Inverse Design of Transmission Lines with Deep Learning

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***Abstract*—Design of microwave structures and tuning parameters, has mostly relied on the domain expertise of circuit designers by doing many simulations, which can be prohibitively time consuming. An inverse problem approach suggests going in the opposite direction to determine design parameters from characteristics of the desired output. In this work, we propose a novel machine learning architecture that circumvents usual design method for given quality of eye characteristics by means of a Lifelong Learning Architecture. Our proposed machine learning architecture is a large-scale coupled training system in which multiple predictions and classifications are done jointly for inverse mapping of transmission line geometry from eye characteristics. Our model is trained by guided manner of using intra-tasks results, common Knowledge Base (KB), and coupling constraints. Our method of inverse design is general and can be applied to other applications.**

***Index Terms*—Inverse design, lifelong supervised learning, eye characteristics, Microwave systems, knowledge base, multi-task neural network, coupled training.**

I. Introduction

Computing the design parameters of circuit topology, geometry, algorithmic specifications from the given objectives of eye characteristics is an ill-posed problem. The same eye-opening can have multiple geometry combinations. Experienced designers and industry gurus need to spend an excessive amount of time to achieve a certain signal quality and eye diagram [1]–[4]. Therefore, in this paper we have proposed an inverse design approach to find the geometric parameters of transmission lines from characteristics of the desired eye diagram, using deep learning. Inverse design of electromagnetics with neural networks has been previously suggested in works such as [5]–[8]; however, these papers have developed basic neural networks. In this paper, we solve the inverse mapping of line width l_w, line thickness t_c, spacing s and substrate thickness h_{sub} of a microstrip link from its eye characteristics using the paradigm of life-long deep learning. We propose a novel intelligent learning architecture, that combines deep neural network and symbolic Knowledge Base (KB) for inverse mapping of geometry parameters from eye characteristics as shown in Fig. 1, [9], [10]. The deep neural network performs a sequence of N supervised learning tasks predicting dependent geometry parameters and classification, and retained the learned knowledge in the knowledge base (KB). Rather than building a separate neural network for each of N individual tasks (prediction, classification), we build a common deep neural network for all the tasks. Our common neural network uses the same input layer for input from all tasks and uses separate output for each individual task [10], [11]. The shared hidden layers are trained in parallel using back-propagation on all the tasks to minimize the error on all the tasks [12], [13]. Thus the shared layer allows features learned for one task to be transferred to other tasks and learned the concept of inverse mapping.

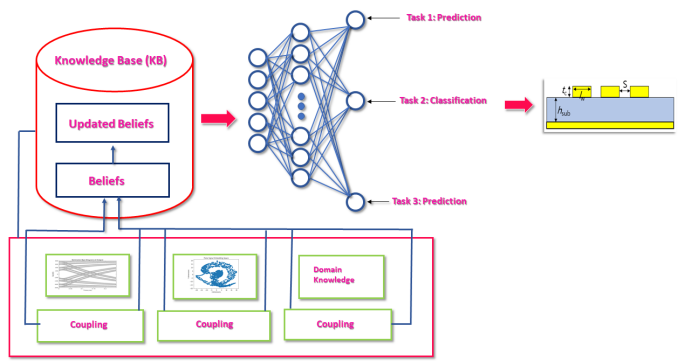

Figure 1: Lifelong Learning Architecture for Inverse Design

We formalize our learning problem for inverse mapping as an ordered pair consisting of: (i) a set $L = \{Li\}$ of learning tasks of prediction and classification of (ii) i^{th} learning task is defined by $L_i =< T_i, P_i, E_i >$, where P_i is the performance metric on the task T_i and gained experience E_i (iii) a set of coupling constraints $C = \{< \phi_k, V_k >\}$, where ϕ_k is a multi-valued function on different tasks, and V_k is a vector of indices of the tasks to be learned. For each inverse prediction task i we learn the function $f^i(x)$ that maps from the 15-dimensional eye characteristics $\chi^i \subseteq \mathbb{R}^{15}$ to 4-dimensional geometry $Y^i \subseteq \mathbb{R}^4 (y^i \in Y^i)$. For a specified loss function $\mathscr{L}$ (mean squared error, categorical cross entropy), our multi-task learning minimizes the objective function as [11]:

$$\sum\sum \mathscr{L}(f^i(x), y^i) \tag{1}$$

II. Proposed Method

Eye diagram is a popular tool for evaluating quality of signals in high-speed communication links. However, achieving the desired eye diagram can be difficult and time consuming. Therefore, we have developed an inverse design approach

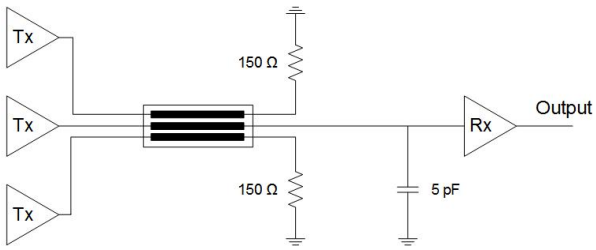

Figure 2: A high-speed channel with three coupled microstrip lines.

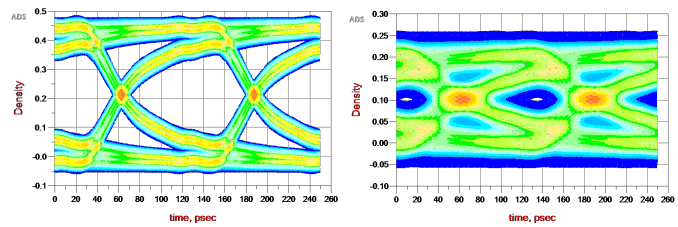

Figure 3: Open (left panel) and close (rigth panel) eye diagrams obtained by exploring the considered parameter space.

that searches appropriate geometric values of transmission lines based on the required eye characteristics. Our inverse design model is trained with 15-dimensional input of eye-characteristics data and 4-dimensional output geometry of line width l_w, line thickness t_c, spacing s, and substrate thickness h_{sub}. We have used multi-tasking learning paradigm and train our deep learning model jointly for prediction (by regression) and classification. The classification problem is artificially induced, where we discretize the geometry parameters l_w, t_c, s, h_{sub} in 10 different classes (class-0, ..., class-9). The distribution of geometry parameters are uniformly distributed between their minimum and maximum values such as $l_w \in [0.300, 3.099]\,\mu m$, $t_c \in [0.300, 3.099]\,\mu m$, $s \in [0.300, 3.099]\,\mu m$ and $h_{sub} \in [0.800, 5.099]\,\mu m$, respectively. We train our model with 4315 input samples of eye-characteristics and output geometry. We have tested our Lifelong learning learning model on 100 unseen samples of data.

III. Algorithms

Our lifelong learning architecture learns from a modified expectation–maximization (EM) algorithm where the tasks are weakly coupled [11]. In the E-like step, beliefs are updated and stored in the knowledge base (KB), and in the M-like step, this updated KB is used for retraining and inference.

Algorithm 1 Lifelong Learning Algorithm

```
procedure EM(b_i); EM for belief b_i
    while n <= M do
        Compute the likelihood of belief b_i
        Store the belief b_i in KB
        Retrain with updated belief
    end while
    return optimum b_i and trained weights
end procedure
```

IV. Results and Analysis

To evaluate the proposed approach, we have considered a high-speed channel with three coupled microstrip lines, with length of 10 *mm*. The microstrip traces and the ground plane are made of copper, and the dielectric is lossy silicon dioxide. The ground plane has a thickness of 0.5 μm, and rest of the geometric parameters, which includes width and height of the microstrip lines, separation between the microstrip lines, and height of the dielectric, are set by the proposed approach.

We extracted S-parameters of the microstrip lines using Ansys Electromagnetics Suite 19.2.0 2D extractor. In this example, we used 15 eye characteristics to predict geometric parameters of the microstrip lines. The microstrip lines are placed as shown in the Fig. 2, where transmitters and receiver are simulated using ideal models, with 100 Ω and 150 Ω inner resistance, respectively. Input is a random trapezoidal pulse with data rate = 8 Gbps, rise/fall time $= 12.5ps$, $V_{High} = 1V$, and $V_{Low} = 0V$. Moreover, the used eye characteristics are mean of the zero logic level, mean of the one logic level, average of one and zero logic levels, difference of average one and zero logic levels, distance between 3-sigma points of the zero logic histogram and the one logic histogram and dB value of this distance, distance between 3-sigma points of two crossing time histograms, maximum height and width of contour at 10^{-12} BER, signal to noise ratio, average rise/fall time between the low and high amplitude thresholds, peak to peak distance of the crossing time (jitter) histogram, distance between 3-sigma points of the jitter histogram, and mean of the crossing point values. We simulated this channel in Keysight Advanced Design System 2019. Fig. 3 (left panel) shows an open eye when, width, height, and separation of the transmission lines, and the height of the dielectric are set to 2.35 μm, 1.44 μm, 3.02 μm, and 5.05 μm, respectively. On the other hand, when the same parameters are set to 0.98 μm, 0.46 μm, 1.75 μm, and 4.92 μm, in the same order, a closed eye is obtained, (see Fig. 3 (right panel)). It can be seen that changing these dimensions greatly affects the quality of the received signals. Moreover, it is difficult to find the values that correspond to the required eye opening. Therefore, the proposed inverse design algorithm is used to estimate the link parameters.

We have validated our inverse design with 3D EM simulations as shown in Fig. 4 and the system performance parameters are shown in Table I. We plot our machine learning predicted geometry parameters versus experimental geometry of l_w, t_c, s, h_{sub} used in the 3D EM simulations and we compute the root mean square error as shown in Table I. The observed mismatch is partly due to the estimated function being *non-injective* (different geometry configurations map to the same eye characteristics). The mismatch increases when the same output maps to several possible inputs.

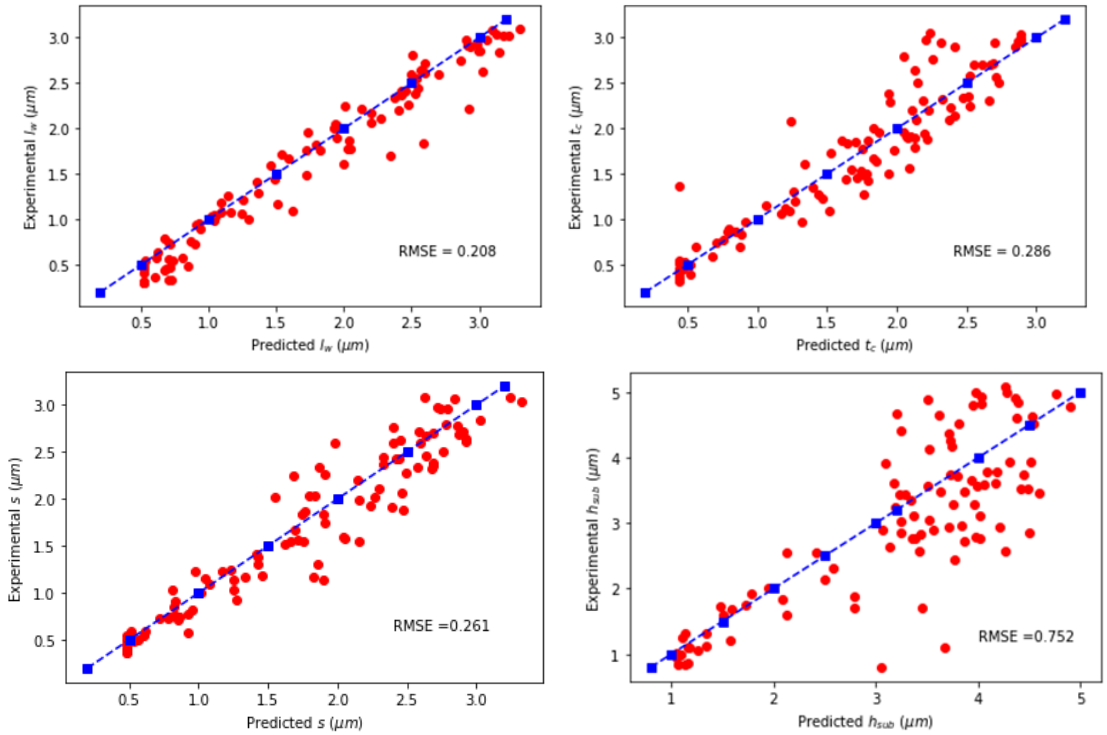

Figure 4: Comparison among the results of the proposed inverse prediction technique and the corresponding ones provided by the 3D EM simulations solver for the parameters l_w, t_c, s and h_{sub}, respectively.

Table I: System Performance Parameters

Geometry Parameter	Error	Epochs	Batch Size
l_w	0.208	900	25
t_c	0.286	900	25
s	0.261	900	25
h_{sub}	0.752	900	25

V. Conclusion.

In this paper we have proposed an inverse design approach to find geometric parameters of transmission lines from eye characteristics. An advanced deep learning method is used to map the desired eye opening by obtaining the corresponding geometrical dimensions. In future work we intend to reduce the number of exploited eye characteristics, and provide all possible solutions for the desired eye opening. We have also achieved good results by training with pulse response of the channel; however we intend to improve the algorithm so it only requires a small number of intuitive eye characteristics to provide the range of geometric parameters.

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