Classification of Microwave Planar Filters by Deep Learning

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Abstract. *Over the last few decades, deep learning has been considered to be powerful tool in the classification tasks, and has become popular in many applications due to its capability of processing huge amount of data. This paper presents approaches for image recognition. We have applied convolutional neural networks on microwave planar filters. The first task was filter topology classification, the second task was filter order estimation. For the task a dataset was generated. As presented in the results, the created and trained neural networks are very capable of solving the selected tasks.*

Keywords

Convolutional neural network, deep learning, band pass filter, low pass shunt filter, low pass stepped filter, order of filter

1. Introduction

Functions and abilities of a brain have been fascinating engineers for decades. First attempts on modeling a brain by electronic systems appeared in years of World War II. In 1943, Warren McCulloch a Walter Pitts developed a simple neural network with electrical circuits. In 1949, Donald Hebb reinforced the concept and pointed out that neural pathways are strengthened each time when being used.

Thanks to advances of computers, Nathanial Rochester from the IBM research laboratories led the first effort to simulate a neural network in the 1950s. In 1956, the Dartmouth Summer Research Project on Artificial Intelligence provided a boost to both artificial intelligence and neural networks. In the years following the Dartmouth Project, John von Neumann developed a simple neuron by using telegraph relays or vacuum tubes. After that, Frank Rosenblatt began to work on the perceptron. The perceptron computed a weighted sum of the inputs, subtracted a threshold, and passed one of two possible values out as the result.

In 1959, Bernard Widrow and Marcian Hoff presented models called ADALINE (adaptive linear elements, see Fig. 1) and MADALINE (multiple adaptive linear elements). MADALINE, an adaptive filter eliminating echoes on phone lines, was the first neural network to be applied to a real-world problem.

Because of the earlier successes, the potential of neural networks was overestimated, particularly due to limitations of available electronics. The unfulfilled claims caused halting the funding.

In 1982, John Hopfield presented an approach to simply model brains and created useful devices. At the same time, Japan announced an effort to further develop neural networks. The US have been funding the research once again. That time, the new area of artificial neural networks has been started.

Most applications of neural networks have been using the feed-forward structure (see Fig. 2). Neurons in the input layer distribute input signals to neurons in the first hidden layer. Hidden neurons multiply input signals by synoptic weights $w_{ij}^{(n)}$. Here, n denotes the number of the hidden layer, i is the number of the neuron in the input layer and j indicates the number of the neuron in the hidden layer [1].

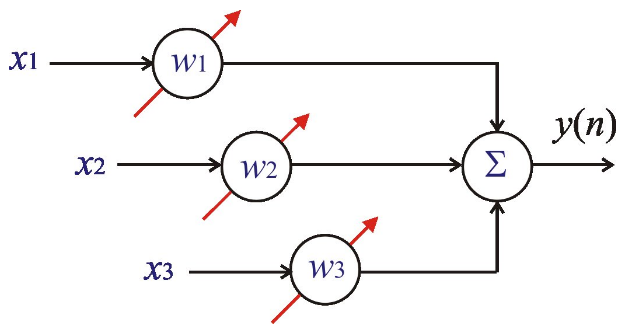

Fig. 1. Adaptive linear element (ADALINE). Synoptic weights and a summer forming the neuron correspond to a finite impulse response adaptive filter.

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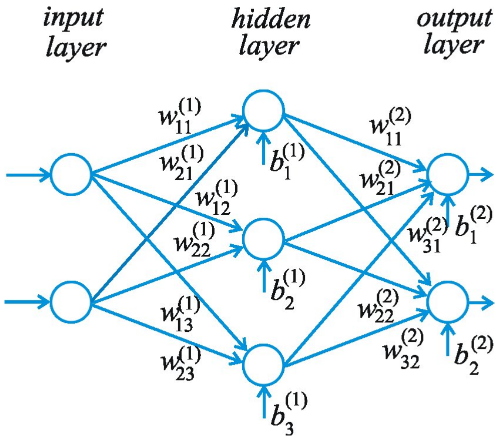


Fig. 2. Feed-forward neural network. Two-element input patterns are statically mapped into two-element output targets [1].

The products of input signals and synoptic weights are summed and the threshold $b_j^{(n)}$ is subtracted. Indexes n and j refer to the layer and the neuron as previously. The output of the summer is limited by a non-linear activation function (a Gaussian function, a unipolar sigmoid or a bipolar one in most cases). That way, the output signal of the neuron is obtained [1].

Feed-forward neural networks are trained to map vectors of input patterns $[p_1, p_2 ... p_M]^T$ into vectors of output targets $[t_1, t_2 ... t_N]^T$ where M is the number of input neurons and N denotes the number of output neurons [1].

Let us assume that a feed-forward network is used to model a patch antenna (see Fig. 3). In order to map dimensions of the antenna (the width A, the length B, the width of the microstrip feeder w) and parameters of the substrate (the dielectric constant ϵ_r, the height h) to the input impedance $(R_{in} + jX_{in})$ at the frequency f, input patterns $[A, B, w, \epsilon_r, h, f]$ have to correspond to 6 input neurons and the output targets $[R_{in}, X_{in}]$ have to be related to 2 output neurons. The number of hidden layers and neurons in those layers should be sufficiently high to have capacity for absorbing stored information [2].

Information is stored in synoptic weights of the network during training: input patterns are introduced to input neurons, and synoptic weights are changed to obtain corresponding output targets at output neurons. Hence, knowledge is distributed over the whole network [2].

Introducing an unknown input pattern to the input of a trained network, a proper output target is obtained at output neurons. Therefore, the feed-forward network is usually used as a black-box model approximating results of measurements or CPU-time expansive numerical analyses [2].

During the latest development of artificial neural networks, several researchers pointed out that artificial neural networks have sometimes been used to understand brain functions but the primary design has not been intended to be realistic models of the biological function. Therefore much more general term **deep learning** is used nowadays [3].

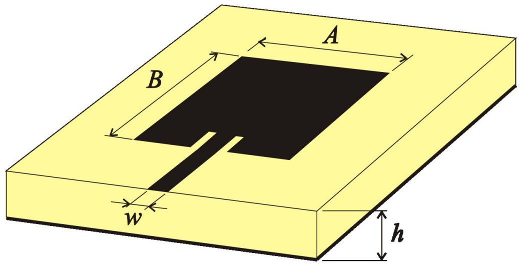


Fig. 3. Patch antenna fed by microstrip transmission line. Dimensions of the layout and parameters of the substrate form the input pattern. Input impedance of the antenna (resistance and reactance) correspond to the output target.

The term deep learning emphasizes the fact that neural architectures consist of a relatively high number of hidden layers. Or, various neural networks are composed into a cascade identifying edges, classifying objects and sorting outputs, for example [3].

When searching for keywords *microwave-filter-deep-learning* in the IEEE Xplore database, about 20 papers published in last years can be obtained. Contributions can be divided into following categories:

- A conventional mapping is performed by **conventional feed-forward networks** [4–6].
- A conventional mapping is performed by **several feed-forward networks** arranged into a cascade creating the deep structure [7–9].
- An inverse mapping is performed by **different types of neural networks** arranged into a cascade creating the deep structure [10], [11].

Moreover, IEEE published in 2021 two special issues devoted to machine learning in microwaves [12] and to artificial intelligence in electromagnetics [13]. From the viewpoint of terminology, the deep learning is a subset of machine learning, and the machine learning is a subset of artificial intelligence [3]. From the viewpoint of contents:

- Feed-forward networks were exploited for fast parametrized electromagnetic modeling of microwave filters [12]. Using transfer functions as prior knowledge for model development, a CPU-efficient tool was obtained for the high-level electromagnetic design with repetitive geometrical variations. Hence, conventional mapping was boosted in a clever way using conventional neural networks.
- An overview of artificial intelligence techniques applied to forward modeling, remote sensing, adaptation of reconfigurable antenna arrays, biomedical imaging and inverse design was provided [13]. Dealing with the inverse design, an application of deep learning techniques covers forward and inverse mapping of electromagnetic structures (meta-structures, reflect-arrays, nano-structures) using feed-forward networks, support vector machines and generative adversarial networks.

Obviously, exploitation of deep learning structures consisting of different neural networks are in field of electromagnetics (and microwave filters, especially) quite rare. Moreover, those structures are dominantly used for an inverse mapping.

In this paper, a deep structure consisting of different neural networks is applied to the identification of planar filters from images of their layout:

- The first neural network identifies edges in the layout.
- Depending on edges, the second network identifies inductive and capacitive segments of the layout.
- Considering topology created by inductive and capacitive segments, the third neural network classifies the filtering structure.
- Identifying the number of repetitions of the fundamental segment of the filter, the fourth network estimates the order of the filter.

According to our knowledge, the described approach has not been published in the open literature yet. In Sec. 2, planar filters used for the training of the deep structure are briefly presented. Section 3 describes particular neural networks creating the deep structure and discusses the software implementation, training patterns and training itself. In Sec. 4, functionality of the trained deep structure is verified. And Section 5 concludes the paper.

2. Planar Filters

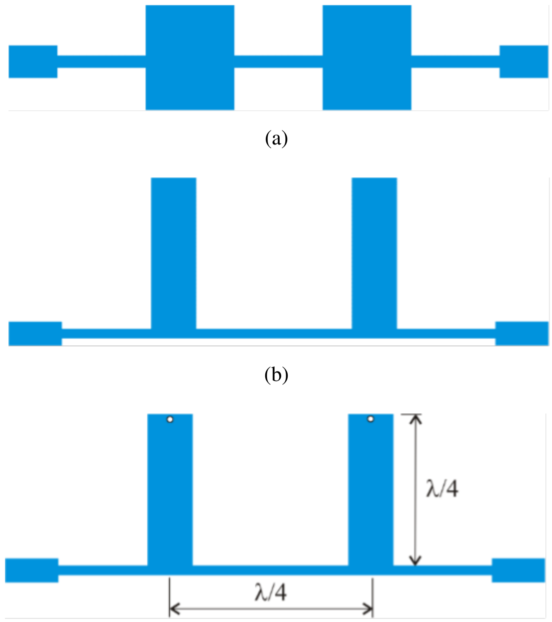
In order to approve functionality of the deep structure classifying planar filters, following filters using design synthesis were included into the training [14]:

- Stepped impedance low-pass filter;
- Low-pass filter with shunts;
- Band-pass filter consisting of short-ended quarter-wavelength shunts.

The training set can be completed by other filter types like elliptic low-pass structures, filters consisting of coupled resonators, etc. [14]. No matter the deep structure becomes larger and the training process takes longer time, the fundamental principles stay unchanged.

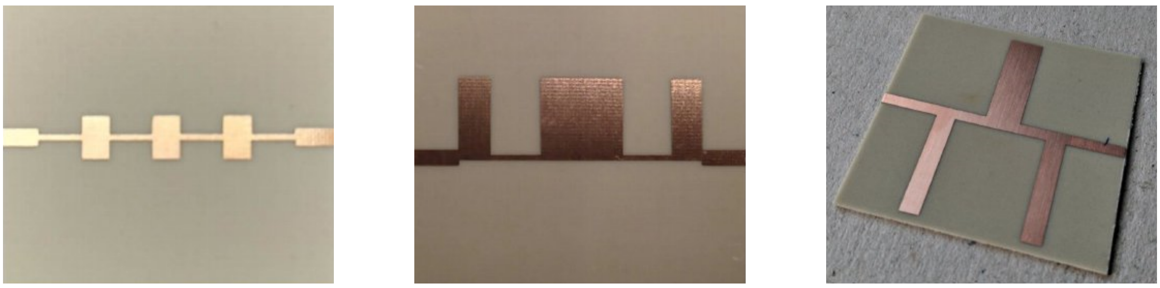
In order to prepare training patterns, a MATLAB script based on closed-form descriptions of planar segments was created. Particular segments were described by ABCD matrices, and the whole filtering structure was cascaded by their multiplication. Accuracy of the generated training models is very limited because mutual couplings among segments are neglected, fringing fields are not taken into an account and parasitic phenomena are not considered.

In order to verify classification abilities of the deep structure, photographs of implemented filters were used. Examples of testing structures are shown in Fig. 4 and Fig. 5. Training details are given in Sec. 3, verification details are provided in Sec. 4.



(a) (b) (c)

Fig. 5. Planar filters included into the training set: (a) stepped impedance low-pass filter, (b) low-pass filter with shunts, (c) band-pass filter consisting of short-ended quarter-wavelength shunts.



(a) (b) (c)

Fig. 4. Planar filters used for verifying functionality of the deep structure: (a) stepped impedance low-pass filter, (b) low-pass filter with shunts, (c) band-stop filter consisting of open-ended quarter-wavelength shunts.

3. Proposed Architecture

CNNs are type of feed-forward neural networks with modified architecture. The architecture of CNNs usually consists of convolutional layers followed by a pooling layers, where each neuron in a convolutional layer is connected to some region in the input. This region is usually called a local receptive field. All weights (filters) in CNNs are shared based on the position within a receptive field. The convolution operation can be described as follows [15]:

$$(f * g)(z) = \sum_x \sum_y f(x, y) \cdot g(z - x, z - y) \qquad (1)$$

where $f(x, y)$ is the input image at position (x, y) and $g(z-x, z-y)$ is a trainable filter. The pooling layers in CNN reduce the dimensionality of features which leads to reduction of connection between layers, hence it reduces computational time [16].

Due to type of input data and required filter classification, CNN was selected and proposed. Selected lightweight CNN architecture described in Tab. 1 represents a good choice compared to state of the art architectures that are purely designed to achieve great results on competitive datasets (NMIST, CIFAR, etc.) containing hundreds of classes. All the layers and it's parameters were used from [17]. These models then have high computational demands [17].

The proposed architecture requires input image of 224×224 px. To comply with this condition, each input image was adjusted to the correct resolution. For both training scenarios, the Adam optimization algorithm with default setting was chosen and the cross entropy method was used as the loss function.

Layer	Activation shape	Activation size	Parameters
Input	224×224×3	150528	0
Convolution 2D	226×226×90	4,596,840	180
Max×Pool	113×113×90	1,149,210	0
Convolution 2D	58×58×100	336,400	1,000
Max×Pool	24×24×100	57,600	0
Convolution 2D	24×24×50	28,800	500
Max×Pool	12×12×50	7,200	0
Convolution 2D	10×10×50	5,000	500
Convolution 2D	6×6×60	2,160	300
Max×Pool	3×3×60	540	0
Convolution 2D	2×2×10	40	100
Fully connected	1×1×40	40	1,600
Fully connected	1×1×40	40	1,600
Fully connected	1×1×40	40	1,600
Output	# of classes	N/A	N/A

Tab. 1. Architecture of used CNN for classification of microwave planar filters.

4. Dataset

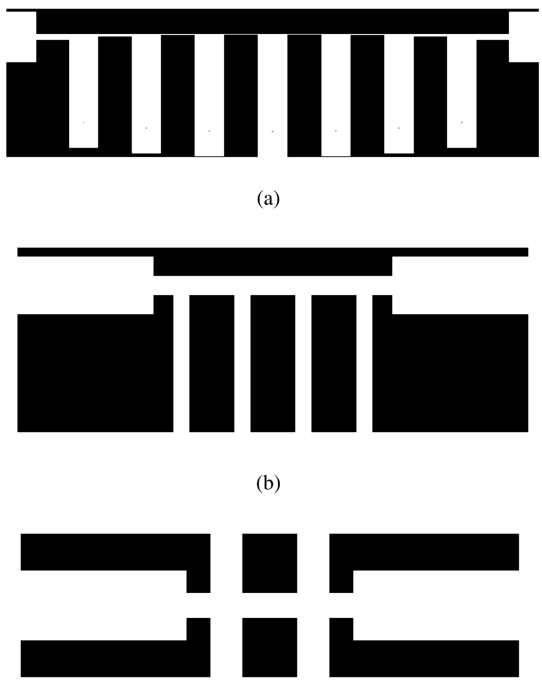
The dataset used was generated by MATLAB program for the purpose of training the neural networks. The aim of the generation was to generate a set of images that represent planar structures and that are physically correct. The generation was based on predefined values of permittivities $\epsilon_r = [2.10, 2.55, 2.55, 2.59, 3.00, 3.38, 3.78, 4.43, 4.80, 6.22]$ and frequencies f_c =[433, 888, 1200, 1600, 2400, 2800, 5200, 8200, 28000, 32000] MHz. The dataset was generated using grayscale pixels. The background is represented by black color, the planar structure is represented by white color, and the vias (an electrical connections between copper layers in a printed circuit board) are represented by gray color.

For the purpose of structure and order recognition of the planar filters, we have generated 2 datasets:

- **Structure dataset** - the dataset consists of three classes split into folders: bandpass, lowpass shunt and lowpass sepped impedance. Each class consists of 1000 images. Hence the total number of images is 3000.

- **Order dataset** - the dataset consists 6 classes representing orders $[3, 5, 7, 9, 11, 13]$. Each folder consist of 500 images. The total number of images is 3000 images.

The presented datasets can be downloaded from [18]. Example of generated structures can be found in Fig. 6.



(a)

(b)

(c)

Fig. 6. Planar filters included into the training set: (a) bandpass filter consisting of short-ended quarter-wavelength shunts - thirteenth order, (b) low-pass filter with shunts - ninth order, (c) stepped impedance low-pass filter - fifth order.

5. Experiments and Discussion

Techniques of data augmentation (rotation, gray scale, normalization, and resizing) were applied to datasets (described in Sec. 4) in order to improve generalization of trained model and increase number of input data. With applied augmentation the number of images in datasets was tripled. After CNN training, the trained models were validated on a separate evaluation dataset that had not been used for training before.

5.1 Filter Classification

Measured results from training and evaluation using CNN architecture from Tab. 1 for classification of microwave planar filters are shown in Fig. 7 and 8. High accuracy (99.8% on evaluation data) and low loss (inverted function of accuracy) was achieved during 20 epochs of training. Figure 8 shows confusion matrix, where each row represents the instances in an actual class (band pass filter, low pass shunt filter and low pass stepped filter) while each column represents the instances in a predicted class. Given 100 evaluation samples per class (in total 300 images), the proposed CNN architecture missed 2 images, which instead of predicted as low pass shunt filters were predicted as band pass filters.

5.2 Filter Order Estimation

Achieved results from training and evaluation using CNN architecture from Tab. 1 for classification of orders are shown in Fig. 9 and 10. High accuracy (94.87% on evaluation data) and low loss (inverted function of accuracy) has been achieved during 20 epochs of training. Figure 10 shows confusion matrix, where each row represents the instances in an actual class (order of filter) while each column represents the instances in a predicted class. Given 26 evaluation samples per class (in total 156 images), the proposed CNN architecture missed 6 images of 3rd order, one image of 5th order and one image on 13th order.

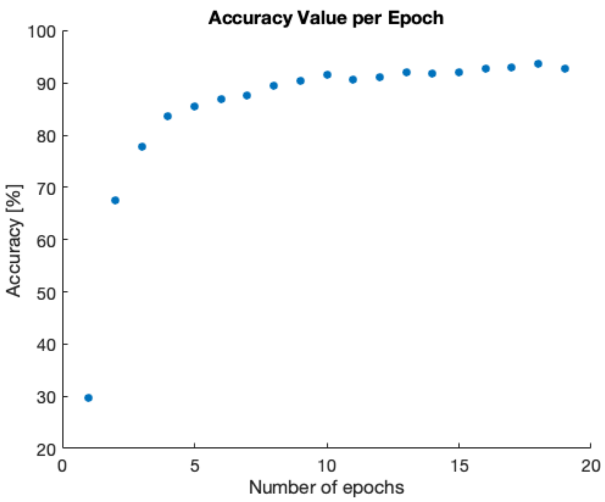


Fig. 7. Accuracy function of CNN during training on basic classification of filters.

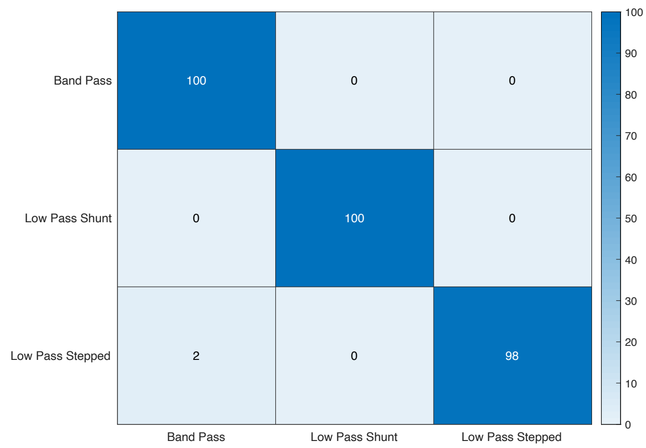


Fig. 8. Confusion matrix representing CNN accuracy on evaluation data. The color bar represents quantity.

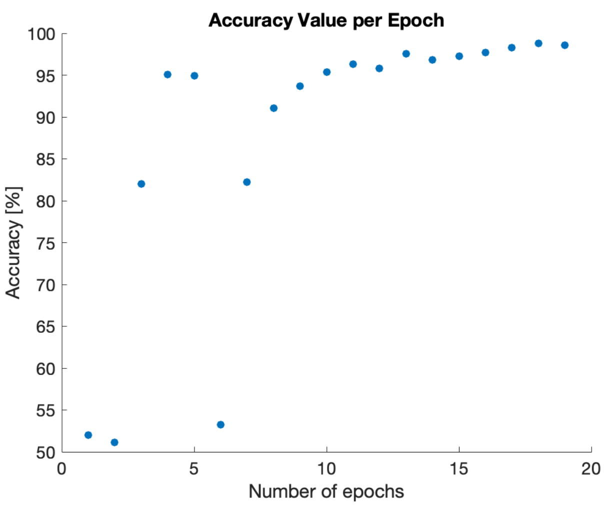


Fig. 9. Accuracy function of CNN during training on classification of orders of filters.

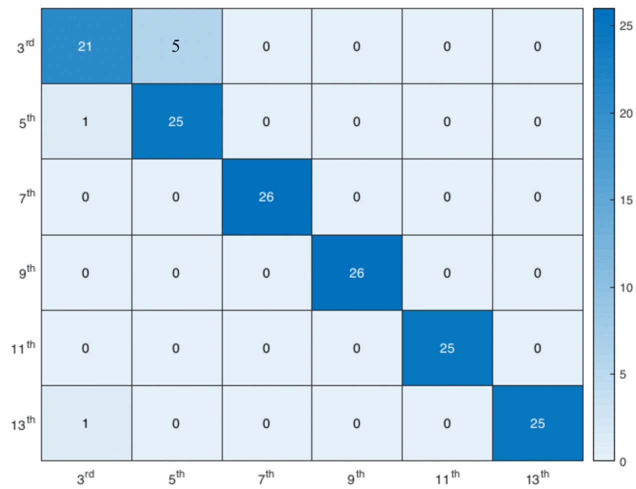


Fig. 10. Confusion matrix representing CNN accuracy on evaluation data. The color bar represents quantity.

5.3 Real Data Evaluation

In order to verify the constructed neural networks, we used photographs of planar filters. Examples of the photographs can be seen in Fig. 4.

Therefore, for the presented mechanism to work, it is crucial to present the image in grayscale, where the white color represents the conductive layer, the black color the surroundings, and the gray color the vias. To function properly, it is necessary to provide high quality patterns - especially sharp edges.

The achieved accuracy for tested images (40 images) for the task of filter classification is 98%. For the task of order estimation, the accuracy is 91%.

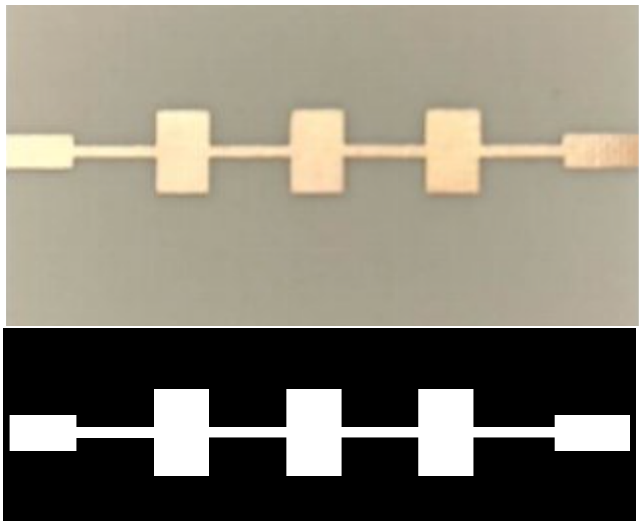


Fig. 11. Upper: Photograph of printed circuit board of low-pass stepped impedance filter. Bottom: Extracted image of the photograph used as an input for NNs.

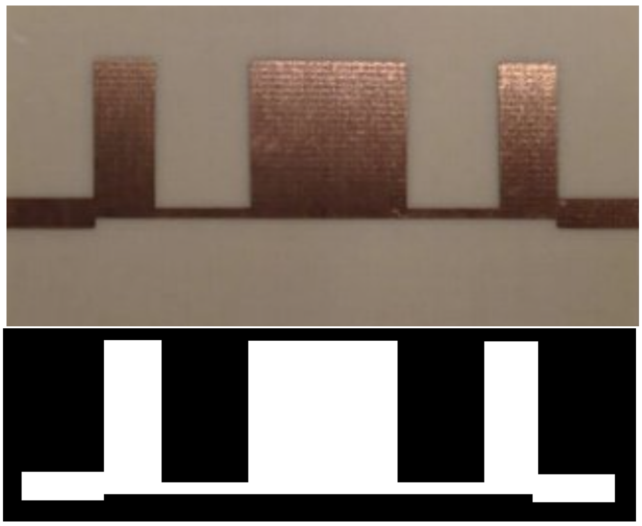


Fig. 12. Upper: Photograph of printed circuit board of low-pass filter with shunts. Bottom: Extracted image of the photograph used as an input for NNs.

6. Conclusion

This paper demonstrates benefits of deploying CNNs for filter classification and its orders. The proposed architecture has been trained to recognize three categories of planar filters and its order (from 3rd to 13th order). In our case we simplified training datasets of filters which were generated by MATLAB due to insufficiency of real data, where mutual coupling among segments was neglected, fringing fields were not taken into an account and parasitic phenomena was not considered. However, the neural network architecture could be extended to recognize additional filter types or adapted for other attributes of filters with minimum modifications. The CNNs themselves could be further improved by trying to use bitwise compression of individual variables to achieve faster network response, but this was not considered [19]. Finally, the presented network was tested using real photographs of planar filters. The accuracy for the filter classification task is 98% and for the order estimation task is 91%. Nevertheless, the algorithm proved to be powerful, the result accuracy highly depends on the quality of input images.

Acknowledgments

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In 1996 and 1997, he occupied the position of independent researcher at Laboratoire de Hyperfrequences, Universite Catholique de Louvain, Belgium, working on variational methods for numerical analysis of electromagnetic structures. He and his team have been researching methods of numerical modeling and optimization of electromagnetic structures, and ways of applying artificial neural networks to solving electromagnetic compatibility issues, and advanced approaches to the design of special antennas. From 2002 to 2006, he occupied the position of the Vice Dean for Research. From 2006 to 2013, he headed the Department of Radio Electronics. Since 2010, he has managed the SIX Research Center. He is a Senior Member of the IEEE. He is active in the Antennas and Propagation Society, Microwave Theory and Techniques Society, Computational Intelligence Society, and Signal Processing Society.