingredient of upcoming wireless systems for information extraction and transfer (e.g., in 6G networks), the role of artificial-intelligence tools to design task-specific metamaterial configurations despite the overwhelming system complexity is discussed.

Introduction

The concept of "information" is to date not very present when wave engineers and wave physicists conceive imaging modalities or design antennas. Yet, the ultimate purpose of such systems and devices is to extract or transfer information through tailored wave-matter interactions. In other words, most wave engineers judiciously design systems to mold the flow of information without explicitly thinking about information. In fact, my question "what is information?" in job interviews is usually met with a blank stare. A basic understanding that information captures the amount of surprise in a signal is not routinely conveyed to engineering and physics students.

Modern wave-engineering challenges are usually overwhelmingly complex; consider, for instance, the recognition of human postures in complex indoor environments or the transmission of data in dynamic and spectrally congested settings. The conventional approach of seeking analytical descriptions and solutions of such complex problems is intractable here. Instead, it becomes increasingly important to take a step back and adopt a more abstract interpretation of the problem in terms of information flow: what information is supposed to be extracted and/or processed and/or transmitted and what physical and digital operations act upon it? Once this is understood, the modern wave engineer can leverage artificial-intelligence (AI) tools to cope with their large data sets and complex problems. Beyond conceiving hardware, the modern wave engineer must increasingly also think about how to make optimal use of their (tunable) hardware. For instance, given programmable metamaterials, what is the best deployment mode in a specific problem?

In this paper, I provide conceptual guidance and sign posts to help wave engineers fully reap the potential of AI in their work. After a brief introduction to AI, I discuss the three possible use-cases of AI in wave engineering as (i) a surrogate inverse model, (ii) a surrogate forward model, and (iii) an end-to-end optimized hybrid analog-digital pipeline. The latter directly integrates tunable physical parameters such as the configuration of a programmable metamaterial into an AI pipeline. Thereby, the physical hardware becomes task-aware, which is the basis of fully reaping the potential of programmable metamaterials for complex communications, imaging and sensing tasks.

What is inside the AI black box?

So, to start, let's open the black box that is AI. What is AI? The media often portray AI as an obscure concept that could one day take over the world. But, seen from a conceptual standpoint, AI is just a very elaborate function-approximation technique. A typical

exercise in freshman lab is to study the displacement y of a spring that is subject to a force x, and to perform a linear regression analysis $y=kx$ to estimate the spring constant k. The students thus fit a model $(y=kx)$ with a single free parameter (k) to their experimental data. Supervised learning in AI fits a more complex and, importantly, nonlinear model with many free parameters (termed weights) to training data. Elaborate algorithms like error backpropagation can efficiently identify the weights and have been known for decades [1]. However, only recently the necessary computational power and large data sets became available to achieve the impressive AI results that fueled the proliferation of AI in all areas of science and engineering.

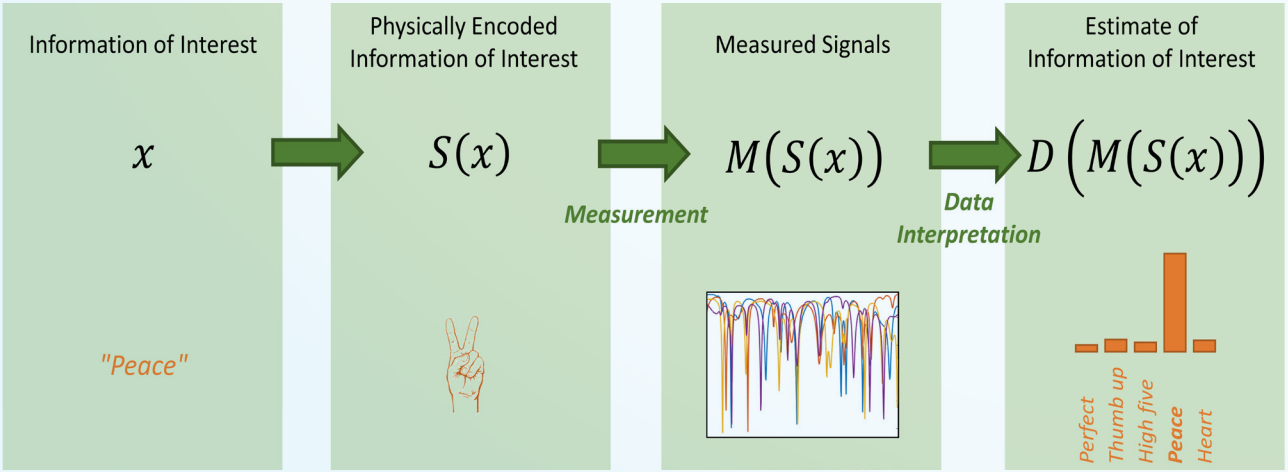
What roles are there for AI in wave engineering?

To understand the various potential roles of AI in wave engineering, let's focus for concreteness on an information-extraction problem such as imaging a hand to recognize a hand sign. First, we denote the information of interest as x. Second, this information is physically encoded in the scene through a function S, for instance, the fingers of a hand may be arranged such that they display a peace sign S(x), in order to physically encode the information "Peace". Third, we perform measurements by illuminating the scene with waves and (partially) capturing the scattered waves, yielding our measured data. The measurement process can be understood as a function M acting on S(x). Fourth, we perform data interpretation by applying a function D to M(S(x)). This finally yields our estimate $\tilde{x}=D(M(S(x)))$ of x. Figure 1 summarizes this information flow.

Surrogate inverse model

The most common use of AI is at the data-interpretation step in order to learn a function D that inverses the information flow from x via S(x) into M(S(x)), in order to obtain an estimate $\tilde{x}$ of x. Because S and M are in general complicated (and maybe not analytically known) functions, we do not tend to know how to invert them analytically. But using sufficient training data, we can train an AI model that approximates the inverse of this information flow. Such an AI model is known as surrogate inverse model and will be used as D in the data interpretation step from Figure 1. Learning surrogate inverse models is the fundamental idea underlying the use of AI in the field of computer vision.

In electromagnetism and other areas of wave engineering (acoustics, etc.), of course, it is also often necessary to approximate the inverse of M(S(x)). One example from my own research was our demonstration of achieving deeply sub-wavelength resolution without using evanescent waves [2]. We hypothesized that if a scene was placed inside a reverberant enclosure as opposed to in free space, then the waves used to probe the scene would ricochet inside the enclosure, encountering the scene multiple times and hence developing a greater sensitivity to sub-wavelength scene details. We were convinced that reverberation yields an interferometric sensitivity that more efficiently encodes sub-wavelength information in the measurements. However, the measurement process also completely scrambles this information. Hence, we trained an AI model to approximate the function D that would unscramble the measured signals of our reverberation-coded aperture. Indeed, this enabled us to confirm our hypothesis and unveil a fundamental relation between reverberation, sensitivity and achievable resolution.



I Figure 1 : Information flow in a generic information-extraction problem. Wave engineering intervenes at the measurement step, e.g., with respect to how to illuminate a scene with programmable-metamaterial hardware to recognize a hand sign.

" Nowadays, the information at hand gets increasingly complex, such that it becomes increasingly important (if not inevitable) to intelligently use available hardware (e.g., a programmable metasurface). "

But using AI as surrogate inverse model is only the most basic purpose that AI can serve in wave engineering. Many groups still limit themselves thereto, without being aware of the more advanced roles that AI can play which are detailed below.

Surrogate forward model

A second use case for AI in wave engineering is to approximate the function M, i.e., to learn a surrogate model of a physical forward process that is too complicated to be described analytically. Again, of course, a large and representative training data set is required to successfully learn such a model. This approach is helpful to predict the scattering properties of a parametrized scattering system. For example, nanophotonic design procedures increasingly rely on learned surrogate forward models of electromagnetic solvers [3–5]. Another timely example is the use of a programmable metasurface (PM) to massively parametrize a wireless propagation environment. The vision of this research thread is a smart radio environment [6] whose propagation properties are customized by tailoring the PM configuration to the needs of a wireless functionality that is desired to facilitate communications, sensing, etc. The PM contains hundreds of elements with individually adjustable scattering properties [7], and their impact on a wireless channel is, in general, highly nonlinear [8]. This should not be confused with the linearity of the wave equation: while the input-output relation of the channel is linear, the dependence of the channel on parameters of the electromagnetic environment is in general nonlinear. In order to capture how a wireless channel of interest in a complex indoor environment depends on the configuration of a PM, the most convenient approach may thus be to train in situ a surrogate forward model mapping a PM configuration to the corresponding wireless channel state.

End-to-end optimized hybrid analog-digital pipeline

Each of the previous two approaches only focuses on one specific step of the information flow in Figure 1. By separately treating measurement and data processing, many research groups deprive themselves to date of fully reaping the potential of their hardware. If the measurement process is optimized independently from data interpretation, then the measurement is task-agnostic and it is impossible to distinguish between task-relevant and task-irrelevant information during the measurement. Consequently, one acquires unnecessary task-irrelevant information and more measurements are needed to capture enough relevant information. Ultimately, the acquisition of irrelevant information deteriorates the latency as well as other metrics (processing burden, power consumption, memory usage, …).

Consider the case of computational imaging with PMs. Therein, a PM is used to sculpt the waves that illuminate the scene during the measurement process. Typically, a known series of random PM configurations is used to perform "compressed sensing" [9]. The measured data is then often interpreted using an AI-based learned surrogate inverse model for D. But the random scene illuminations, captured by the measurement function M, are completely agnostic to our task of, say, recognizing a hand sign.

How can we do better? "Learned sensing" formulates a single pipeline that includes both M (with trainable physical weights) and D (with trainable digital weights), mapping S(x) to $\tilde{x}$. Based on training data, one can then simultaneously optimize all weights in this end-to-end pipeline, i.e., both the physical measurement and the digital processing steps. Thereby, the measurement is automatically tailored to the task such that it will highlight salient scene features, converting the measurement into an analog over-the-air wave processor. Ultimately, more task-relevant information is acquired per measurement such that remarkably fewer measurements are needed to answer the task [10].

Incidentally, to formulate the end-to-end pipeline, a differentiable forward model of the measurement process is needed. Where this cannot be formulated analytically, one can learn an auxiliary surrogate forward model for that purpose (see above).

This "learned sensing" approach, in contrast to a task-agnostic conventional "compressed sensing" approach [11], is a powerful example of how the potential of a given hardware, e.g., a PM, can only be fully reaped through an end-to-end optimized approach. PM hardware has been around since at least 2014 [7] but only now do we know how to make full use of it by tailoring its configuration in situ to a specific task. The direct integration of programmable meta-atoms into an AI pipeline merges the worlds of wave engineering and information science. Interestingly, the use of AI does not preclude intuitive insights into the optimal metamaterial configurations: trends in their "macroscopic" properties, ●●●

for instance, how their overlap and intensities are adapted to noise, can be comprehended [12].

Conclusions

The ultimate purpose of most efforts in wave engineering is to mold the flow of information through tailored wave-matter interactions. Nowadays, the information at hand gets increasingly complex, such that it becomes increasingly important (if not inevitable) to intelligently use available hardware (e.g., a PM). Hybrid end-to-end pipelines capture the flow of information in its entirety and thereby enable task-specific hardware configurations that fully reap the potential of PMs. The work of a modern wave engineer is increasingly multidisciplinary and requires awareness of the concept of "information". To solve the challenges of tomorrow, an information theory of waves in matter is needed. In my own "Intelligent Wave Systems" research group, I seek to establish a culture in which we always think about the information flow in its entirety to guide our understanding and conception of wave systems. ■

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Résumé

Exploiter pleinement les avantages des métamatériaux programmables pour l'extraction d'informations (imagerie, détection, localisation) ou le transfert d'informations (communications sans fil) nécessite une optimisation de bout en bout du flux d'informations, ce qui inclut les couches physiques et numériques. Une synergie délibérée entre l'ingénierie des ondes et la science de l'information est donc essentielle pour faire face aux problèmes complexes de l'ingénierie de demain. Les outils d'intelligence artificielle permettent aux ingénieurs des ondes d'optimiser les processus de mesure spécifiques à leur tâches malgré la complexité (souvent insoluble sur le plan analytique) de la couche physique impliquant des métamatériaux programmables ainsi que des tâches. ■

Abstract

Fully reaping the benefits of programmable metamaterials for information extraction (imaging, sensing, localization) or information transfer (wireless communications) requires an end-to-end optimization of the information flow, including physical and digital layers. A deliberate synergy of wave engineering and information science will be pivotal to face the complex engineering problems of tomorrow. Artificial-intelligence tools allow wave engineers to achieve optimized task-specific measurement processes despite the (oftentimes analytically intractable) complexity of programmable-metamaterial hardware and task. ■