Eye-width and Eye-height Estimation Method based on Artificial Neural Network (ANN) for USB 3.0

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***Abstract*— As technology develops, the amount of data used increases exponentially and the operating speed of electronic devices increases accordingly. As the operating speed increases, the transmission speed of data exchanged through the channel also increases. To get an eye-diagram, a time-domain simulation is required, which consumes a lot of time and computer power. However, a channel simulation in frequency-domain is fast and it consumes less computer power. Therefore, using the frequency-domain simulation data is more efficient than the time-domain simulation. This paper proposes an eye-width and eye-height estimation method using an artificial neural network (ANN). The input of the ANN is insertion loss and the outputs of the ANN are eye-width and eye-height. Finally, the performance of the proposed method is verified by transient eye-diagram simulations with arbitrarily-selected channel parameters.**

Keywords*— *Artificial neural network (ANN), eye-diagram, eye-diagram Estimation method, signal integrity (SI).

I. INTRODUCTION

Over time, the data rate of high-speed channels is rapidly increasing. A universal serial bus (USB) is the most commonly used among these high-speed channels. The USB has been released as 3.2 standard specifications and was announced at a maximum data rate of 20 Gbps [1]. As the data rate increase, more signal integrity problems occur [2]-[4]. As a result, signal integrity analysis becomes important to solve these signal integrity problems. In the signal integrity analysis, the eye-diagram shows how much the output signal is degraded when the input signal is sent. Eye-diagram distortion of USB 3.0 channel is shown in Fig. 1. The distorted signals can cause the system to malfunction. The eye-diagram is the result of the overlapping of received signals. Due to the feature of these eye-diagrams, the process of obtaining an eye-diagram takes a lot of time. The time to design and obtain an eye-diagram every time can eventually take up a large portion of the overall design time. Therefore, many methods for estimating eye-diagrams are being studied to reduce the time [5]. Since these methods use a single bit response, requiring time domain input data, they still have long simulation time. . There is another way to predict eye-diagrams without time domain results.

One way to improve efficiency and accuracy when estimating eye-diagram is using an artificial neural network (ANN). The ANN is an algorithm that simulates in the way a human brain recognizes patterns. The ANN interprets the relationship between input data and output data using perceptron. With this result, the ANN can find a specific pattern between the input and the output [6]. So the ANN can be used to estimate eye-diagram in the high-speed channel for accurate and fast signal integrity analysis without complex knowledge about signal integrity. In the previous works, the ANN is used for the efficient statistical analysis and nonlinear modeling of high-speed systems [7]. In addition, a multi-layer perceptron (MLP) method to train the ANN models is used to predict eye-width and eye-height [8]. The previous studies used two types of data: insertion loss and reflection loss, so two types of data are needed for predict eye-diagrams.

In this paper, accurate and fast eye-height and eye-width estimation method is proposed based on ANN. The proposed method use only insertion loss value extracted by three-dimensional electromagnetic (3D EM) simulation as input data. USB 3.0 channel is used for channel simulation up to 20 Gbps. The 3D EM simulation provides a more accurate insertion loss value than the circuit simulation insertion loss value. Eye-width and eye-height are obtained by changing the width and thickness of the signal line, all at a data rate of 5 Gbps. The performance of the proposed eye-diagram

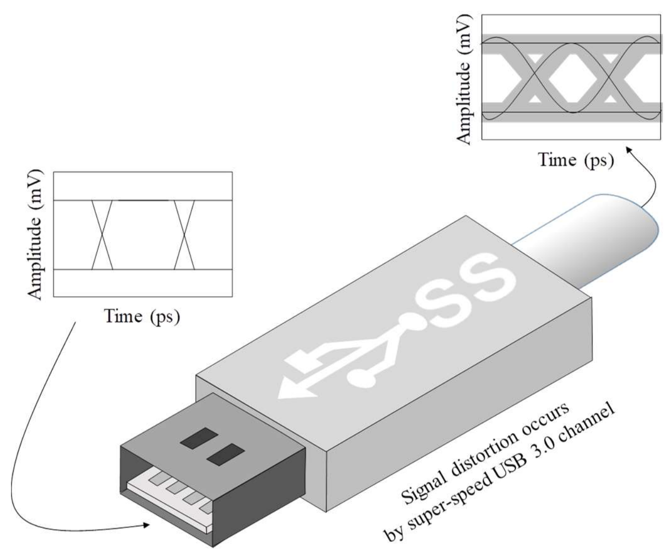


Fig. 1. Signal distortion occured by USB 3.0 channel. The distorted signals can cause the system to malfunction.

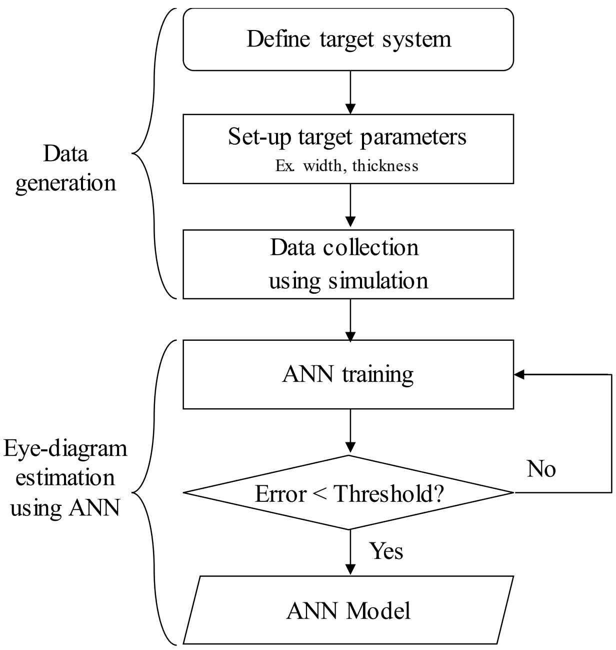


Fig. 2. Flowchart of data generation and training for the proposed ANN-based eye-diagram estimation method .

estimation is validated by transient simulation. As a result, this method enables accurate and fast eye-height and eye-width estimation.

II. Proposed Eye Diagram Estimation Method

Fig. 2 is a complete flowchart of the proposed method, which is divided into two parts: data generation and eye-diagram estimation using the ANN. The first step is to define the target system and set up the target parameters. The target system is USB 3.0 and the target parameters are signal line width and height. After, the input and output of the ANN model are defined. The input data is the insertion loss value generated by changing the channel parameters in the 3D EM simulation. Since the input data is a wide frequency data, reducing the number of input data is necessary. So selecting input data is performed based on the Nyquist frequency which greatest effect on eye-diagram. The output is the eye-width and eye-height values extracted from transient simulation. The ANN can be modeled by learning the relationship between nonlinear input and output. Therefore, the ANN model needs hidden layers but one hidden layer is sufficient. The number of the input, hidden and output nodes are 40, 10 and 2. The Fig. 3 shows the ANN model for eye-width and height estimation.

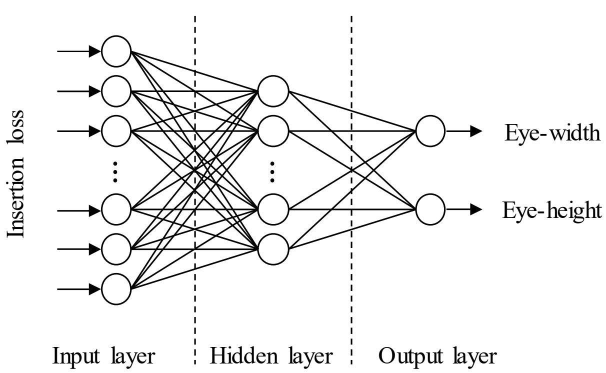


Fig. 3. The proposed ANN model for estimating eye-width and eye-height.

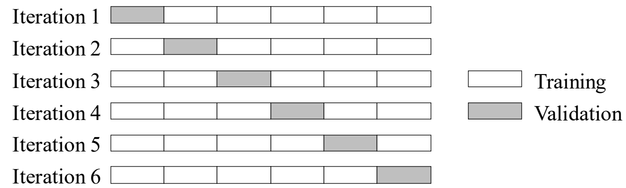


Fig. 4. K-fold cross-validation method applied in the proposed method.

The ANN model can be more accurate when the number of input and output, or datasets, is larger. However, the datasets created by 3D EM tool were only 35 sets. Because it takes lots of time to get insertion loss value upon actual USB model. So, in order to make good use of it, 30 random data sets were used to train and validate the ANN model by applying k-fold cross-validation method. In addition, the remaining 5 datasets were used for test sets. The k-fold cross-validation method is shown in Fig. 4. It is a way to train not only the training set but also the validation set, which increases the statistical reliability when the amount of data is insufficient. A total of 6 iterations were performed, dividing 30 datasets into 6 sub-sets having 5 datasets each. The performance of the model is checked by training the model with 5 sets of datasets and validating with the other set. This process was performed six different times.

III. Verification of the Proposed Method

The ANN model is trained to estimate the eye-width and eye-height together. The learning rate is 0.1 and the maximum number of iteration is set to 160. The eye-width and eye-height in the dataset vary from 97.3 ps to 164 ps and 32 mV to 590 mV. The results of eye-width and eye-height estimations are as shown in Table I and Table II. Each Table shows the root mean square error (RMSE) and relative error. The RMSE is below:

$$\sqrt{\frac{\sum_{i=1}^{N}\left(Y_{true_i}-Y_{estimated_i}\right)^2}{N}} \quad (1)$$

The relative error is below:

$$\frac{Y_{true}-Y_{estmiated}}{Y_{true}} * 100\ (\%). \quad (2)$$

Since the error value changes every time whenever the ANN model is created, the error values are averaged over k iterations and compared, where k is set to 100 to get the average error. Also the maximum and minimum errors are also shown in the table during 100 iterations.

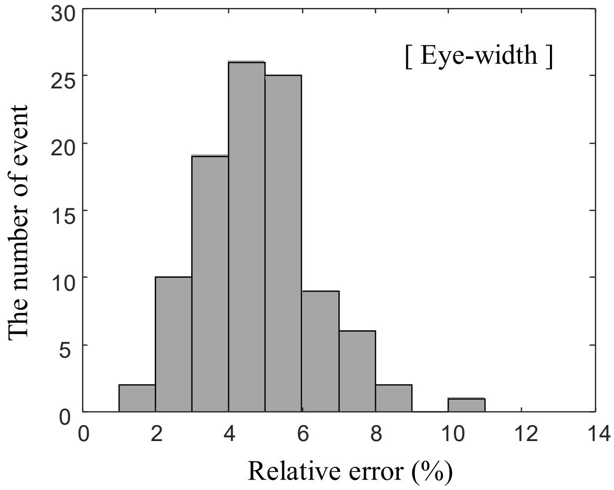
The proposed model achieves 10.57 % the maximum relative error and 4.32 % the average relative error on the test set in eye-width estimation. Additionally, the proposed model

TABLE II. Error of Estimated Eye-widths

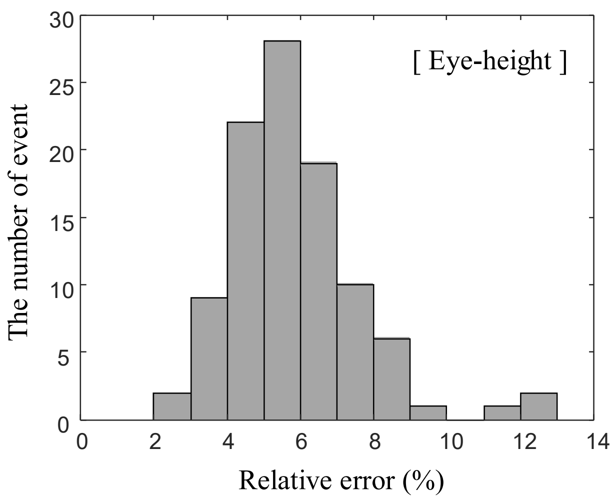
	Minimum	*Maximum*	*Average*
RMSE (mV)	0.0093	0.0855	0.0361
Relative error (%)	1.25	10.57	4.32

TABLE I. Error of Estimated Eye-heights

	Minimum	*Maximum*	*Average*
RMSE (ps)	0.0045	0.0294	0.0124
Relative error (%)	2.05	13.12	5.38



(a)



(b)

Fig. 5. Histogram of relative errors of the estimated (a) eye-width and (b) eye-height from the proposed ANN model on the test set.

achieves 13.12 % the maximum relative error and 5.38 % the average relative error on the test set in eye-height estimation. Fig. 5 shows the histogram of the relative errors of the estimated eye-width and eye-height from the proposed ANN model on the test set. The transient simulation shows entire contour of the eye-diagram as shown in Fig. 6. In contrast, the proposed method estimates only eye-width and eye-height values. We compare the transient and the estimated eye-diagram by the proposed method as shown in Table III. the proposed method successfully provides the accurate eye-diagram. After the training is finished, the ANN model can quickly estimate the eye-width and eye-height. it takes less than a second to estimate the eye-diagram. Therefore, the proposed method provides accurate and fast eye-height and eye-width estimation.

IV. Conclusion

In this paper, ANN-based eye-width and eye-height estimation method was proposed. The proposed method only requires insertion loss to estimate eye-diagram. Moreover, one simple ANN model can estimate two values of eye-diagram. For verification, the transient and the proposed method were compared. The errors of eye-width and eye-height were 1.31% and 5.42% respectively. Thus, the proposed method achieves fast and accurate eye-diagram estimation. With more iterations of designing the channel, the simulation data will be gathered over time. therefore, it will further improve the accuracy of the ANN model.

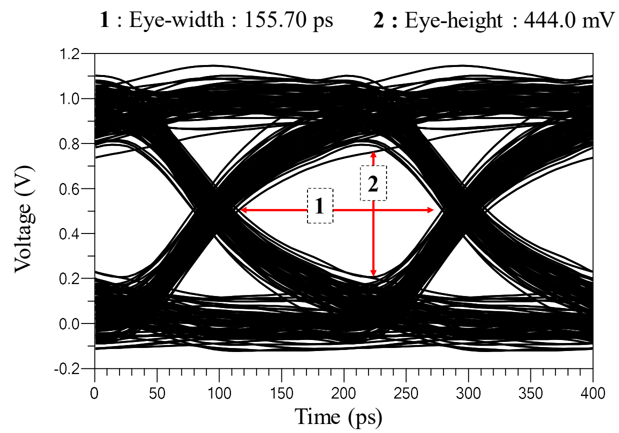


Fig. 6. Transient simulation results for verification of the proposed method.

TABLE III. Comparison of the Transient Simulation and Proposed Method

	Eye-width	*Eye-height*
Transient simulation	155.70 ps	444.0 mV
Proposed method	153.65 ps	419.9 mV
Relative Error	1.31 %	5.42 %

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