Surrogate Eye Modeling for the Statistical Assessment of a Smart Textile Interconnect

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***Abstract*—This paper focuses on the generation of a compact and accurate model of the eye aperture for a differential textile interconnect. The considered eye metric is computed through a simple and effective procedure based on a polygonal approximation of the clean inner eye area. Least squares support vector machine regression is used, yielding a fast and accurate surrogate model of the link, providing a quantitative information of the data communication quality. The generated model turns out to be a parametric description which is used in the framework of stochastic analysis and uncertainty quantification, allowing to take into account the effects of the variation of the electrical and geometrical parameters of the link. The accuracy and convergence of the proposed machine learning solution are thoroughly discussed.**

***Index Terms*—signal integrity, high-speed interconnects, smart textiles, wearable electronics, eye diagram, uncertainty quantification (UQ), least-squares support vector machine (LS-SVM).**

I. Introduction

In the past decades, a large number of techniques have been developed to provide designers with a set of robust and effective tools for the statistical or parametric analyses of circuits and systems, including high-speed interconnects. Among them, Monte Carlo and its enhancements offer the more classical and simplest approach, allowing to easily collect easily quantitative information of the possible spread of a given system response due to the variation of electrical and geometrical parameters [1], [2]. Monte Carlo is, however, computationally costly and, in recent years, more efficient techniques, either based on polynomial chaos expansions or machine learning, have been developed (e.g., see [3]–[5] and the references therein).

This paper focuses on the latter class and on the least squares support vector machine (LS-SVM) regression which has been demonstrated to be extremely effective for a number of problems in the area of high-speed electronic design [4], [5]. Specifically, the LS-SVM regression is here used to build a compact surrogate model of the eye aperture of a realistic textile interconnect structure inspired by [6]. The contribution of this paper is twofold: on one hand, it explicitly details the algorithmic steps for the efficient computation of the eye aperture; on the other hand, it proves that the considered machine learning solution enables the generation of an accurate parametric model, obtained form a limited number of samples, in a particularly challenging context: numerous sources of uncertainty and intrinsically high tolerances.

II. Test case

The results obtained in this paper are based on the serial link shown in Fig. 1, which has been implemented and simulated in LTSPICE [7]. It consists of a differential data communication channel implemented by conductive copper wires weaved in a textile structure [8]. The link features a differential driver at the near end and its paired receiver at the far end. A passive equalizer is inserted between the driver and the line. It is assumed that the equalizer and drivers are implemented either using conventional electronics or semi-flexible substrates and are also affected by uncertainties. The center section of the interconnect (identified by a transmission line segment with length L_2 in the schematic) accounts for a potentially altered geometry. This can either take the form of compression due to external mechanical action or to the very nature of the application (e.g. bending at knees or elbows) or on the contrary stretching of the material. Either situation introduces a discontinuity in the distance between the conductors.

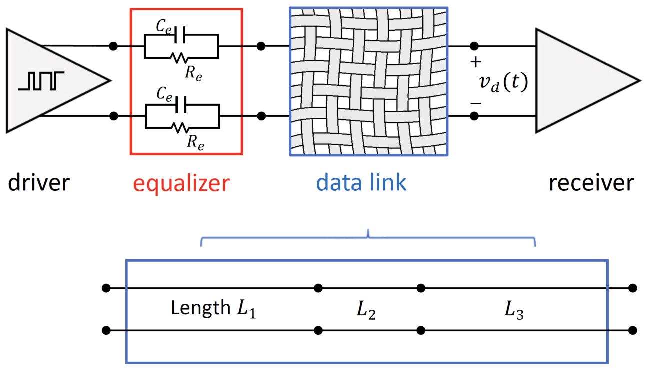

Fig. 1. System under test: digital link for wearable applications. The nominal values of the equalizer and of the line lengths are: $R_e = 70\,\Omega$, $C_e = 3.2\,\mathrm{pF}$ $L_1 + L_2 + L_3 = 33\,\mathrm{cm}$,

An NRZ encoding is assumed at a data rate of 2 Gbps. For the sake of simplicity linear models (similar to the ones implemented in IBIS-AMI simulations) were used to model both the driver and the receiver. If needed, enhanced models of such devices can be adopted [9]–[11]. The geometrical parameters of the interconnect, including the fabrication tolerances, are those of [6]. The selected structure is labelled as GSSG-1 (see Fig. 3 of the above mentioned reference paper) and consists in a differential pair between two ground conductors.

Note that wearable electronics are generally affected by larger tolerances than standard PCB applications. The distance between the signal lines is $411\,\mu$m $\pm 7.3\,\%$. The distance between each signal line and the adjacent ground line is $481\,\mu$m $\pm 6.7\,\%$. Conductor diameter is $228\,\mu$m $\pm 11.1\,\%$. The total length of the link is 33cm ± 1cm (mainly due to sizing). The section suffering deformation varies in length from 2 to 5 cm and the compression [stretching] factor is $25\,\%$ [$10\,\%$]. Tolerances of $1\,\%$ were assumed for the elements of the equalizer. Overall, 11 stochastic parameters are considered. Each eye diagram is computed for 4000 bits.

III. Eye aperture

In this paper, the quality and performance of the data link communication is quantitatively assessed by computing the eye aperture on the receiver side, generated from the differential voltage response $v_d(t)$.

The eye aperture is defined by the area of a polygonal representation of the eye inner clean zone, which is efficiently computed from the recorded sequence of the sampled voltage waveform $v_d(t)$. The proposed algorithm is described below, through a procedure with the essential steps outlined using a metalanguage description and a MATLAB-like code. It is assumed that the sampled response of $v_d(t)$ is stored in the vector `vd`. It collects the values of the received differential voltage at the time samples stored in vector `t`. Also, due to the differential communication scheme, a zero-threshold (`threshold=0` in the code) is assumed for computing the state (i.e., bit) transitions.

The main steps af the algorithm are:

1) the estimated crossing times are store in vector `tz` and are determined via linear interpolation:

```
>> vd = vd-threshold;
>> iz = find(diff(sign(vd)));
>> a  = (vd(iz)-vd(iz-1))./(t(iz)-t(iz-1));
>> tz = (-vd(iz)+a.*t(iz))./a;
```

2) the time axis and the crossing times are wrapped into the unit interval defined by the bit time (`TBIT`); also, the jitter width (`JITW`) is computed by considering the largest and the smallest wrapped (i.e., normalized) transition times:

```
>> tzoffset  = mod(tz(1),TBIT);
>> tzw       = mod(tz-tzoffset,TBIT);
>> JLEFT     = TBIT-min(tzw(tzw>TBIT/2));
>> JRIGHT    = max(tzw(tzw<TBIT/2));
>> JITW      = JLEFT+JRIGHT;
```

3) within the unit interval, a number of sampling points is set (e.g., `POINTS=[0.1,0.2,......,0.9]`) and the minimum and the maximum values of the received signal observed at these sampling points are computed, $v_d(t =$ `(POINTS(kk)+(n-1))*TBIT`). In the above notation, the index `kk` varies from one to the max number of items in vector `POINTS`, and `n` ranges from one to the maximum number of bits composing the bitstream. The procedure in this step is suitably modified to avoid probing the differential signal in the jitter region. It is important to point out that the above mentioned max and min values define, for a given point in the unit interval, the vertical eye height;

4) the eye aperture is hence estimated by computing the area defined by an inner polygonal shape built based on the above points. Figure 2 shows two example eye diagrams which can be obtained for the example test case, together with its inscribed inner polygons (see the blue thick lines).

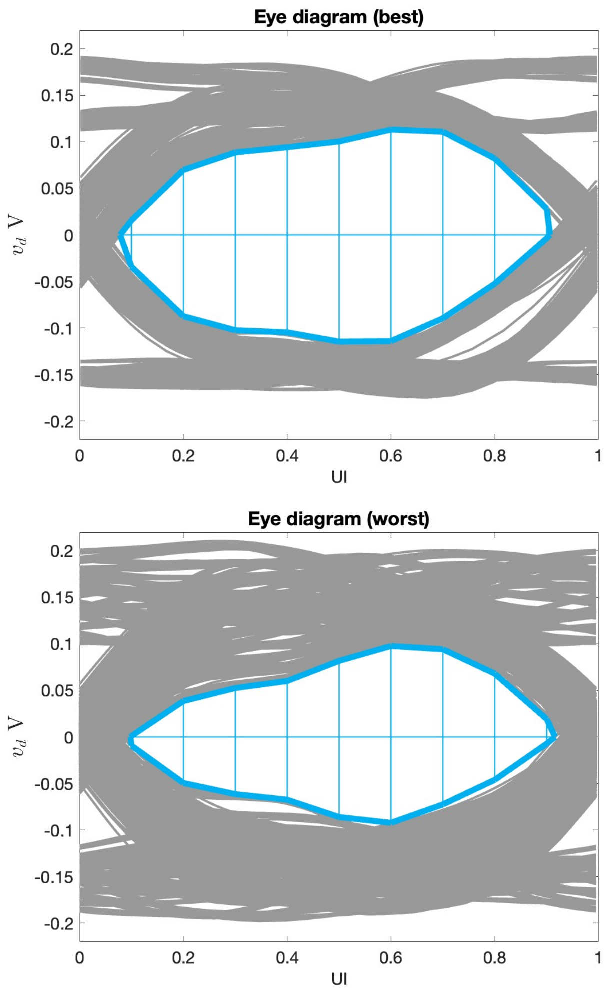

Fig. 2. Eye diagram obtained for the example data link of Fig. 1. Top panel: best case, bottom panel: worst case.

IV. Surrogate modeling via LS-SVM regression

Let us consider the problem of approximating the eye area starting from the information available in the training set $\mathcal{D} = \{(\boldsymbol{x}_l, y_l)\}_{l=1}^{L}$, where the vector $\boldsymbol{x}_l \in \mathcal{X}$ with $\mathcal{X} \subset \mathbb{R}^p$ is a vector collecting the l-th configuration of the input parameters (i.e., in the considered application $p = 11$)

and y_l is the corresponding output (i.e., the eye area). The LS-SVM regression allows building a surrogate model based on the following kernel formulation [12]:

$$\mathcal{M}_{LS\text{-}SVM}(\boldsymbol{x}) = \sum_{i=1}^{L} \beta_i k(\boldsymbol{x}_i, \boldsymbol{x}) + b \quad (1)$$

where $\beta_i \in \mathbb{R}$ are scalar coefficients, $k(\cdot,\cdot) : \mathbb{R}^{p \times p} \to \mathbb{R}$ is the kernel function and $b \in \mathbb{R}$ is the regression bias term. Several kernel functions $k(\cdot,\cdot)$ have been proposed in the literature. Hereafter in this work we will adopt the radial basis function (RBF) kernel, which writes [13]:

$$k(\boldsymbol{x}_i, \boldsymbol{x}) = \exp\left(-\frac{\|\boldsymbol{x}_i - \boldsymbol{x}\|^2}{2\sigma^2}\right) \quad (2)$$

where σ^2 is the kernel hyper-parameter tuned via leave-one-out cross validation.

The LS-SVM regression estimates the optimal set of regression coefficients β_i and bias b in (1) minimizing the squared loss computed between the model predictions and training outputs together with a Tikhonov regularized. It provides an alternative interpretation of the standard SVM regression [13] without losing its the advantages [12]. Indeed, for the LS-SVM regression, the model coefficients can be computed in a closed-form as the solution of a linear system of equations. The LS-SVM regression is already implemented within LS-SVMLab Toolbox version 1.8 [14], which is fully compatible with the MATLAB environment.

V. Numerical results

The above simulation framework has been used to generate the training and test sets used to construct and assess the accuracy of a surrogate model built via the LS-SVM regression presented in Sec. IV. These training and test sets are generated by randomly varying the parameters defining link, according to the range of variations discussed in Sec. II. For each set of parameters, the received differential voltage $v_d(t)$ is recorded and the eye aperture is computed according to the procedure of Sec. III.

Figure 3 shows the accuracy of the surrogate expressed in terms of relative root mean square error (RMSE) computed on 1000 test samples for an increasing number of training samples (i.e., $L = 50, 100, 200, 300$ and 1000). The plot shows a constant reduction of the model error with respect to the number of training samples (i.e., L), thus highlighting the capability of the proposed surrogate model of learning the actual information provided by the training set.

Moreover, Fig. 4 compares the PDFs computed from the considered 1000-sample test set, used as reference, with the corresponding one obtained from a surrogate model trained with $L = 300$ samples. The above comparison highlights the excellent accuracy of the proposed model, being the two histograms almost perfectly overlapped.

Concerning the computational cost, the training time required to train a surrogate model via the LS-SVM regression goes from less than 1 s for $L = 50$ training samples to 42 s for $L = 1000$ training samples. After the training, the evaluation of the obtained model on the 1000 test samples required few millisecond, while the corresponding SPICE simulations required several hours (around 36 in this case).

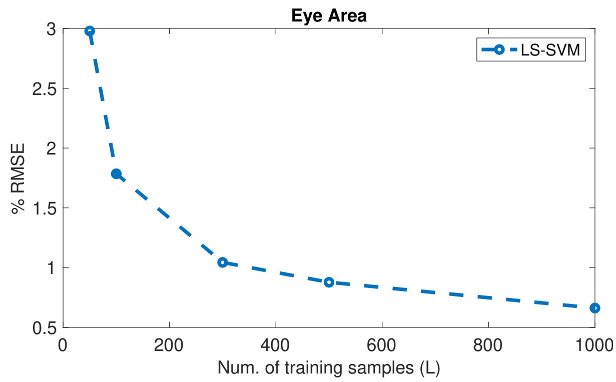

Fig. 3. Relative RMSE computed from the predictions of the surrogate models trained with an increasing number of training samples by considering 1000 test samples.

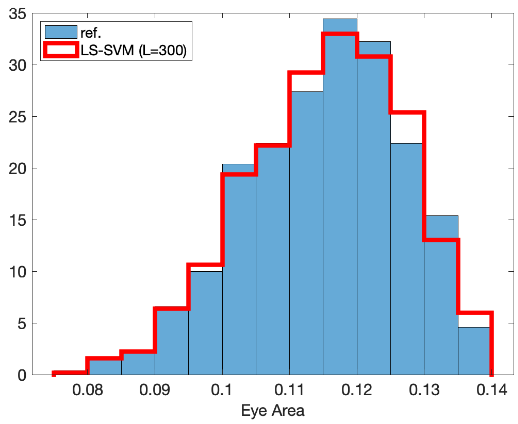

Fig. 4. Comparison between the PDFs of the eye area computed from the predictions of the surrogate models built with $L = 300$ training samples and the corresponding one calculated on 1000 test samples

VI. Conclusions

This paper discussed the application of LS-SVM regression for the surrogate modeling of the eye aperture of a textile link with uncertain electrical and geometrical parameters. The proposed approach led to an accurate and compact parametric model allowing to quantitatively assess the data communication performance. The eye aperture was computed by means of a suitable polygonal approximation of the inner clean area of the eye pattern. The procedure was presented in detail, the authors providing the outlines of a compact, custom implementation of the algorithm. Each step leading to the computation of the eye metric was explained. A deliberately challenging test-case was selected, a flexible differential interconnect operating at 2 Gbps in a smart textile application. The results proved the feasibility and strength of the proposed machine learning solution.

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