APPLICATION OF THE ARTMAP NEURAL NETWORK IN THE DESIGN OF CASCADED GRATINGS AND FREQUENCY SELECTIVE SURFACES

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A. Introduction. Currently, there is no closed form solution that can directly relate a desired frequency response to a corresponding frequency selective surface (FSS). Trial and error procedures are used until a frequency selective surface matches the desired criteria. One way of avoiding this laborious process and obtain a synthesis procedure is to utilize the training capabilities of neural networks. A neural network can be trained to keep changing the dimensions of the metallic strips or patches, their distance of separation, their shape, and the number of layers required in a multilayer structure until the frequency response matches the desired one.

In the past, to achieve this goal, the back propagation learning algorithm was used in conjunction with an inversion algorithm [1]. Unfortunately, both the back-prop algorithm and the inversion procedure are slow to converge [2]. Others used "genetic algorithms" to solve the same problem [3].

In this work the Fuzzy ARTMAP neural network is utilized. The Fuzzy ARTMAP is faster to train than the back-prop and it does not require an inversion algorithm to solve the FSS problem. Several results (frequency responses) from cascaded gratings for various angles of wave incidence, layer separation, width strips, and interstrip separation are presented and discussed.

B. The ARTMAP Neural Network

B.1 Fuzzy ARTMAP Architecture

Fuzzy ARTMAP [4] is a neural network architecture which can learn to approximate a piecewise-continuous function from R^n to R^m. It consists of three modules: ARTa, ARTb and the Inter-ART module as shown in Figure 2. The ARTa and ARTb both have an architecture of Fuzzy ART so that they can accept analog patterns as their inputs. Each of ARTa and ARTb classifies its input into an appropriate category by some similarity rule. The function of Inter-ART module is to learn the mapping between the pattern pair fed to ARTa and ARTb.

ARTa and ARTb each consists of three layers: F_0, F_1 and F_2. The preprocessing layer F_0 performs the complement-coding of its input, which is necessary for the successful operation of Fuzzy ART and ARTMAP [5]. The F_2 layer is the category representation layer because its nodes denote the categories to which the inputs at the F_0 belong. The F_1 layer receives signals from both F_0 and F_2 and it evaluates whether an input pattern at the F_0 are close enough to the template of the chosen F_2 node. The criterion of the closeness is controlled by the vigilance parameter ρ_a for ARTa and ρ_b for ARTb. If a node J in the F_2 layer is chosen and the closeness criterion is passed, then the learning of the connections associated with node J (i.e. the bottom-up weights $\mathbf{Z}_J$ and the top-down weights $\mathbf{z}_J$) occurs. Otherwise, a reset signal will be sent to F_2 layer and then a search for another node in F_2 starts. This procedure repeats until an appropriate node in the F_2 layer is found to represent the input pattern at the F_0 layer.

In order for Fuzzy ARTMAP to learn the mapping between an input pattern $\mathbf{I}_0$ and an output pattern $\mathbf{O}_0$, the input $\mathbf{I}_0$ should be fed to the F_0 layer of ARTa (i.e. ${F_0}^a$), and the output $\mathbf{O}_0$ to F_0 layer of ARTb (i.e. ${F_0}^b$). When an input-output pair is presented to Fuzzy ARTMAP, ARTa classifies the input $\mathbf{I}_0$ to an appropriate category represented by a node (e.g. J) in ${F_2}^a$, while ARTb classifies the output $\mathbf{O}_0$ to an appropriate category represented by a node (e.g. K) in the ${F_2}^b$. There are three cases concerning the learning in the Inter-ART: (1) No mapping between node J in ${F_2}^a$ and any node in the ${F_2}^b$ has been established. Then the learning in the Inter-ART module occurs by setting $\mathbf{W}_{JK}$=1 and $\mathbf{W}_{jk}$=0 for any other j and k. (2) The mapping between node J in ${F_2}^a$ and the node K in ${F_2}^b$ has been established. In this case, no learning is necessary in the Inter-ART for this presented input-output pair. (3) The mapping between node J in ${F_2}^a$ and a node in ${F_2}^b$ other than K has been established. In this case, the vigilance parameter ρ_a is increased by a minimum amount which causes node J to reset, and then another node $\hat{J}$ is selected. Repeat this if $\hat{J}$ still falls in this case.

In order for Fuzzy ARTMAP to learn a list of input-output pairs, the pattern pairs should be repeatedly presented to the Fuzzy ARTMAP until all the input-output pairs are correctly mapped and no learning occurs.

B.2 Fuzzy ARTMAP applied to the design of cascaded gratings

During the training, ARTa is fed with the normalized grating parameters: incident angle θ (normalized by 100), physical sizes b and d (both normalized with a). ARTb is fed with the samples of the transmission coefficient curve corresponding to the grating parameters.

After the Fuzzy ARTMAP learned all the mapping of the training data, the desired set of transmission coefficients are fed to the F_0 layer of ARTb. Then a node in the ${F_2}^b$ (a category of ARTb) will be selected by the similarity rule. By the connections between this ${F_2}^b$ node, the nodes in the Inter-ART and the ${F_2}^a$ nodes, one or more corresponding ${F_2}^a$ node(s) will be picked. The weights associated with the picked ${F_2}^a$ node(s) determines the designed grating parameters. If the ${F_2}^a$ node has learned only one set of the normalized grating parameters, the designed grating parameters will be of single value. Otherwise, a range for either b or d or θ will be determined.

C. Results

Several cases of cascaded gratings were used to train the Fuzzy ARTMAP neural network. Basically, the width of the strips, their distance of separation, the distance of layer separation, and the angle of wave incidence

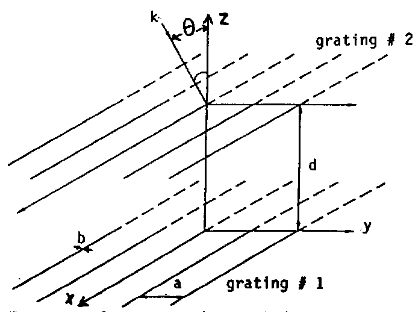

Figure 1: Geometry of cascaded gratings

were the parameters used for training of the neural network. For each change in the above parameters a different frequency response is obtained and fed to the network. Once the training is accomplished, a desired frequency response is fed as input to the neural network which in return yields the appropriate dimensions and parameters required to obtain such a response. Figures 3 and 4 are two examples of results obtained from the ARTMAP neural network at theta=0 and theta=60 degrees, respectively.

D. Conclusions. The training of a Fuzzy ARTMAP neural network to synthesize a desired frequency responce is presented and discussed. Unlike the back-prop method, this network does not require any inversion algorithms to yield the dimensional parameters of the FSS.

References

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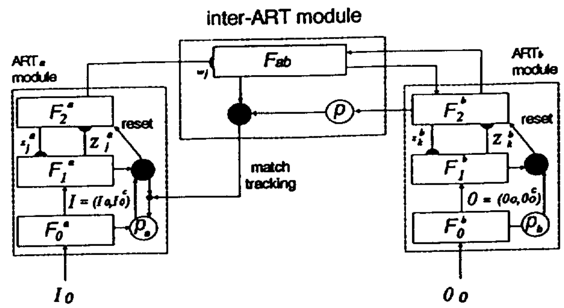

Figure 2: A block diagram of the Fuzzy ARTMAP architecture

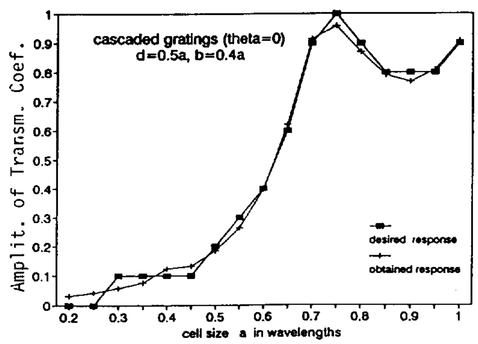

Figure 3: Comparison between desired and obtained responses for a cascaded grating at normal incidence

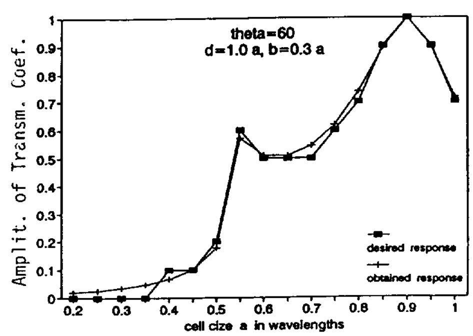

Figure 4: Comparison between desired and obtained responses for a cascaded grating at theta=60 degrees