SPIE School of Physics
November 9-11

SPIE Student Chapter Delft

ABSTRACTS

Prof. dr. Carl Bender

Washington University in St. Louis

Part 1: Wednesday November 9, 14:00-17:00
Part 2: Thursday November 10, 9:30-12:30

How to sum a series (1) if it converges and (2) if it diverges

It almost never happens that one can find the exact analytical solution to a research problem in physics. Usually, the best one can do is to obtain an accurate approximation to the exact solution. The standard approach is to use perturbation theory, but perturbation series almost always diverge, and even if they converge, they often do so painfully slowly. Therefore, it is important to know how to extract information from a slowly convergent or a divergent series. In these lectures we introduce methods for accelerating the convergence of a slowly converging series (Shanks transformation, Richardson extrapolation) and for making sense of and summing a divergent series (Borel and Padé summation).

Prof. dr. Ari Friberg

University of Eastern Finland

Thursday November 10, 14:00-16:00

Geometric Phase and Complementarity

We begin by analyzing the intensity and polarization-state modulations in vectorial Young's dual-pinhole interference and the consequent emergence of the Pancharatnam-Berry geometric phase and the vector wave-particle complementarity. We then examine the intrinsic properties of three-dimensional (3D) light fields whose polarization state does not admit the conventional beam-field representation. Finally, we explore polychromatic surface-plasmon polariton (SPP) fields, establish methods of tailoring their coherence and polarization features, and illustrate planar SPP fields that exhibit orbital and spin angular momentum.

Dr. Stefan Witte

VU / ARCNL

Friday November 11, 9:30-12:30

Imaging with and without lenses

ABSTRACT FOLLOWING SOON

Dr. Yifeng Shao

Utrecht University / TU Delft

Friday November 11, 14:00-16:00

New paradigm for solving inverse problems: Combining physics knowledge with AI by automatic differentiation

Conventionally, solving inverse problems requires iterative optimization based on a model that simulates the processes of measurement, and building the model requires the knowledge of physics to describe the simulation by mathematics for implementation. Such a procedure often faces two challenges: finding the proper mathematical description and performing the simulation both efficiently and accurately. In the contrast, artificial intelligence (AI), e.g., (deep learning) neural networks, allows building models to approximate the processes of measurement using the knowledge learned from the data.

It is thus of great interest for researchers in various fields to design hybrid models that can benefit from both the physics knowledge accumulated in human history and the flexibility AI offers. In ideal cases, one prefers to describe the measurement processes by physics knowledge, while replacing some key parts of the model with AI. However, integrating AI into conventional models remains a challenge as the optimization relies on computing the gradients of the variables in the models using analytical formulas derived by hand. On one hand, as the model complexity increases, the tedious hand derivation is increasingly impossible. On the other hand, because AI can only be treated as black boxes, in which the derivative of the input with respect to the output is not explicitly known, the chain rule breaks for models involving AI parts.

The remedy to this issue is to build the model, in the conventional sense, on a mainstream AI platform, like *TensorFlow* or *PyTorch*, that provides automatic differentiation (AD) functionality. By designing the model as a concatenation of a series of sub-models and guaranteeing that these sub-models, based on either physics knowledge or AI, are differentiable, one can simulate arbitrarily complex measurement processes and always compute the gradients of the variables by AD. This approach thus provides maximum freedom for solving the inverse problems as one only needs to focus on the simulation model and let AD handle the optimization.

In this workshop, we will introduce applying AD to solving a number of inverse problems on the *TensorFlow* platform. We will illustrate examples from simple cases of solving systems of equations and curve fitting by regression, to more complicated cases of image processing and phase retrieval. We expect the participants to be experienced in programming, preferably in *Python*, and to have a basic understanding of the math for optimization.