A neural network to explore the Fresnel diffraction of a sharp opaque semi-infinite screen

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Abstract: We describe the use of a neural network to investigate a very well-known problem of wave optics, i.e. the diffraction of an opaque semi-infinite screen. The inverse problem is also discussed.

1. Introduction

Wave optics and the study of diffraction are among the most stimulating subjects for a student of physics at Bachelor level. But it is also a demanding one, relying on mathematical prerequisites of electromagnetism and wave physics. A problem apparently as simple as the image of a semi-infinite opaque screen edge illuminated by a coherent light is not intuitive to solve and the analytical solution requires specific integral functions known as Fresnel integrals [1, 2].

In this context and taking advantage of the celebration of the bicentenary of Augustin Fresnel's pioneering work, awarded in 1819 by the Grand Prix of the Academy of Sciences, we wanted to test with a group of physics students the possible use of artificial intelligence. This subject is currently in the media spotlight through its use in social networks, in innovative companies or for image recognition and processing.

We will describe the physical problem that we tackled in the context of a supervised research project for a Bachelor's degree and its academic treatment, before describing the solution based on a neural network. We will then test the ability of the neural network to efficiently predict the diffraction pattern, as well as the possibility of extracting from an unknown diffraction pattern the distance to the diffracting object.

2. Problem under investigation and tools

Figure 1a shows the well-known diffraction problem we have been studying, i.e. the pattern resulting from the diffraction by an opaque screen edge illuminated at normal incidence by a monochromatic plane wave of wavelength λ. We observe this pattern at a distance z from the screen. Such a configuration was known to the students who had the opportunity to work on it both in lectures and in tutorials and they were aware that the resulting oscillating intensity profile $I(x')$ (Fig. 1b) can be expressed in terms of Fresnel integrals C_f and S_f [3]:

$$I(x',z) \propto \left[C_f\left(\sqrt{\frac{2}{\lambda z}}\, x'\right) + \frac{1}{2} \right]^2 + \left[S_f\left(\sqrt{\frac{2}{\lambda z}}\, x'\right) + \frac{1}{2} \right]^2 , \qquad (1)$$

which can then be graphically interpreted with the help of the clothoid plot or Euler spiral.

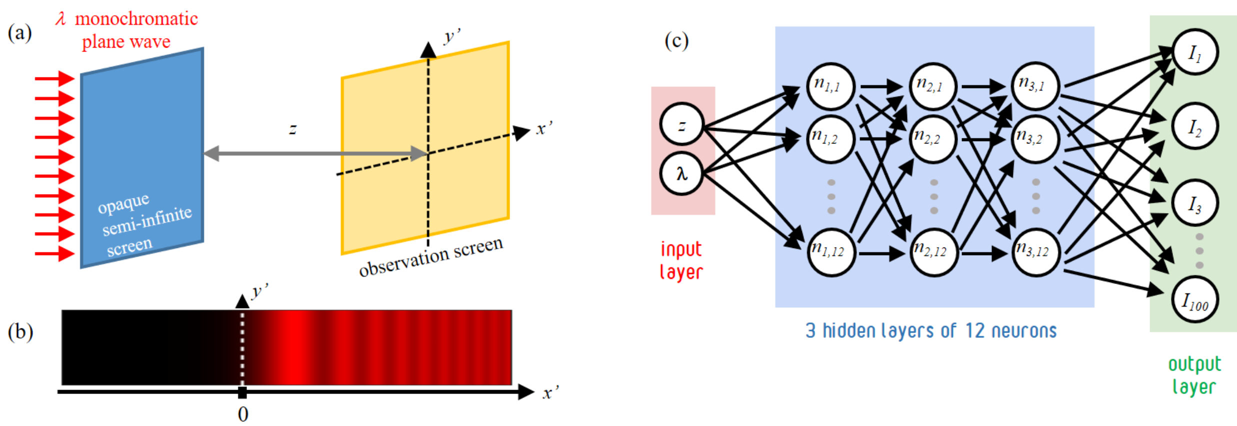

Fig. 1 **(a)** Problem under investigation. **(b)** Diffraction pattern typical of the semi-infinite screen. **(c)** Artificial neural network used to predict the output intensity profile.

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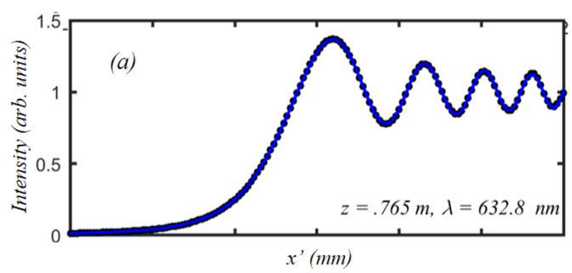
Artificial intelligence was a subject to be discovered completely by our students, as their degree only includes the basics of programming. The essential building block of the neural network is the artificial neuron. Such a neuron has several inputs, e_1, e_2, ..., which are linearly combined by weighting them with values w_1, w_2, ..., w_n and with a possible bias b [4]. The output s of the artificial neuron is the result of this combination by an activation function f such as a sigmoid function. The neural network results from the arrangement of several artificial neurons and efficient structures can be achieved when neurons are spread over several layers (Fig. 1a). The number of connections is then increased, which requires powerful algorithms to determine the optimal structure to match inputs and outputs: this is the learning stage that relies on a large dataset. In our case, the input parameters were the distance between the screen and the observer and the wavelength of operation whereas the output was the intensity profile discretized over 100 points. A dataset of 220 examples was involved.

In terms of software implementation, taking into account the computer skills of our students, we have opted for the open-source library *nnet* in octave language that can be run on laptops with modest performances. A solution in Python is of course totally feasible, especially since this language dominates in the artificial intelligence community.

3. Results

We first tested the neural network on a perfect case, i.e. on a dataset consisting of noiseless diffraction patterns - the analytical solution of Eq. (1). We compared Fig. 2a the profiles found for values not used for training: the network predictions and the analytical solution are in perfect agreement. This demonstrates its universal interpolation capability. Additional tests were performed on data affected by various sources of noise. Despite the imperfect quality of the training data, the network is able to predict the diffraction patterns efficiently: the network is found to be even able to denoise the experimental recordings to some extent, making them closer to the analytical pattern.

We then turned our attention to the inverse problem, i.e. determining from a recorded diffraction pattern the distance and the wavelength. Such a problem requires a priori the use of another neural network, where the input is now the discretized intensity profile, while the output parameters are the wavelength and the distance. From their first investigations, the students could notice that there were problems with the learning stage. Indeed, from Eq. (1), the wavelength and the propagation distance play a similar role. In other words, for a given diffraction pattern, there are an infinite number of possible combinations of λ and z. Given the previously highlighted constraint, we evaluated the ability of the network to recover the propagation distance for a fixed wavelength. The error between the distance predicted by the network and the actual distance (Fig 2b) is remarkably small (well below 1 mm), validating the recognition of noiseless patterns.



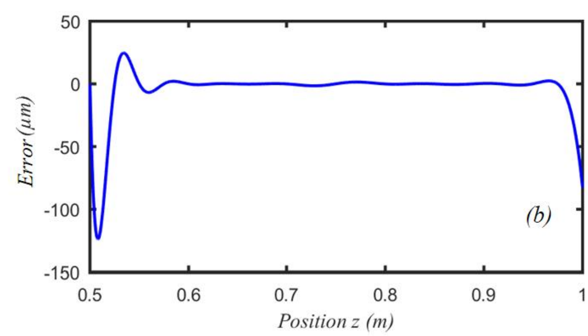


Fig. 2 (a) Comparison of the prediction of the artificial neural network (blue line) with the analytical prediction (black circles). **(b)** Error in the distance z retrieved from the neural network according to the distance z.

To conclude, this few-days project made it possible to introduce the interest of machine learning techniques using the example of a known optical problem. Without going into the details of the algorithms and with only a few lines of code, the students were able to identify the potential usefulness for the recognition or prediction of a diffraction pattern. The students were able to finish the project by reading some recent research papers using artificial intelligence to provide new advanced ways to engineer the various degrees of freedom of light [5, 6].

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