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Shock Properties Characterization of Dielectric Materials using Millimeter-wave Interferometry and Convolutional Neural Networks

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Abstract: In this paper, a neural network approach is applied for solving an electromagnetic inverse problem involving solid dielectric materials subjected to shock impacts and interrogated by a millimeter wave interferometer. Under mechanical impact, a shock wave is generated in the material and modifies the refractive index. It has been recently demonstrated that the shock wavefront velocity and the particle velocity as well as the modified index in a shocked material can be remotely derived from measuring two characteristic Doppler frequencies in the waveform delivered by a millimeter-wave interferometer. We show here that a more accurate estimation of the shock wavefront and particle velocities can be obtained from training an appropriate convolutional neural network, especially in the important case of short-duration waveforms of few micro-seconds.

Keywords: convolutional neural network, shock properties, mm-wave interferometry, metrology, shock velocity, particle velocity, shock permittivity.

1. Introduction

The physical understanding and modelling of the shock wave propagation in solids has many applications in defense, aeronautics, space and civil areas. In order to simulate the behavior of solids subjected to an impact, it is mandatory to know the mechanical and thermodynamic properties of the pristine and shocked materials. According to the well-documented theory (see, e.g., [1]), the shock wave in a dielectric material acts as a moving dielectric interface (or boundary) that propagates faster than the sound in the shocked solid. In the region behind this interface, called the shocked medium, the wave modifies the refractive index of the solid at rest. Moreover, the mechanical impact gives motion to the material and consequently, it creates a discontinuity in the velocity profile. The velocity of the shocked medium is called the *particle velocity*, and the fundamental relationship between the shock wavefront velocity V_1 and particle velocity V_2 is called the shock polar of the material, which can be approximated as follows [2] :

$$V_1 = C_0 + s.V_2 \quad (1)$$

where C_0 (m.s⁻¹) denotes the speed of sound in the pristine medium at the reference state (i.e., in the solid at rest) and s is a dimensionless constant. The determination of C_0 and s has been the subject of many studies (see, e.g., [2]) and is usually performed from the measurement of V_1 and V_2 [3, 4] by using research guns with light gas or powder [5], laser shock [6] or explosives set-ups [7]. Non-invasive techniques has reported to remotely and simultaneously derive the shock wave velocity V_1 , the particle velocity V_2 and possibly the refractive index N_2 of the shocked medium from the measurement of two Doppler frequencies in the waveform delivered by a radiofrequency interferometer [8-13]. The method in [8] consists of detecting the two Doppler frequencies in the waveform by a fitting process using the linear combination of two sine functions. The Figure 1 shows the teflon dielectric waveguide with a variable length (ranging from 2 m to 5 m according to the needs) used for guiding the millimeter waves to the dielectric sample under shock, and the 16 mm diameter and 80 mm long teflon cone glued at the back side of the target to ensure the transition between the dielectric waveguide and the dielectric

sample surface. The dielectric cone transition allows delivering the millimeter wave generated by the interferometer into the sample during a mechanical impact and to collect the electromagnetic waves reflected by the shocked medium and the surface of the metallic impactor. The impactor is propelled by the Pyrene gas gun and creates a shock at the front surface of the sample, opposite to the dielectric cone interface. We have observed that, for waveforms of sufficiently long duration ($> 5 \mu\text{s}$), the detection and accurate estimation of two Doppler frequencies from this fitting technique are possible (see, e.g., [9] and [10] for the investigation of shocked PolyMethylMetAcrylate dielectrics and TriAminoTrinitroBenzene solids, respectively). However, as the waveform duration decreases and is only of few microseconds, even less than pulsation period, lower Doppler frequencies may not be accurately estimated and consequently, the wavefront and particle velocities V_1 and V_2 cannot be derived from the fitting technique reported in [8]. Short-duration waveforms occur in many circumstances. For instance when the waveform to be processed is only of 1/4 time period long due to dielectric losses. Therefore, it is crucial to extend significantly the applicability of millimeter-wave interferometry to the analysis of very short-duration waveforms of few microseconds. An Artificial Neural Network technique is proposed in this paper to derive V_1 , V_2 and the refractive index N_2 as output neurons of shocked media from time-domain samples of waveforms as input neurons delivered by a millimeter-wave interferometer.

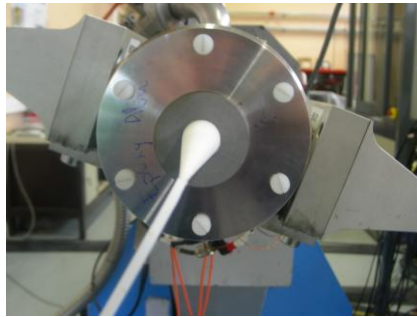


Figure 1. Detail of the experimental setup to estimate the shock wavefront and particle velocities in dielectric materials using a 94 GHz interferometer [8].

Fully dense Neural Network (NN) models have been applied in [14 - 19] to extract frequencies of interest from some waveforms, but these models are not suitable here. As they require a fixed number of input neurons, these models cannot process waveforms with variable number of samples. An alternative NN technique consists of using Convolutional Neural Network (CNN) models (see, e.g., [18, 19]). We show in this paper that the accurate estimation of velocity V_1 of the shock wavefront, the particle velocity V_2 and the refractive index N_2 of the shocked medium can be estimated from a dedicated CNN, especially for waveforms less than a pulsation period.

The manuscript is organized as follows. Section 2 describes briefly the previously reported method used to derive the shock wavefront and particle velocities from the estimation of two Doppler Frequencies, and discusses the limitations of this method. Section 3 describes the development of a new method based on Convolutional Neural Networks to overcome the limitations of the previously reported method. In Section 4, the performances of the two methods are compared for the derivation of the shock wavefront and particle velocities from the same set of measured waveforms.

2. Shock Wavefront and Particle Velocities Derived from Doppler Frequencies

The shock wavefront in a dielectric material is usually modeled by a moving interface (see, e.g., [20]), which separates the material in two dielectric regions: the region in front of the interface is called the *pristine medium* with a refractive index N_1 , while the region behind the interface is called the *shocked medium* with a refractive index N_2 . The incident electromagnetic field is then subjected to the reflection by and transmission through the dielectric interface with a Doppler frequency shift. In addition, the electromagnetic field encounters losses in the material. Two configurations are analyzed throughout the paper: the single and double interface configurations.

In the so-called *single interface configuration*, the dielectric interface models the shock wavefront. It moves towards a millimeter-wave interferometer, and the velocity V_1 of the interface is derived from the extraction of the Doppler frequency shift in the waveform delivered by the interferometer. The extraction requires the prior knowledge of pristine medium refractive index N_1 . The single interface configuration offers an exact solution for the waveform [8], which is used here to investigate the eventual benefits of the Neural Network approach for estimating the shock wavefront velocity V_1 .

The *double interface configuration* takes into account the metallic impactor or the transfert plate. Therefore, in addition to the reflection by (E_R) and transmission through the shockwave interface (E_T), the electromagnetic field transmitted by the interferometer experiences the reflection by and transmission through the moving interface between the shocked medium and the metallic plate (see Figure 2). In this study, the metallic plate is assumed to be perfectly conductive, and consequently total electromagnetic reflection occurs at its surface, called E_{RC} . Following [8], both the velocity V_1 of the shock wavefront and the velocity V_2 of the metallic interface between the impactor (metallic plate) and the shocked medium (second layer) may be derived from the measurement of two Doppler frequencies in the reflected electric field $E_R = E_{R1} + E_{R2} + E_{R3} + \dots$

As illustrated in Figure 3, typical measured waveforms exhibit actually two oscillations, whose frequency and magnitude are used here to estimate the velocities V_1 and V_2 (it is assumed here that refractive index N_1 of the studied pristine material is known). This estimation may be performed from a fitting process which approximates the waveform by the linear combination $s(t)$ of two sine functions given by :

$$s(t) = A_1 \sin(2\pi f_1 t + \varphi_1) + A_2 \sin(2\pi f_2 t + \varphi_2) \quad (2)$$

where the fitting parameters are f_1 and f_2 (i.e., the unknown Doppler frequencies), A_1 , A_2 , φ_1 and φ_2 . We have observed that, for waveforms of sufficiently long duration ($> 5 \mu s$), the fitting process allows detecting the two Doppler frequencies of interest but, as the waveform duration decreases, the accuracy of the lowest frequency estimation degrades gradually and as a result, velocities V_1 and V_2 cannot be estimated precisely.

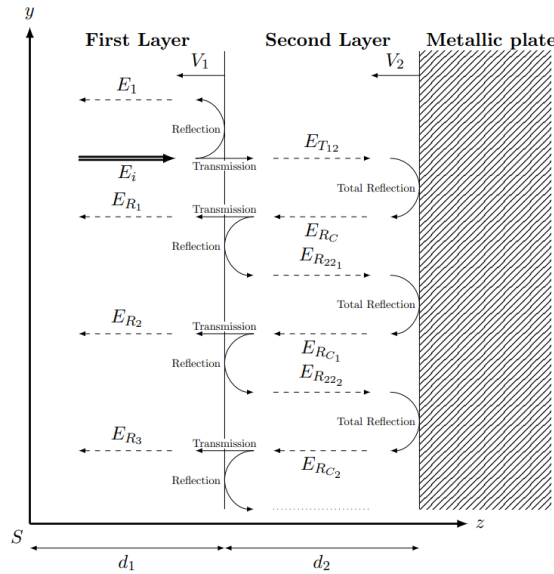


Figure 2. Scheme of the double interface configuration. The incident electric field E_i is normal to the shock wavefront, that is, the moving interface between the First Layer (pristine material) and Second Layer (shocked medium), with E_1 first reflection, E_{Ri} following transmission / reflection / transmission, E_T first transmission, E_{RCi} reflections on the metallic plate.

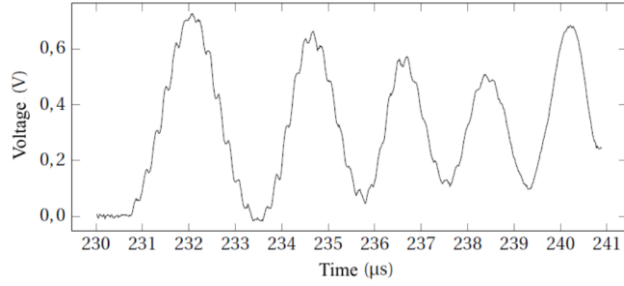


Figure 3. Typical long-duration waveform delivered by a 94 GHz interferometer during impact experiment on a TriAminoTrinitroBenzene (TATB) material (refractive index N_1 is of 1.78). The derivation of Doppler frequencies from the fitting process reported in [8] gives the following estimation: $N_2 = 2.37$ (shocked medium refractive index), $V_1 = 3850 \text{ m.s}^{-1}$ (shock wavefront velocity) and $V_2 = 385 \text{ m.s}^{-1}$ (particle velocity).

3. Shock Wavefront and Particle Velocities Derived from CNN Approach

The proposed approach requires the careful selection of the triplets (V_1, V_2, N_2) that are used in the simplified electromagnetic model of moving dielectric interface(s) reported in [8] for computing the waveforms and training the CNN.

An Artificial Neural Network (NN) with Multi-Layer Perceptron (MLP) [14] is an assembly of layers, each composed of several neurons. As a biological one, each neuron combines linearly the outputs of the previous layer and applies an activation function to obtain the output. This function is often non-linear. Once the architecture of the NN is chosen, the learning process is launched. This stage consists of adjusting the parameters of each node to fit on a combination of inputs and outputs of the network. Here, the input is N samples of the time-domain waveform delivered by the millimeter-wave interferometer during an impact experiment on dielectric materials, and the single output is the velocity V_1 of the shock wavefront, or the particle velocity V_2 , or else the refractive index N_2 of the shocked medium. The Figure 4 shows an example of such NN. It consists of 3 layers: the first one has five inputs and one bias, the second layer has three neurons and one bias and the third layer is composed of one output neuron which provides the estimation of the quantity of interest (that is, V_1, V_2 or N_2). The bias is used to influence the output without interfering with the weights and the inputs. In the second layer, the output of each node is computed as follows using relation (3).

$$\text{Output} = f(w_1 \times \text{Input}_1 + w_2 \times \text{Input}_2 + w_3 \times \text{Input}_3 + w_4 \times \text{Input}_4 + w_5 \times \text{Input}_5 + w_b \times b) \quad (3)$$

where f is the scoring function, b denotes the bias, w_b designates the weight of the bias, Input_i are the inputs i and w_i is the weight of Input_i .

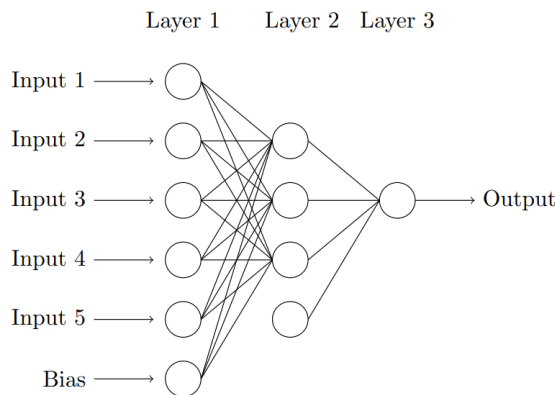


Figure 4. Simple architecture of a Neural Network.

In our investigation, the measurement data used in the input layer of the NN are annotated, i.e. they are known before they are processed in the NN. This case is also known as “supervised learning”, which is generally used to sort two types of problems:

- Regression problems, where the problem is to estimate a quantity variable (V_1 , V_2 or N_2 in our study);
- Classification problems, where the problem is to predict a qualitative variable (i.e. a state, a category, etc.).

For any architecture, it would be possible here to process the waveform as a regression or classification problem because, either it would be possible to obtain the accurate value of a velocity as output after the waveform processing or to determine a range in which the velocity may be included. Anyway, for reasons of diagnostic accuracy, the analysis of waveforms will be considered here as a regression problem.

In view of the state-of-the-art (see, e.g., [15, 16]), a fully connected dense model – i.e. each neuron in a layer receives an input from all the neurons of the previous layer – can accurately estimate the spectral content of some waveforms. The major drawback of this model is that the number of input neurons is fixed and consequently, the same NN cannot process variable number of waveform samples. Another limitation is that NN-based spectral analysis is not automated, so the signal processing is applicable to specific waveforms. Therefore, fully connected dense model is not suitable to solve our inverse problem, either from using regression or classification methods. Another approach, based on a Convolutional Neural Network (CNN), is implemented here for the two configurations described in Section 2. This is a well-known technique in raw signal processing [18, 19]: the convolutional layers are filters that extract patterns from the signal, then these patterns are processed by the dense layers to fit the output. The CNN is implemented here using Python 3.7.6 with the module Keras [21] and the backend TensorFlow [22]. The number of convolutional and dense layers is computed by fitting various architectures on validation waveform data. The architecture of the network is identical for the two configurations:

- In the *single layer configuration*, two networks are studied: the first having the shock wavefront velocity V_1 as single output, the second having only the refractive index N_2 of the shocked medium as output;
- For the *double layer configuration*, three networks are studied: the first network has the shock wavefront velocity V_1 as output, the second one having the particle velocity V_2 , the third one having the refractive index N_2 of the shocked medium.

The waveform samples are normalized from a Glorot normal initialization [23]. This approach was found to be more efficient than a single CNN with two or three outputs. The inputs for the networks are the refractive index N_1 of the pristine material, the operating frequency (94 GHz) of the millimeter-wave interferometer, the time step used for the sampling of waveforms and the samples of waveforms delivered by the interferometer. The final network has four convolutional layers and seven dense layers (see Table 1). Convolutional layers perform the filtering operation, while dense layers create linear combinations with bias. The maximum pooling layer selects the maximum value in a range of neurons. Batch normalization is a well-known technique in neural networks to overcome overfitting which may occur when the algorithm performs well on training data, but performs badly on any other data. This regularization technique allows the algorithm to keep its generalization ability [24]. The global average pooling layer makes the average in the selected range and flattens the filters from the previous convolutional layer to decrease the data size for the next layer and consequently, to reduce the calculation time without interfering with the training process. The Figure 5 sketches the action of every layer.

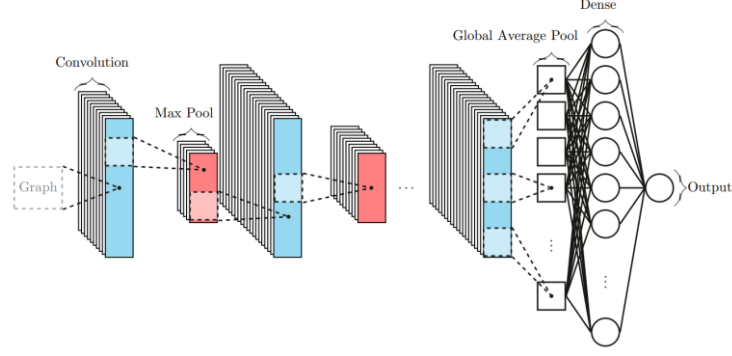


Figure 5. Scheme of the CNN used for determining the shock wavefront V_1 , the particle velocity V_2 or the refractive index N_2 of the shocked medium from waveforms delivered by the 94 GHz millimeter-wave interferometer.

Table 1. Final CNN for each parameter V_1 , V_2 and N_2 as output.

Index of layer	Type of layer	Keras name	Activation function	Properties
1	Convolution	Conv1D	Rectified Linear Unit (ReLU)	72 filters, length 10
2	Normalization	BatchNormalization		
3	Convolution	Conv1D	ReLU	144 filters, length 10
4	Normalization	BatchNormalization		
5	Pooling	MaxPooling1D		
6	Convolution	Conv1D	ReLU	288 filters, length 10
7	Normalization	BatchNormalization		
8	Pooling	MaxPooling1D		
9	Convolution	Conv1D	ReLU	576 filters, length 10
10	Normalization	BatchNormalization		
11	Pooling	GlobalAveragePooling1D		
12	Dense	Dense	ReLU	50 neurons
13	Dense	Dense	tanh	60 neurons
14	Dense	Dense	tanh	40 neurons
15	Dense	Dense	tanh	30 neurons
16	Dense	Dense	ReLU	20 neurons
17	Dense	Dense	tanh	10 neurons
18	Dense	Dense	hard sigmoid	1 neuron

The learning process is performed from the simulated waveforms provided by the electromagnetic model developed in [8]. The model is applied to create waveforms with multiple initial parameters. It allows using larger networks and prevents overfitting, which may occur when a limited number of experimental data is available. Moreover, the main advantage of using simulated inputs for the CNN training is that we can generate large data set which makes possible the derivation of the accurate estimation of velocities or refractive index. The main idea is that the waveform is composed of two main contributions. The first is the electric field directly reflected by the shock wavefront. The second contribution combines multiple reflections of the electric field inside the dielectric sample. For each of contributions, the reflection and transmission coefficients are computed. The adequate number of reflections in the second layer (see Figure 2) is derived from the numerical convergence of the total reflected electric field. Table 2 reports the mean difference between the computed waveforms. The chosen number of reflections in the second layer is set to 4, as the difference with the waveform with 5 internal reflections does not exceed 0.004%. The learning process is performed with Adam optimizer with coefficients given in [25] and with a mean squared error loss. The maximum number of full training cycles or *epochs* is set to 200. However, the learning rate decreases if the loss is constant over five epochs. In practice, the maximum number was never reached, as the loss converged rapidly. To ensure that the

loss is not on a plateau, ten more epochs are computed after reaching numerical convergence. To avoid overfitting, new validation data are computed at each epoch.

Table 2. Mean difference of the total reflection between signals for different number of internal reflections in the shocked dielectric sample.

Number of considered reflections in the second layer	Total reflection mean difference (%)
1 and 2	5.7
2 and 3	0.5
3 and 4	0.05
4 and 5	0.004
5 and 6	0.0004

The refractive index of both the pristine material and the shocked material, denoted respectively by N_1 and N_2 , and the velocity V_1 of the shock wavefront and the particle velocities V_2 are randomly generated for each waveform. The time duration of waveforms is also randomly modified to account for various experimental conditions. The quantities of interest are normalized before the validation step during the learning phase. The boundaries for each parameter are listed in Table 3. These bounds are chosen to be representative of experimental values. Following [26], the refractive index of the dielectric material increases when submitted to a shock wave. Therefore, during the learning stage, N_2 is computed as the summation of N_1 with a random number ranging from 0 to 1.

Table 3. Parameters boundaries for the learning step of the CNN.

Parameter	Minimum value	Maximum value
Material at rest refractive index N_1	1	2
Shocked material refractive index N_2	1	3
Particle velocity V_2 (m s ⁻¹)	300	500
Shock wavefront velocity V_1 (m s ⁻¹)	3000	5000
Measurement duration (μ s)	2	3.5

4. Results and Discussions

4.1. Single layer configuration

To compare the performances of the two methods reported in Sections 2 and 3, that is, the technique based on the extraction Doppler frequencies [8] (DFA, which stands for Doppler Frequency Approach) and the proposed Neural Network Approach (NNA), many random waveforms are computed and processed. With the chosen CNN, the output values are obtained from the predict method from the Keras module [21]. As the fitting process is direct, the value is simply calculated by the Fast Fourier Transform and directly compared with the outputs of the CNN. The procedure is sketched in Figure 6. No difference is obtained between the DFA and NNA for the single layer configuration, as it can be observed from the Figure 7. For the shock wavefront velocity V_1 and the refractive index N_2 of the shocked medium, the two methods give similar results and accuracy. Following this encouraging results, the neural network is applied in section 4.2 to the double layer configuration, which consists of a much more realistic model for the practical situation.

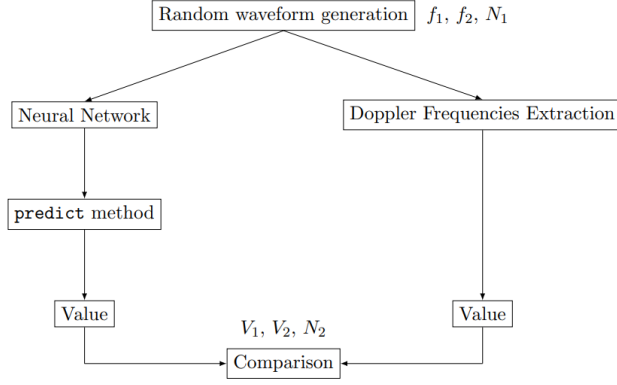


Figure 6. Sketch for the comparison of the Neural Network Approach (see section 3) and the Doppler Frequency Approach (see section 2) applied to the single layer configuration.

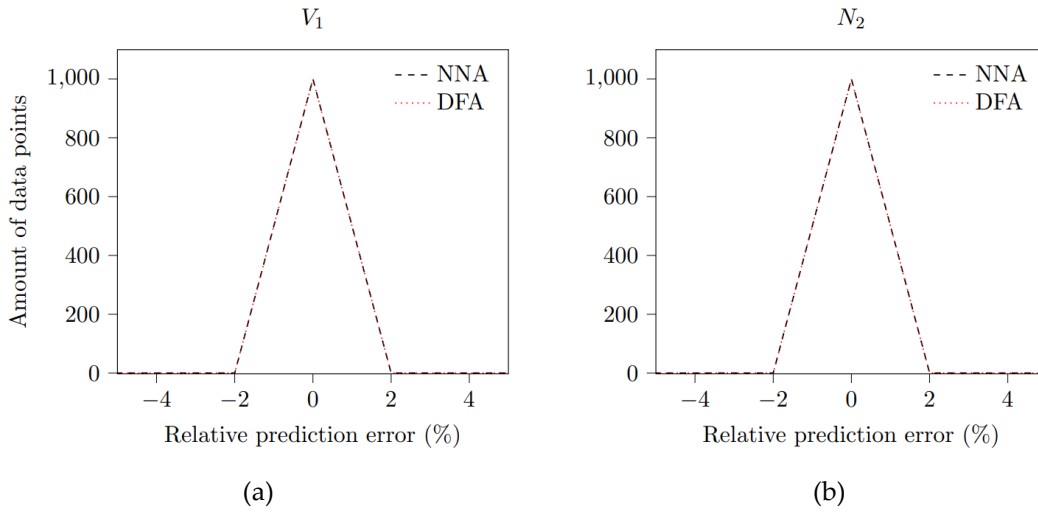


Figure 7. (a) Relative prediction error distribution on V_1 derived from NNA and DF, and (b) Relative prediction error distribution on N_2 determined from NNA and DF (single layer configuration).

4.2. Double layer configuration

For the double layer configuration, many random waveforms are computed from the electromagnetic model reported in [8] and are used for training the CNN. As in Section 4.1, the output values are obtained by using the predict method from the Keras module. For deriving the velocity V_1 or V_2 from the DFA, the resolution is not straightforward: as the number of comparison points increases, the fitting process using two sine functions (see section 2) must be performed automatically by using an initial guess vector for the parameters. The fitted waveform is computed and correlated with the input waveform. Let the correlation coefficient $\rho_{X,Y}$ of two investigated waveforms X and Y be defined as follows:

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} \quad (4)$$

where cov denotes the co-variance operator, while σ_X and σ_Y designate the standard deviation of X and Y . If $\rho_{X,Y}$ is smaller than a prescribed threshold, the input waveform is discarded because the fitting process is considered as unsuccessful. This method is repeated until 1000 waveform samples have been obtained. Two examples of computed waveforms are plotted in Figure 8, as well as the result of the DFA and corresponding correlation coefficients. The procedure is sketched in Figure 9. For comparison purpose, we determine the difference between V_1 , V_2 and N_2 estimated from DFA and NNA, with the exact values selected for the waveform computation. The mean value M of the difference and the standard deviation for each method are reported in Table 4. A systematic error (i.e., the mean is not

zero) is present for both methods but, it is smaller for the NNA than for the DFA. The NNA yields also a smaller standard deviation than the DFA. As expected, the higher the correlation coefficient $\rho_{X,Y}$ (or equivalently, more accurate the derivation of Doppler frequencies and magnitudes), the more accurate the estimation of V_1 , V_2 and N_2 provided by DFA. However, as the correlation coefficient increases, the systematic error on the estimation of V_1 , V_2 and N_2 provided by the NNA is constant, even for short-duration waveforms. In Figure 10, the distribution of the difference between the predicted and true values of V_1 , V_2 and N_2 are displayed for three different correlation coefficients. On one hand, the estimations given by the DFA are found to be either accurate (near the origin) or false (elsewhere). On the other hand, the NNA estimations are quite accurate (the prediction error remains actually between -25% and 25%). As typical experimental values for the correlation coefficient are between 0.9 and 0.99 [10], the NNA should then be preferred when processing short-duration waveforms, especially for estimating the particle velocity V_2 and refractive index N_2 of the shocked medium.

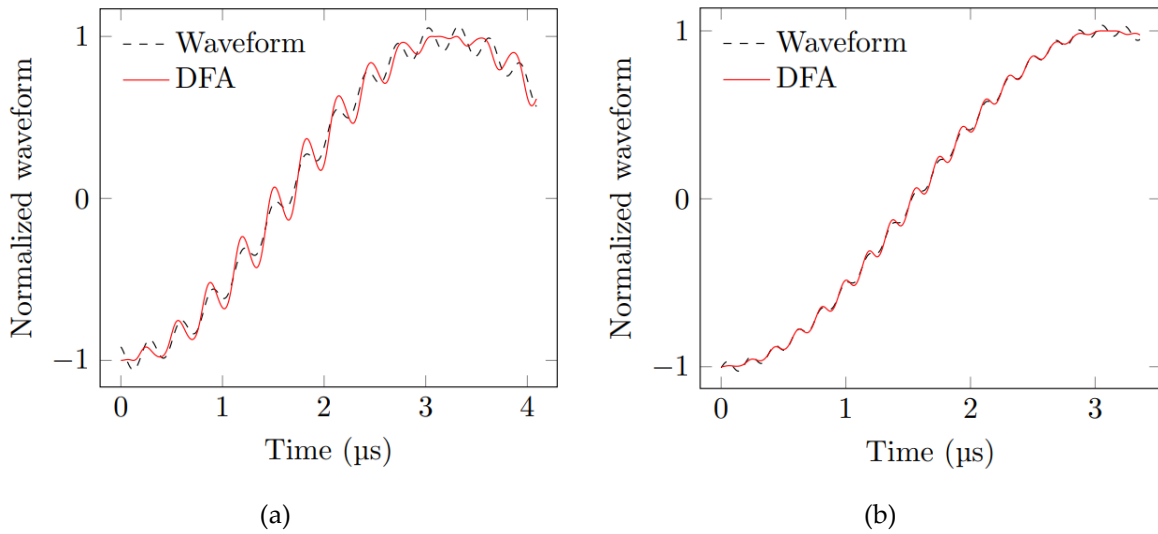


Figure 8. Dimensionless waveforms computed from [8] with $V_1 = 4000 \text{ m s}^{-1}$, $V_2 = 400 \text{ m s}^{-1}$ and $N_2 = 2$ (dashed line) and the waveforms derived from the DFA fitting process (in red line) for various correlation coefficients: (a) $\rho_{X,Y} = 0.997$ and (b) $\rho_{X,Y} = 0.9998$.

Table 4. Mean and standard deviation of the difference between V_1 , V_2 and N_2 estimated from DFA and NNA, with the exact values selected for the waveform computation.

Method Name	V_1		V_2		N_2		$\rho_{X,Y}$
	M (%)	σ (%)	M (%)	σ (%)	M (%)	σ (%)	
Neural Network Approach	-0.1	9.8	0.6	9.4	-0.1	-0.1	0.9
Doppler Frequency Approach	-5.9	38.1	37.9	115.2	1.4	1.4	
Neural Network Approach	-1.1	10.0	0.1	9.2	-0.1	-0.1	0.99
Doppler Frequency Approach	-9.6	29.8	32.2	100.7	7.0	7.0	
Neural Network Approach	-1.0	11.4	-1.6	9.3	0.0	0.0	0.999
Doppler Frequency Approach	-7.6	33.3	-6.5	35.9	2.6	2.6	

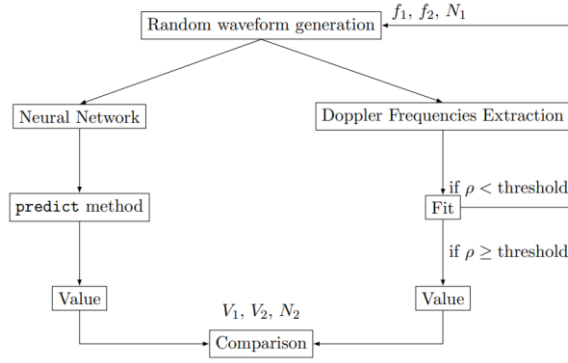


Figure 9. Sketch for the comparison of the Neural Network Approach (see section 3) and the Doppler Frequency Approach (see section 2) applied to the double layer configuration.

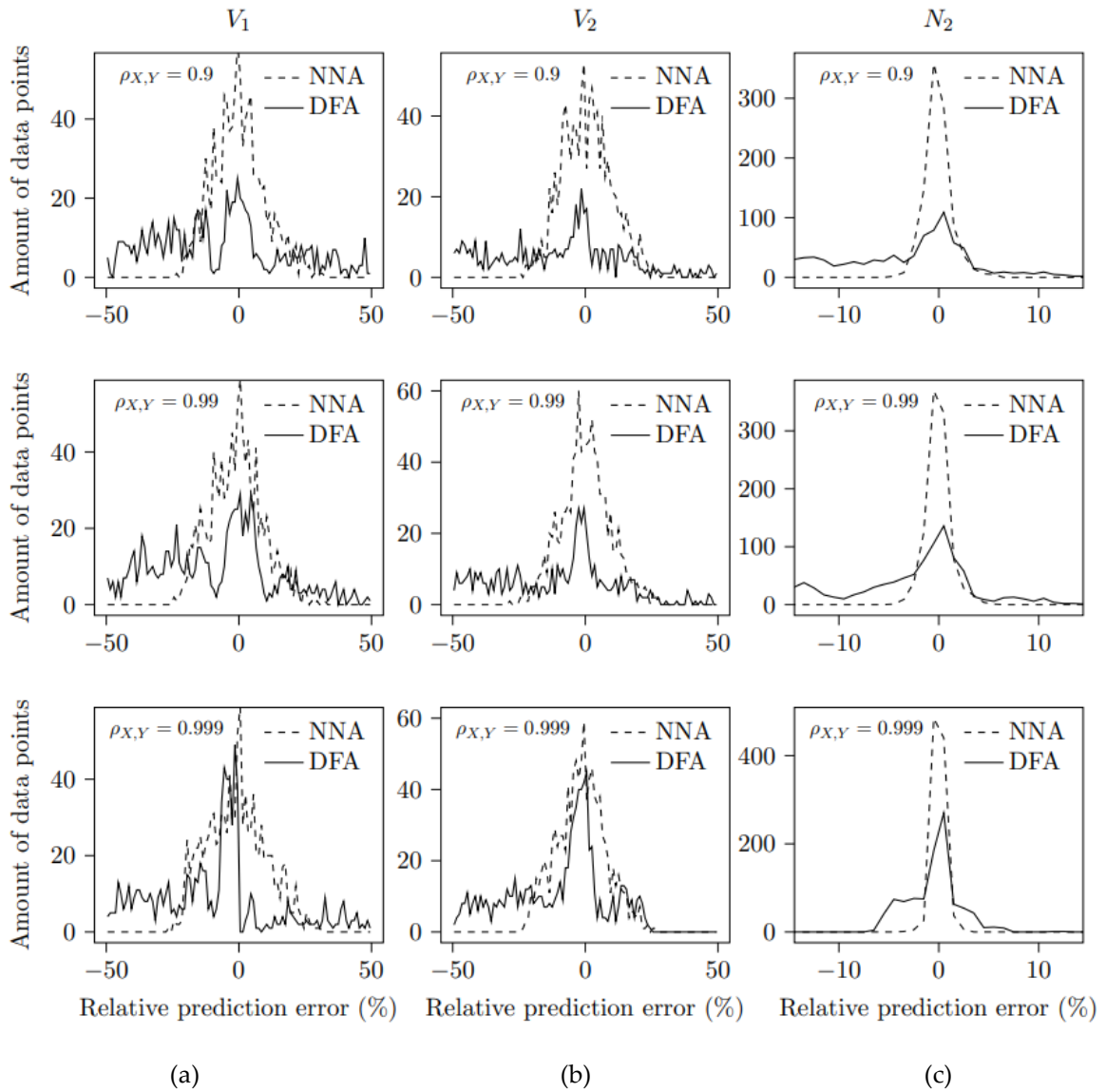


Figure 10. Relative prediction error distribution given by NNA and DFA with thresholds $\rho_{X,Y} = 0.9$ (up), 0.99 (middle) and 0.999 (down) for determination of: (a) the shock wavefront velocity V_1 , (b) particle velocity V_2 and (c) the refraction index N_2 of the shocked medium.

5. Conclusions

In this paper, a convolutional neural network is proposed for solving an electromagnetic inverse problem involving solid dielectric materials subjected to mechanical impacts. From the computed waveforms delivered by a millimeter-wave interferometer, the convolutional network provides more accurate estimations of the shock wavefront velocity in the shocked materials, the particle velocity, as well as the refractive index of shocked medium, for short-duration waveforms of few microseconds less than a time period long, compared to the Doppler frequency analysis, based on the fitting parameters of the sum of two sine functions. These results extend significantly the application of millimeter-wave interferometry to the investigation of dielectric materials subjected to steady shocks. Work is ongoing to improve the network architecture in order to reduce the standard error prediction for each parameter.

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