Deep Learning of GNSS Signal Correlation

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ABSTRACT

This paper studies the use of deep learning models to model the complex effects of multipath propagation on GNSS correlation outputs. Particularly, we aim at substituting standard correlation schemes (that are optimal under nominal conditions) with Neutral Network (NN)-based correlation schemes, that are able to learn multipath channels, otherwise challenging to be captured by physics-based models. The solution involves the use of a Deep Neural Network (DNN) structure, which exploits the optimality of standard correlation schemes at the same time that adjusts its behavior to better model multipath. The proposed solution can be used in substitution of standard correlation, then seamlessly plugged on acquisition and tracking receiver blocks. Results on the currently trained model show promising time-delay tracking performances, when compared to standard correlation processing.

INTRODUCTION

Global Navigation Satellite System (GNSS) has been widely used in position-based applications with high accuracy and precision needed [2, 7, 8]. The growing dependence on GNSS within critical infrastructures has posed some concerns about the potential threats to GNSS. Therefore, techniques have been studied for years to mitigate the influence of a variety of error sources such as multipath propagation or interference-rich environments [12, 16, 17]. In GNSS processing, tracking block is applied to follow the evolution of the signal synchronization parameters.

In the tracking block, correlation between GNSS signal and local replicas of satellite's pseudo-random codes is a fundamental component that is used to build the so-called Cross Ambiguity Function (CAF), which the receiver aims at optimizing. The described correlation approach used to compute the CAF is i) mathematically simple to implement, but computationally intensive; and ii) optimal under white-Gaussian noise, but easily spoiled in non-nominal situations, such as in the presence of outliers for instance due to multipath conditions. Focusing on distortions due to multipath propagation, as an example, the type of distortions caused in the CAF are such that time-of-arrival estimates become positively biased due to the induced extra propagation path [13]. This article proposes to train NN to substitute standard correlation operations in a way that maintains high accuracy in outlier-rich environments, where the traditional correlation-based method would degrade or even become unreliable.

Many methods have been proposed in the literature in order to mitigate those effects. Most of those works are either studying 1) enhanced discriminator functions, such that the delay/phase lock loops (DLL/PLL) are less sensitive to multipath effects. For instance, the Narrow Correlator [16], the Pulse Aperture Correlator (PAC) [10], the Double Delta Correlator [12], the Early1/ Early2 (E1/E2) tracking technique [15] or the Multipath Elimination Technology (MET) [14] are classical solutions within that approach; or 2) advanced receiver architectures that jointly estimate the line-of-sight and multipath components for each satellite link, in a typically computationally complex process. For instance, the Multipath Estimating Delay Lock Loop (MEDLL) [17], the Vision Correlator [9]te, the Multipath Mitigation Technique (MMT) [18], or the use of particle filtering to discriminate among propagation paths [6]. These methods can yield to robust correlation and tracking results, however, it is worth noting that they heavily rely on accurate physics-based models and deviations from those might cause dramatic degradations in performance. In real-world experiments, models might result inaccurate in a variety of situations. This article proposes to substitute correlation-based CAF computations (which inherently rely on physics-based models), with correlation schemes purely derived from a data-driven paradigm in which the complexity of the channel is learned from data.

With the popularity of Artificial Intelligence, machine learning and deep learning begin to play an important role in adapting traditional algorithms, especially when it comes to estimation and classification tasks. At a glance, deep learning algorithms (for instance, the variety of Neutral Networks (NNs) architectures currently available) are data-driven models that, instead of using complex-to-derive physics-based models, use vast datasets to learn the correlations in the data. Therefore, a computer uses large datasets to train multiple layers of a neural network, in a time-consuming process until acceptable accuracy performance is achieved. When physics-based models are available, as is the case for the so-called correlation used in CAF computation, the use of NNs might seem redundant. However, the appeal of such deep learning methods comes in situations where a physics-based model is either too complex to use or not available at all. This is the case, for instance, of multipath channels. In the context of GNSS, Deep NN (DNN) models have been recently considered in various contexts of the receiver design [1, 4].

In this article, DNN is applied for regression, which is a typical NN, as a regularized version of Multilayer Perceptron (MLP). The input for DNN is usually an image and therefore we keep our input as 3D when training the model. Similar to MLP, DNN also contains multiple hidden layers, especially the convolutional layer, pooling layer, and fully connected layers. With those layers above, DNN can thus transform input (usually an image) layer-by-layer from the elements to regression values. Particularly, considering the complex signal as the input to the neural network, as well as Pseudo-Random Noise (PRN) number for the specific satellite, the length of the input variable is $2 \times N \times 1$, where N is the length of the signal in samples (related to sampling frequency and the integration time). The two columns correspond to the real and imaginary parts of the complex GNSS signal. Since the GNSS signal is a complex signal, so are the CAF values, the real and imaginary part of correlation results are computed separately, therefore, the output is a $2L \times 1$ vector containing the real and imaginary components of the CAF where L is now the number of correlation outputs evaluated by the NN-based correlator scheme.

To test the performance of the trained model, in addition to the validation, the model is also applied in a signal tracking task. The objective is to evaluate the performance of the tracking phase using the proposed NN-based correlation approach. A standard tracking method using correlation-based CAF-computation is also used for comparison over the same GNSS signal.

SIGNAL MODEL

The signal received by the antenna of a GNSS receiver can be modelled as:

$$y(t) = \sqrt{2C}d(t-\tau_0)c(t-\tau_0)\cos(2\pi(f_{RF}+f_0)t+\phi_0)+\eta(t)+\mathcal{M}(t) \tag{1}$$

where C is the useful signal power, $d(\cdot)$ is the navigation message, $c(\cdot)$ is a pseudo-random code from a family of quasi-orthogonal sequences. f_0 is the Doppler shift with respect to the nominal signal Radio Frequency (RF), f_{RF}, and τ_0 and ϕ_0 model the delay and phase shift introduced by the communication channel. $\eta(t)$ is a zero-mean Additive White Gaussian Noise (AWGN). In the absence of multipath $\mathcal{M}(t)$ is the dominating term and the reason why $y(t)$ follows a Gaussian distribution. Signal $\mathcal{M}(t)$ is the multipath term. In this article,we are considering a single satellite in the model (1) since the proposed processing is also applied on a satellite-per-satellite basis.

After amplification, filtering, down-conversion and sampling at $f_s = \frac{1}{T_s}$, the signal provided by the receiver front-end is a baseband complex sequence:

$$y[n] = \sqrt{2C}\,\underbrace{\tilde{d}(nT_s - \tau_0)\tilde{c}(nT_s - \tau_0)\mathrm{e}^{j(2\pi f_0 nT_s + \phi_0)}}_{x_\theta[n]} + \eta_{BB}[n] + \mathcal{M}_{BB}[n] \tag{2}$$

where n is the time index, and square brackets are used to denote discrete time sequences. Notice that $\boldsymbol{\theta} = (\phi_0, \tau_0, f_0)^\top$ is a vector that gathers the parameters of the signal for the satellite of interest, namely its phase, delay, and Doppler. The corresponding baseband waveform is then $x_\theta[n]$. The subscript 'BB' is used to indicate filtered signals down-converted to baseband. The symbol $\tilde{\cdot}$ indicates the impact of front-end filtering on the useful signal component. $\eta_{BB}[n]$ is AWGN with independent and identically distributed (i.i.d.) real and imaginary parts, each with variance σ^2, which together makes the total variance of the complex signal $\eta_{BB}[n]$ equal to $2\sigma^2$. Commonly, σ^2 can be modeled as:

$$\sigma^2 = N_0 B_{Rx} \tag{3}$$

where B_{Rx} is the front-end one-sided bandwidth, and N_0 is the Power Spectral Density (PSD) of the input noise, $\eta(t)$ in (1).

Either in acquisition or tracking, the task of the receiver is to accurately estimate the parameters in $\boldsymbol{\theta}$. This is typically accomplished through ML estimation (MLE), where it is typically assumed that the parameters in $\boldsymbol{\theta}$ are piece-wise constant within the N samples of $\mathbf{y} = (y[0], \ldots, y[N-1])^\top$ and that the codes have ideal cross-correlation properties so they can be processed independently at the receiver. It is known that the solution to such estimation process results in the maximization of the correlation between the received signal and a locally generated code. This correlation operation is encoded in the so-called Cross Ambiguity Function (CAF), which is nothing but the correlation between $y[n]$ and the spreading code of the i-th satellite, at a given delay/Doppler pair (in discrete-time):

$$\mathcal{C}_i(\tau, f_d) = \frac{1}{N}\sum_{n=0}^{N-1} y[n]\,\underbrace{c_i(nT_s - \tau)\exp\{-j2\pi f_d nT_s\}}_{\text{Local replica}}\,, \tag{4}$$

which can be expressed more compactly in vector notation after gathering N samples from the samples and the local code as $\mathbf{y}, \mathbf{c}_i \in \mathbb{C}^{1\times N}$ as

$$\mathcal{C}_i(\tau, f_d) = \frac{\mathbf{y}\mathbf{c}_i^H}{N}\,. \tag{5}$$

The CAF is crucial in the acquisition (and tracking) of the satellites' signals. The MLE of $\boldsymbol{\theta}$ can be expressed in terms of it as

$$\begin{aligned}(\hat{\tau}_0, \hat{f}_0) &= \arg\max_{\tau, f_0}\left\{|\mathcal{C}(\tau, f_0)|^2\right\} && (6)\\ \hat{\alpha}_0 &= \left|\mathcal{C}(\hat{\tau}_0, \hat{f}_0)\right| && (7)\\ \hat{\phi}_0 &= \angle\mathcal{C}(\hat{\tau}_0, \hat{f}_0)\,, && (8)\end{aligned}$$

where $\hat{\alpha}_0$ is the MLE for $\sqrt{2C}$, the line-of-sight signal amplitude.

In the presence of a multipath signal, the CAF is distorted in a way that the MLE estimates of $\boldsymbol{\theta}$ are biased. The baseband multipath signal, $\mathcal{M}_{BB}[n]$, is indeed a distorted version of transmitted GNSS signal is modeled as

$$\mathcal{M}_{BB}[n] = \tilde{A}_{\mathcal{M}} x_\theta[n - n_{\mathcal{M}}]\,, \tag{9}$$

where $\tilde{A}_{\mathcal{M}}$ is the amplitude of transmitted signal after transmission loss and $n_{\mathcal{M}}$ is the delay caused by multipath propagation [5]. In standard GNSS signal processing, influence of multipath signal in normalized correlation result is shown in Fig. 1, where we can observe how the correlation results are distorted, ultimately impacting the estimation of LOS' time-delay τ_0.

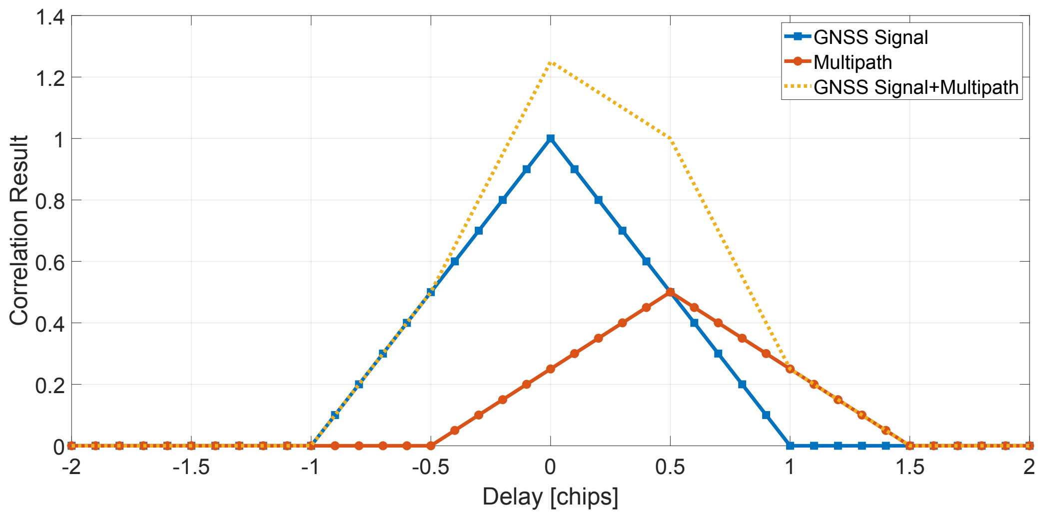

Figure 1: Normalized correlation result in the presence of a single multipath replica.

NEURAL NETWORK ARCHITECTURE

This section describes the architecture of the DNN used in this article. Deep learning involves training a model by using a given dataset to the NN, that consists of a combination of neurons and layers. The neuron is nothing but a mathematical function that computes weights for averaging incoming input, and then applies a predefined active function. A collection of neurons forms a layer. The NN consists of an input layer, a output layer, and a number of hidden layers. As shown in Fig. 2, a connection between neuron j in layer $l-1$ and neuron i in layer l is given by

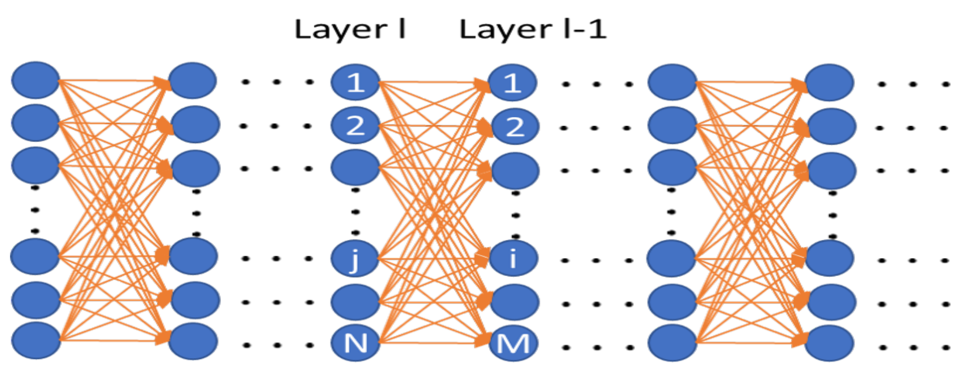

Figure 2: General NN Architecture

the weight w_{ij}^l, which represents the significance of the connection between layers, and a bias term is also applied for output x_i^l to become [3]:

$$x_i^l = f(b_i + \sum_{j=0}^{D} w_{ij}^l x_j^{l-1}) \tag{10}$$

where $f(\cdot)$ is the activation function and D is the number of neurons in layer $l-1$. Following (10), the output of layer l is:

$$\boldsymbol{x}^l = \boldsymbol{f}(\boldsymbol{b}_l + \boldsymbol{W}_l \boldsymbol{x}^{l-1}) = \boldsymbol{f}_l(\boldsymbol{x}_{l-1}) \tag{11}$$

Thus, the entire NN can be expressed sequentially as:

$$\boldsymbol{y} = \boldsymbol{f}_L(\boldsymbol{f}_{l-1}(\cdots \boldsymbol{f}_1(\boldsymbol{x}))) \tag{12}$$

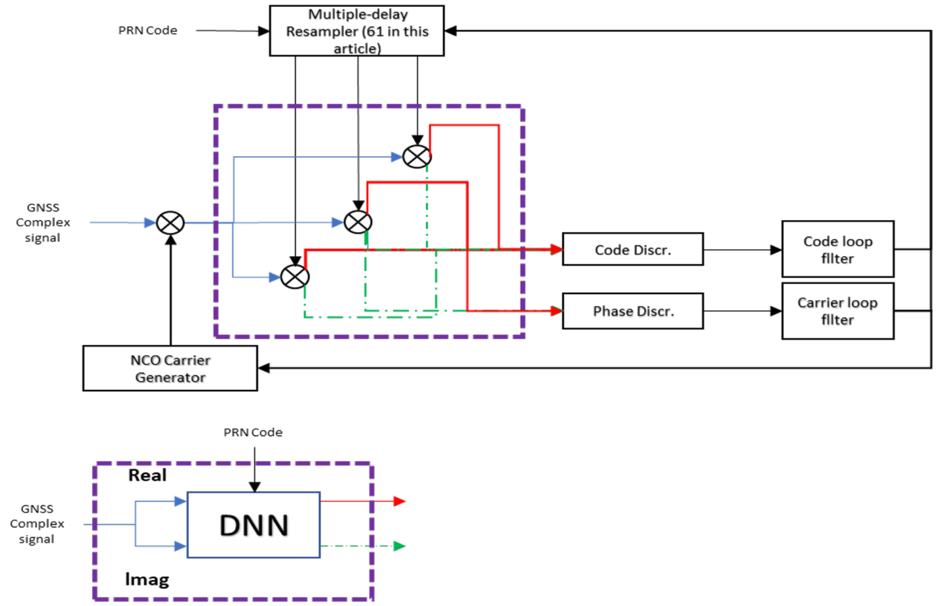

Figure 3: DNN Goal:Substitute the classical correlation in tracking block to birng robustness against multipath affect.

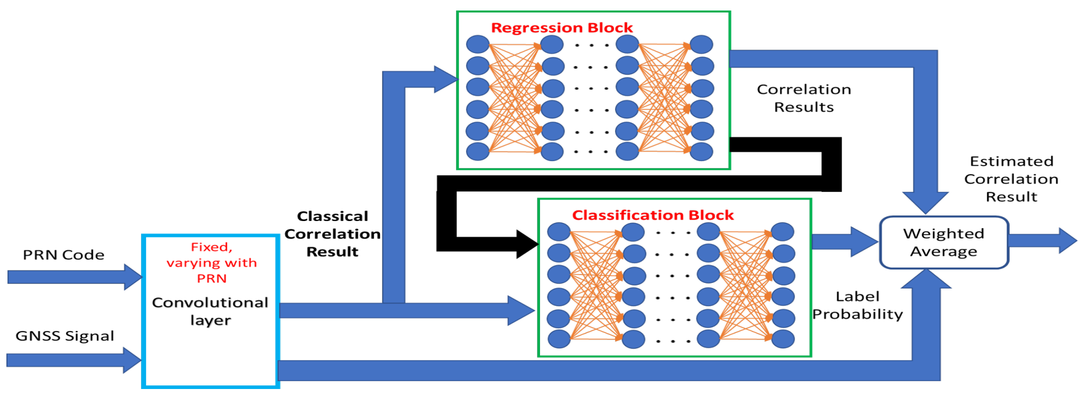

Figure 4: Architecture of the DNN model considered in this article.

where $\boldsymbol{x}$ is the input to NN and $\boldsymbol{y}$ denotes its output.
In this article, DNN is trained specifically to substitute correlation in tracking black as shown in Fig.3. Therefore, the input of DNN is PRN code and GNSS signal, the output is a set of correlation values (for instance, a Prompt and an arbitrary number of Early/Late samples). The main architecture of the proposed DNN for correlation is shown in Fig. 4. In this DNN, the first convolutional layer is fixed with parameters based on PRN code to simulate standard method for correlation. Then, the classical correlation result is send into MLP models for regression and classification. Note that the classification block and regression block are training independently. In regression block, the output is correlation results with no multipath affect, while the output of classification block is a binary label to classify whether multipath occurs in Early-Late (E-L) spacing or not. To improve the NN performance, 61 correlators are spreading from -2 chips to 2 chips, with 41 of them spread from -0.2 chips to 0.2 chips. With outputs of regression and classification blocks, a weighted average is calculated to get the final output of the whole DNN model:

$$\boldsymbol{y_o} = w_1 \times \boldsymbol{y_1} + w_2 \times \boldsymbol{y_2} \tag{13}$$

where $\boldsymbol{y_1}$ is the classification correlation result, output of convolutional layer; $\boldsymbol{y_2}$ is output of regression block, correlation results with multipath affect removed; w_1 and w_2 are probabilities of estimated binary label by classification block; $\boldsymbol{y_o}$ is output containing 61 estimated correlation results, among which Early/Late/Prompt samples could be sent to discriminators.

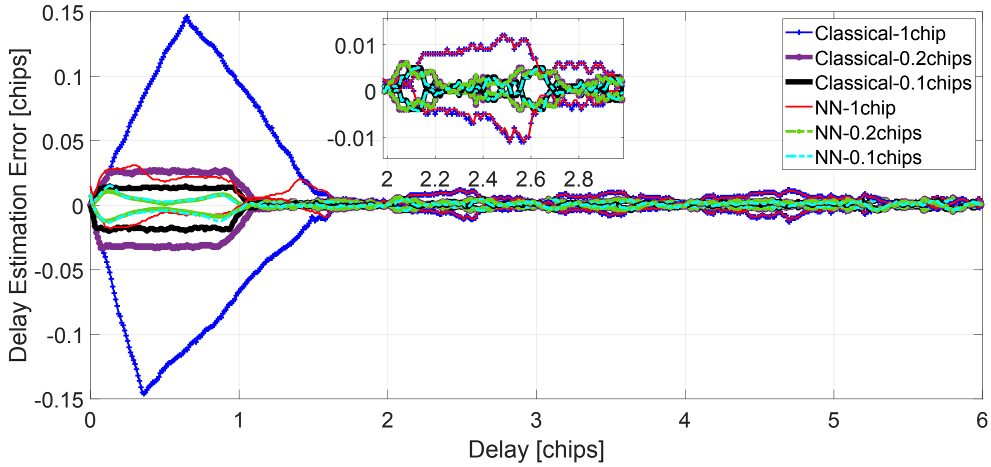

Figure 5: Noiseless Multipath Envelope with single multipath of Signal-to-Multipath Ratio (SMR)=5.2 dB.

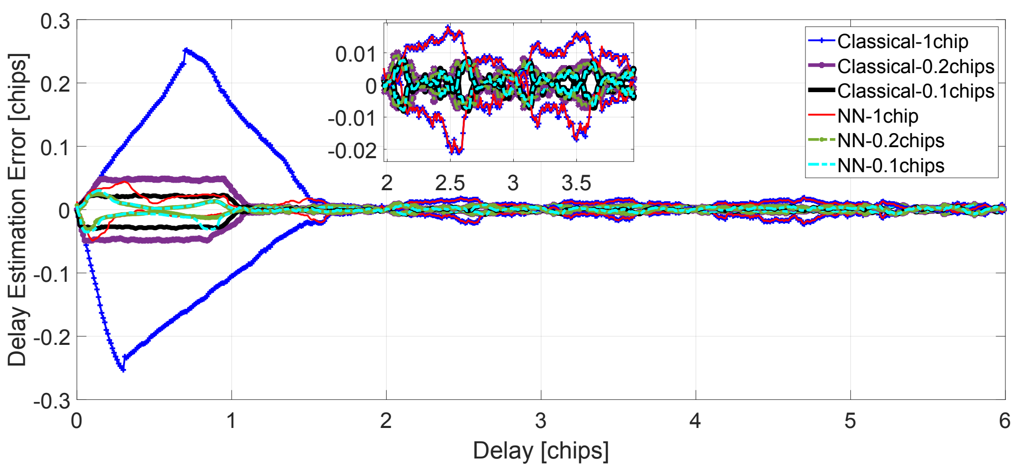

Figure 6: Noiseless Multipath Envelope with single multipath of SMR=3 dB.

SIMULATION RESULTS

In NN training, single multipath is generated with SMR as 3 dB, 5.2 dB and 0.97 dB, random relative delay between GNSS signal and multipath varies from 0 to 6 chips, Doppler shift error is also initialized randomly from -1 kHz to 1 kHz. Global Positioning System (GPS) L1 signal is sampled at $f_s = 2$ MHz, while CN0 varies from 37 dB-Hz to 43 dB-Hz, and a special case $C/N_0 = \infty$ is considered in order to generate the so-called multipath error envelope. The parameters of DNN in this simulation is shown in Table. 5. To test the performance of DNN, Early minus Late Discriminator is applied to noiseless signal to acquire multipath envelope as shown in Fig.5, Fig.6 and Fig.7. In Fig.5, SMR=5.2 dB, Early minus Late Discriminators with three different E-L spacing are applied to show the differenes

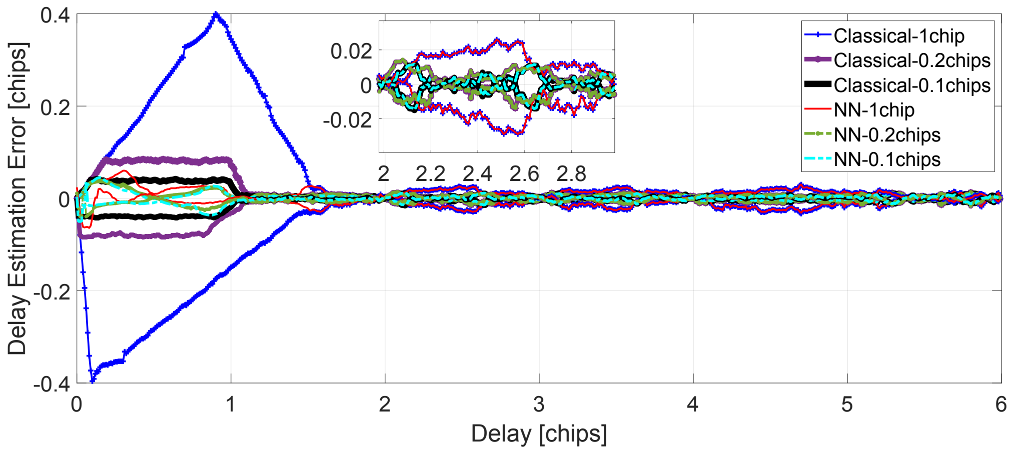

Figure 7: Noiseless Multipath Envelope with single multipath of SMR=0.97 dB.

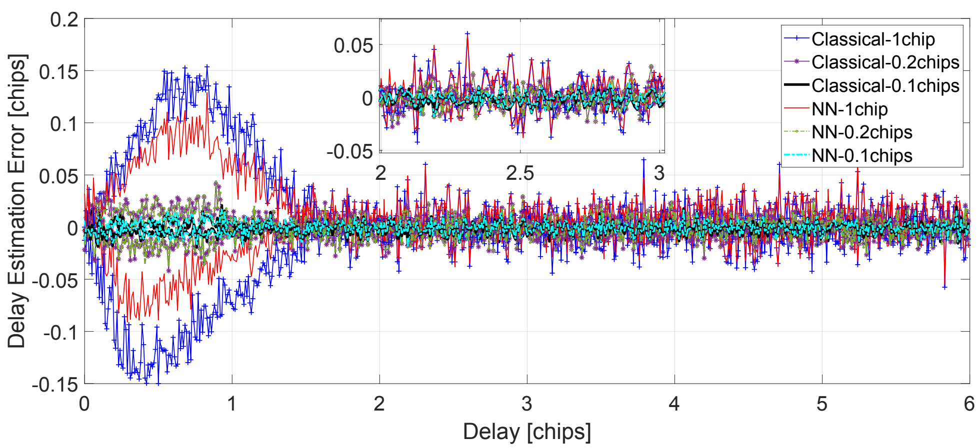

Figure 8: Noisy Multipath Envelope with single multipath of SMR=5.2 dB.

between classical correlation method and NN-based correlation method, which is 1 chip, 0.2 chips and 0.1 chips. In Fig.5, small disadvantage of NN-based method is shown around 0 chips relative delay, while NN-based method brings a lower delay estimation error than classical one with all three E-L spacing, when multipath occurs. However, with the decrease of E-L spacing, the advantage of NN-based method in estimation error also decreases. Besides, when multipath goes beyond E-L spacing, NN-based method can still hold a similar performance as classical method. The same trend can also be observed in Fig.6 and Fig.7, while the decreasing SMR causes a degrading performance in NN-based method, which is obvious in Fig.7 with 0.1 chips as E-L spacing.

To further test NN-based method, noise is injected in GNSS signal with CN0=43 dB, and 50 Mante Carlo runs to get noisy version of multipath envelope as shown in Fig.8, Fig.9 and Fig.10. In Fig.8, we can see a clear advantage of NN-based method over classical method with E-L spacing as 0.5 chips, while NN-based methods with the other two E-L spacing hold a similar level as classical methods. According to Fig.9 and Fig.10, increasing multipath amplitude causes a clear degradation of NN-based method performance, while in Line-of-Sight (LOS) case (when multipath goes beyond E-L spacing), NN-based methods perform similarly as classical method.

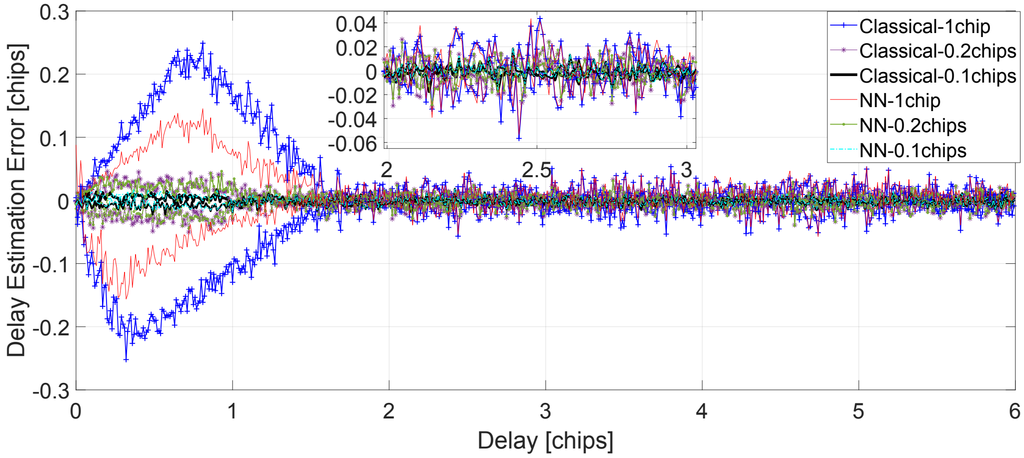

Figure 9: Noisy Multipath Envelope with single multipath of SMR=3 dB.

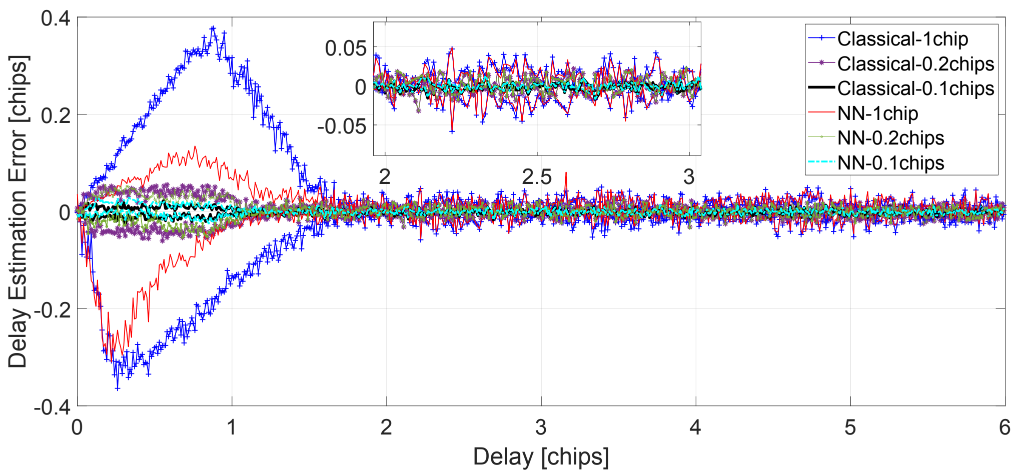

Figure 10: Noisy Multipath Envelope with single multipath of SMR=0.97 dB.

Additionally, MSE of delay estimation error by discriminator is shown as a functio of CN0 in Fig. 11, Fig. 12 and Fig. 13. In the three figures, we can find NN-based method holds lower MSE against classical method with E-L spacing as 1 chip and 0.2 chips, while the two method with E-L spacing of 0.1 chips perform similarly in Fig. 11 and Fig. 12. Note that classical method outperforms NN-based method in Fig. 13, while the difference is still small to be acceptable.

Considering loss of efficiency in LOS case, Fig. 14 presents a comparison between NN-based method and classical method with three different E-L spacing. In Fig. 14, the methods with three E-L spacing avoids loss of efficiency in terms of MSE in high CN0, while small disadvantage of NN-based method shows when CN0 varies from 35 dB to 37 dB, this can be exlained by the fact that DNN model is trained by dataset with CN0 varying from 37 dB to 43 dB.

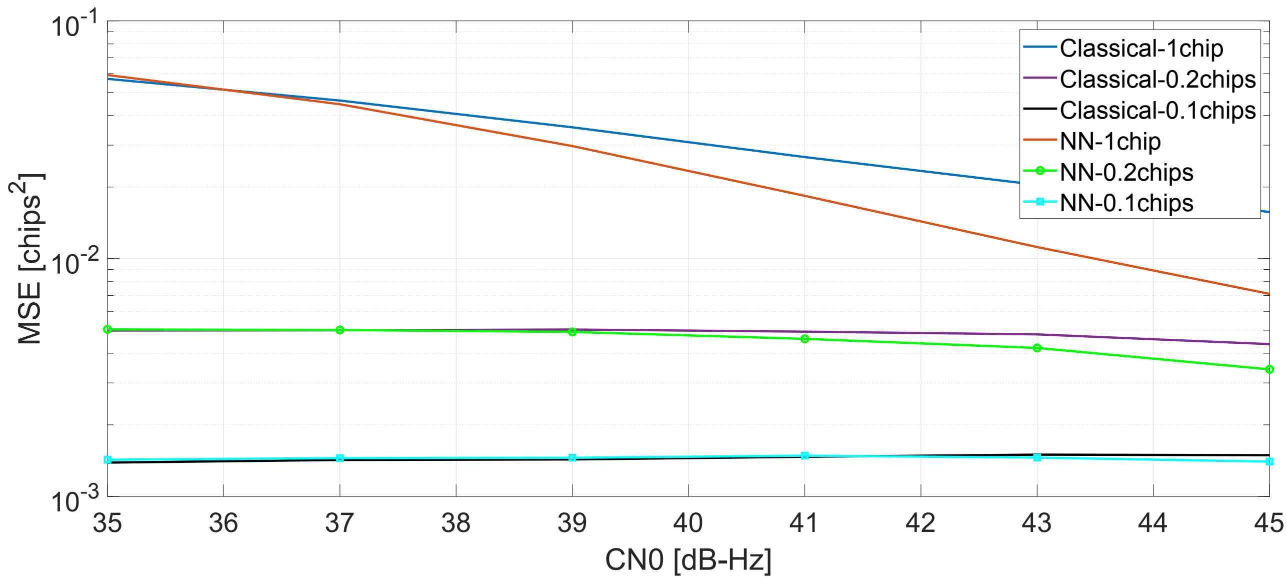

Figure 11: MSE vs Carrier-to-noise ratio (CN0) with single multipath of SMR=5.2 dB in NLOS case.

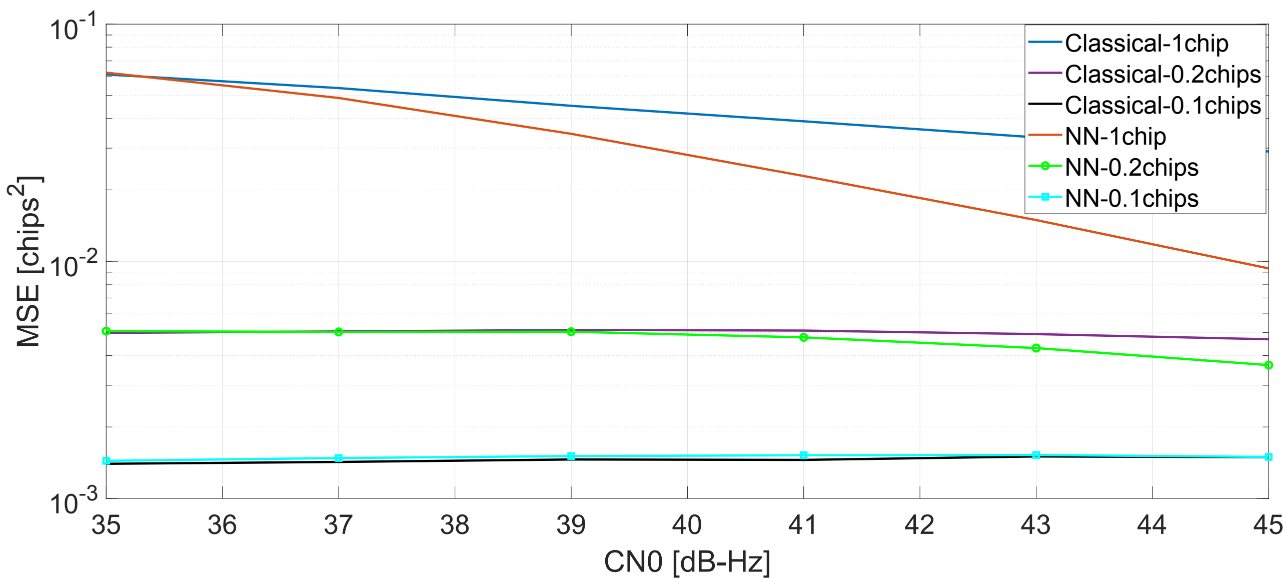

Figure 12: MSE vs CN0 with single multipath of SMR=3 dB in NLOS case.

CONCLUSIONS

This article studied the feasibility of a deep learning approach to enhance the correlation process in GNSS baseband signal processing, potentially substituting classical correlation method with NN-based correlation methods.

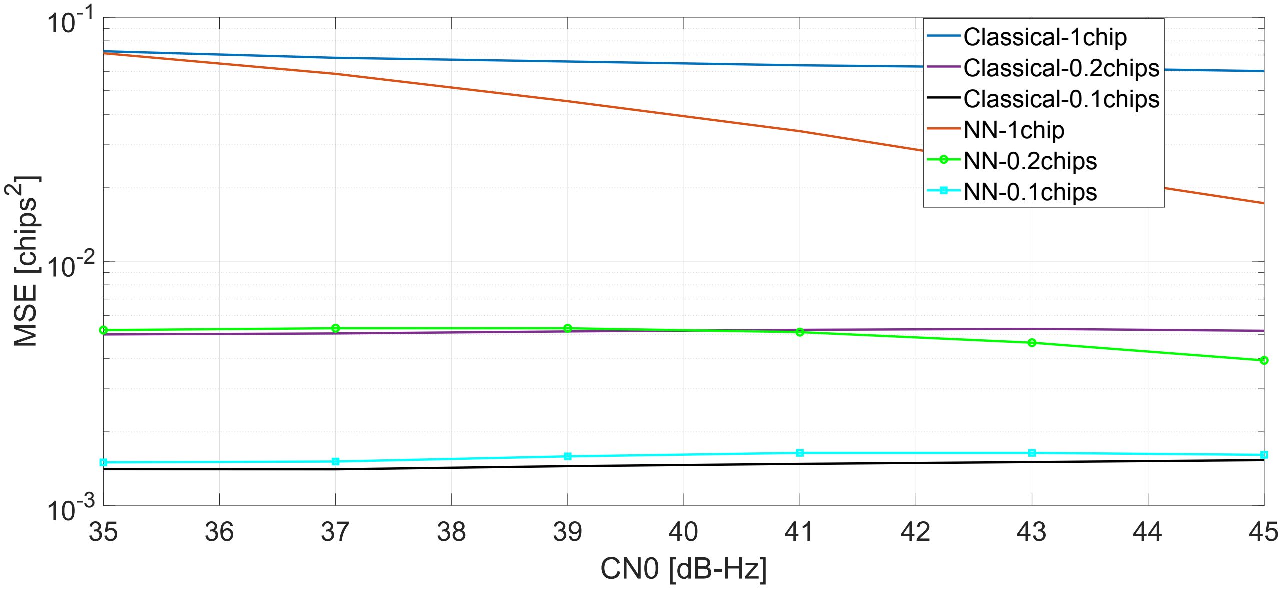

Figure 13: MSE vs CN0 with single multipath of SMR=0.97 dB in NLOS case.

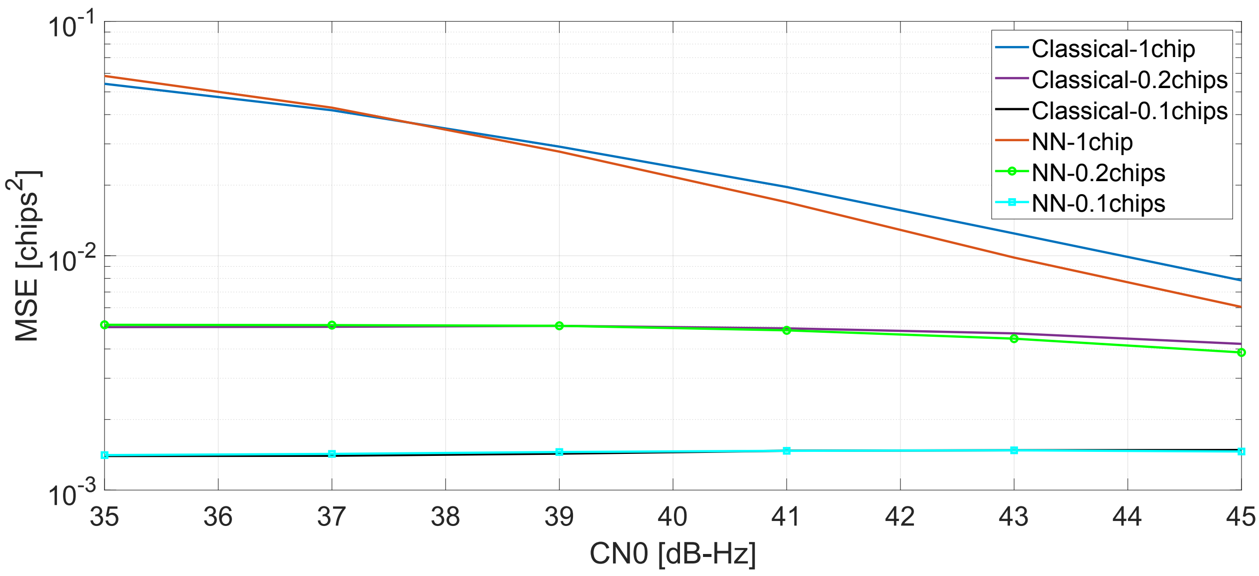

Figure 14: MSE over CN0 with no multipath to show loss of efficiency in LOS case.

The objective of such scheme is to provide enhance robustness to the receiver in challenging environments where physics-based models typically fail, for instance under multipath propagation, by training data-driven that can learn the complex characteristics of the GNSS satellite-to-land channel [11]. It is observed that the investigated NN model requires a multi-correlation scheme, thus involving an increased computational cost when compared to standard

	Regression Block	Classification Block
Number of Layers	**9**	**5**
Active Function	**ReLu**	**ReLu and Softmax**
Initial Learning Rate (LR)	**1e-4**	**1e-4**
Training Epochs	**30**	**15**
Training Dataset	**2688000**	**2688000**
Test Dataset	**105000**	**105000**
LR Optimization Method	**Adam**	**Adam**
Batch Size	**1500**	**1500**

Table 1: Parameters of DNN applied in simulation.

methods. The results in this article show an advantage of NN-based method in most cases, while several aspects remain under investigation such as the simulation against multiple multipath and improvement of NN-based correlation method with narrow E-L spacing.

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