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COMMUNICATIONS

A HYBRID ALGORITHM TO SOLVE LARGE SCALE ELECTROMAGNETIC PROBLEMS

Abdelmadjid Nouicer — Mohamed Elhadi Latreche *

In this paper, the use of feed forward neural networks (FNN) coupled with the wavelet transform to solve electromagnetic problems is investigated. The direct use of the FNN to solve large scale electromagnetic problems needs a lot of CPU time and computer memory because we deal with a large size of training data base. So, the wavelet transform is proposed in order to reduce the data base size, in other terms using wavelets coefficients as training data instead of the original signal. A simple example shows the feasibility of our approach.

K e y w o r d s: feed-forward neural networks, finite elements computation, large-scale problems, wavelet transforms

1 INTRODUCTION

The use of conventional methods to solve the electromagnetic problems needs a lot of CPU time and computer memory. Moreover, when dependences on different parameters are present, *eg*, influence of the mobile part positions, of temperature, *etc* [1], the computational burden is increased. To overcome this drawback, the FNN, which can provide an effective means for the solution of electromagnetic problems such as inverse problems or optimization problems, has aroused the researcher's attention [2, 3]. Using available training sets, FNN can establish an approximation model by fitting the relation ship between the given input/output data without requiring any fundamental physical theories [1]. However, the neural networks cannot be used efficiently in some problems because we deal with a large scale training data base, such as in detecting cracks in a magnetic material where we generally use the flux leakage signal as the testing signal (defaults signature). The proposed paper presents two coupled algorithms between FNN and wavelets. The use of the wavelet transform has its goal in reducing the size of the training data base in order to make the use of FNN efficient (using the wavelets coefficients instead of the original signal). In the second algorithm, we propose an amelioration of the reconstructed solution yielded by FNN.

2 WAVELET TRANSFORM

For many signals, the low-frequency content is the most important part. This is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavour or nuance. It is for this reason that, in wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components [8]. Therefore, decomposition consists of discrete convolutions followed by operations of decimation (down-sampling).

Figure 1 shows the decomposition process. Here S is the original signal, A and D are the approximation and detail parts, respectively. H and G are the low-pass and the high-pass filters, respectively. (↓2) represents the down-sampling (we take a sample on two).

This process, which includes down-sampling, produces the discrete wavelet coefficients.

The decomposition process can be iterated, with successive approximations being decomposed in turn,

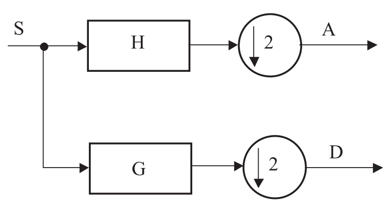

Fig. 1. One stage decomposition

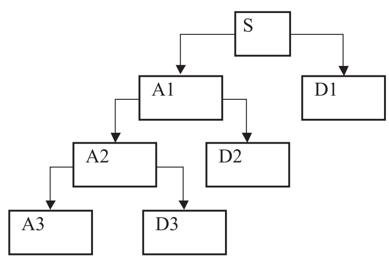

Fig. 2. Multiple-level decomposition

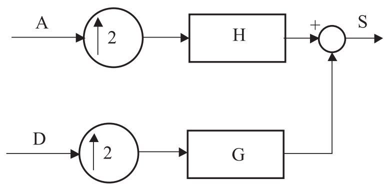

Fig. 3. Reconstruction procedure

* Département d'électrotechnique, Université Mentouri, route Ain Elbey, Constantine (25000), Algérie
E-mail: nouicer_abdelmadjid@yahoo.fr, latreche_med@yahoo.fr

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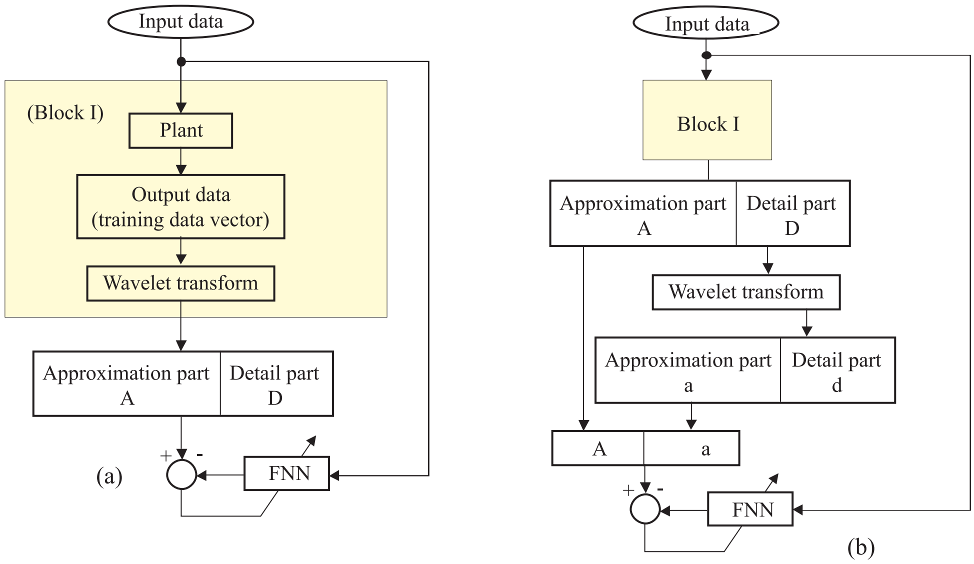

Fig. 4. The first - (a), and the second - (b) learning scheme

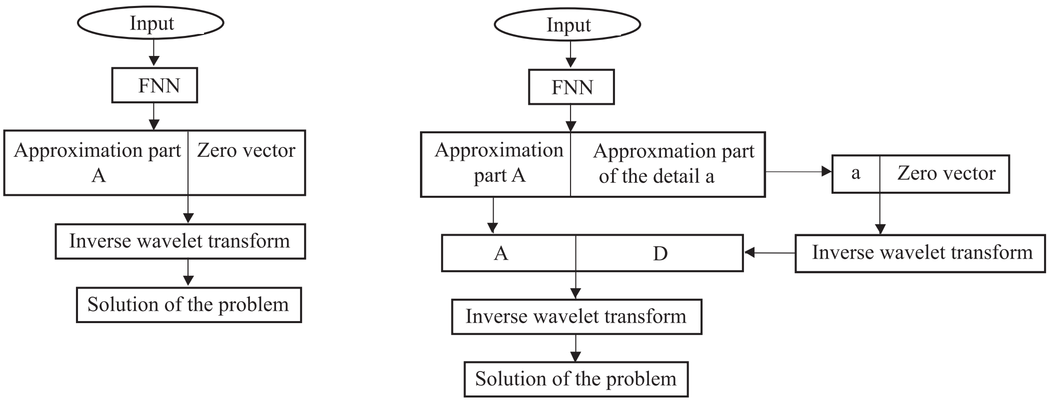

Fig. 5. The first - (a), and the second - (b) reconstruction schemes

so that one signal is broken down into many lower-resolution components. This is called the wavelet decomposition tree [8].Since the analysis process is iterative, in theory it can be continued indefinitely. In reality, the decomposition can proceed only until the individual details consist of a single sample or pixel.

The other half of the story is how those components can be assembled back into the original signal. This process is called *reconstruction* or *synthesis*. The mathematical manipulation that affects synthesis is called the inverse discrete wavelet transform (IDWT). Where wavelet analysis involves filtering and down-sampling, the wavelet reconstruction process consists of up-sampling and filtering. Up-sampling is the process of lengthening a signal component by inserting zeros between samples [8]. In Fig. 3 $\textcircled{\uparrow 2}$ represents the up-sampling.

2 COUPLED ALGORITHMS

The key idea is that before the procedure of learning, the training vectors (target vectors) are transformed into a space of wavelet spectrum. The space of the wavelet spectrum is composed of two representative spectra; one group has a larger absolute value (approximation), the other has nearly a zero value (detail) [5]. To apply this methodology we present two different schemes; in the first one, the FNN is learned using only the approximation part of the transformed target vector (Fig. 4a). So, this configuration presents much loss of information because, in the procedure of the reconstruction, the detail part vector is considered to be equal to zero. To minimize this loss, we propose a second learning scheme. In this second configuration, the detail part is not completely neglected but it is reduced in turn to its approximation and detail parts, the FNN learning is carried out using the approximation part of the transformed target vector and the approximation part of its transformed detail part (Fig. 4b). To reconstruct the original signal, we must first reconstruct the detail vector. Figures 5a and 5b present the reconstruction algorithms.

The proposed algorithms can be used efficiently in the electromagnetic diagnostic domain. That is, the testing signal is regular, when no crack is present (no abrupt variation). However, this signal present a high variation in the defaults regions. It is well known that the basic

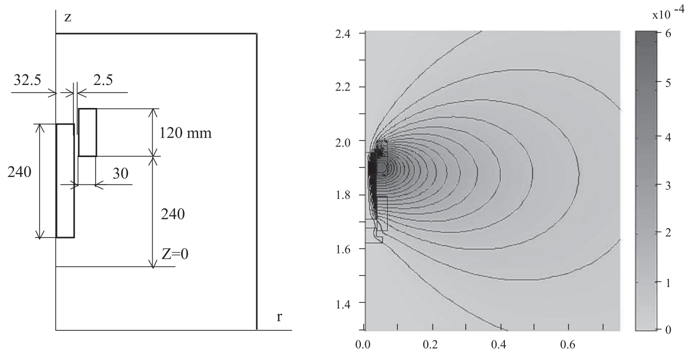

Fig. 6. (a) - The electromagnetic solution domain, (b) - Distribution of the magnetic vector potential **A**

characteristic of the wavelets transform is that its coefficients are very small in the zones where the signal is regular and large in the abrupt variation zones. Thus the wavelets coefficients reflect the signature defaults and this can be used as a testing signal. Then, the size of the training vectors is reduced.

3 VALIDATION AND RESULTS

To show the efficiency of the proposed algorithms, an FNN coupled with a wavelet software emulation system has been implemented in MATLAB to compute the trasnsformed solution of the magnetostatic equation of the axisymmetric actuator given in Fig. 6. In such a configuration, the magnetic vector potential **A** has only one component A_φ, and the magnetostatic equation takes the following form in the (r, z) plane [6, 7]:

$$\frac{\partial}{\partial r}\Big(\frac{1}{r}v\frac{\partial(rA_\varphi)}{\partial r}\Big) + \frac{\partial}{\partial z}\Big(\frac{1}{r}v\frac{\partial(rA_\varphi)}{\partial z}\Big) = -J\,. \qquad (1)$$

v is the magnetic reluctivity and J is the current density.

Figure 6a presents the object of our application, an axisymmetric actuator used to produce striking forces. It is composed of a coil and a cylindrical unsaturated steel armature moving following -z- axis when a voltage is applied to the coil. The characteristics of the experimental system which exist in IREENAI laboratory are [6]: $M = 5.52$ kg (mass of moving part), $v = 4.35 \times 10^{-3}$ (the relative reluctivity of the armature), $R = 3.21\,\Omega$ (the coil resistance).

In order to generate the training vectors for the neural network, 80 variations in the position of the moving armature had been done, performing 80 FEM simulations. Finite element meshes with 573 elements and 320 nodes were used in the simulations. After FEM simulations, the obtained vectors are compressed using the discrete wavelet transform.

We used a three layer FNN, the first layer is constituted by one unit with a sigmoid activation function, the second layer is constituted by fifteen units with a sigmoid

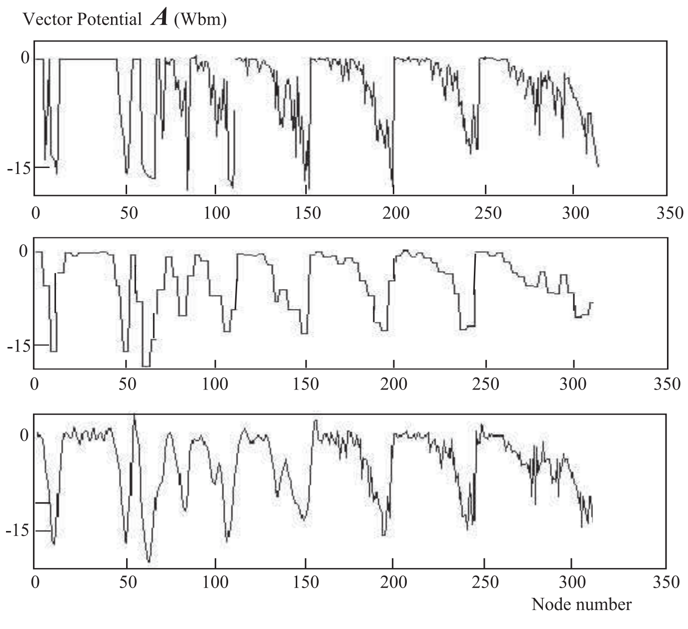

Fig. 7. Solutions of (1) obtained by: (a) - FEM, predicted, reconstructed using: (b) - the first learning scheme, (c) - the second learning scheme

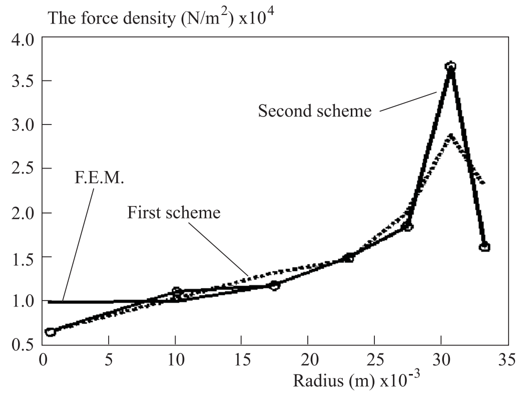

Fig. 8. Force density as a function of radius for a decomposition level 2 and Daubechies-4- as wavelet basis function

activation function and the third layer is constituted by N units with a linear activation function. N is the length of the compressed training vectors. The input of FNN model is the position of the mobile part, whereas the FNN returns the predicted transformed solution of (1) (vector potential $\mathbf{A}$). The training algorithm used in simulation is the Levenberg-Marquard algorithm. The training procedure is stopped when the error is inferior to 10^{-6}.

Figures 7 show the solution of (1) obtained by the FEM and that predicted by the FNN (after the reconstruction procedure).The training vectors are compressed at the decomposition level 2 using Haar wavelet as a basis function. For the second algorithm, the detail part is compressed at the decomposition level 3 and Daubechies-4-wavelet as a basis function.

Table 1 summarizes some results. The size of the training vectors obtained by FEM is 320.

Table 1.

Wavelet basis functions		Decom-position level	Size of compressed training data vector	Average Error (%)
Haar	First scheme	2	160	9.742
		3	80	17.989
	Second scheme	2	240	8.759
		3	120	13.589

We notice that the average relative error is calculated with regard to the solution obtained by FEM, this error is negligible at the decomposition level 1 while using the second scheme and lower than 5 % when we use the first scheme.

After calculating the solution of the magnetostatic equation, we have exploited this result to calculate the force exerted on the moving armature. Figure 8 shows the force density acting on the superior surface of the moving armature calculated by the use of Maxwell's stress tensor at $Z = 60$ mm. For the second algorithm, details were compressed at the decomposition level 4 using Haar wavelet.

4 CONCLUSION

The use of neural networks in solving the electromagnetic problems is an efficient tool. However, neural networks cannot be used efficiently in some problems because we deal with large scale training vectors. The main idea behind this work is to present a new approach allowing to make an efficient use of neural networks by reducing the size of the training vectors using the wavelets transform.

The proposed algorithms offer an efficient tool for the electromagnetic diagnostic where the wavelet coefficients are used instead of the real signal as defaults signature, this problem will be the object of a future work.

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Abdelmadjid Nouicer received a diplôme d'ingénieur en électrotechnique from Mentouri University, Constantine, Algeria, in 1998, and his magistère degree from Badji Mokhtar University, Annaba, Algeria, in 2001 and the docteur en sciences degree in 2005 from Mentouri University. His research interests include the application of neural networks, genetic algorithms and wavelet transform for modelling and optimization of electromagnetic devices.

Mohamed Elhadi Latreche received his diplôme d'ingénieur en lectrotechnique from l'Ecole Polytechnique d'Alger, Algeria, in 1983 and docteur du LEEI de l'Institut National Polytechnique de Toulouse, France, in 1987. Actually he is professor in the Department of Electrical Engineering of Mentouri University and director of research and director of LEC laboratory. He is interested in numerical modelling of electromagnetic devices.