# Metric Learning-Based Timing Synchronization by Using Lightweight Neural Network

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Abstract—Timing synchronization (TS) is one of the key tasks in orthogonal frequency division multiplexing (OFDM) systems. However, multi-path uncertainty corrupts the TS correctness, making OFDM systems suffer from a severe inter-symbolinterference (ISI). To tackle this issue, we propose a timingmetric learning-based TS method assisted by a lightweight onedimensional convolutional neural network (1-D CNN). Specifically, the receptive field of 1-D CNN is specifically designed to extract the metric features from the classic synchronizer. Then, to combat the multi-path uncertainty, we employ the varying delays and gains of multi-path (the characteristics of multi-path uncertainty) to design the timing-metric objective, and thus form the training labels. This is typically different from the existing timing-metric objectives with respect to the timing synchronization point. Our method substantively increases the completeness of training data against the multi-path uncertainty due to the complete preservation of metric information. By this mean, the TS correctness is improved

 International uncertainty due to the complete preservation of metric information. By this mean, the TS correctness is improved against the multi-path uncertainty. Numerical results demonstrate the effectiveness and generalization of the proposed TS method against the multi-path uncertainty. *Index Terms*—Timing synchronization, OFDM, lightweight CNN, timing-metric objective, multi-path uncertainty
 I. INTRODUCTION
 Orthogonal frequency division multiplexing (OFDM) has been subject to extensive research efforts not only from the fifth generation (5G) systems but also from the Internet-of-Things (IoT) systems [1]. In OFDM systems, a correct timing synchronization (TS) aims to find the starting of the receiver discrete Fourier transform (DFT) window within an intersymbol-interference (ISI)-free region of an OFDM symbol [2]. Although synchronizing to this ISI-free region produces a phase rotation, this impairment can be easily countered by the channel equalization [3]. However, achieving this task is not easy due to the multi-path uncertainty. The multi-path uncertainty is caused by the rich and diverse communication environments [4] and manifested in wireless channels with varying power [4] and manifested in wireless channels with varying power delay profile (PDP). Because of the multi path uncertainty delay profile (PDP). Because of the multi-path uncertainty, the timing metric is usually corrupted in non-light-of-sight (NLOS) scenarios. Consequently, the timing error, i.e., starting of receiver DFT window located outside the ISI-free region, is appeared, which will in turn affect the subsequent signal processing.

To combat timing errors caused by the multi-path uncertainty, an alternative method for improving the TS correctness is to employ the joint mode, such as joint the TS and channel estimation, as done in [5]. The method of joint TS and channel estimation [5] improves the TS correctness by partially counteracting the interferences of multi-path uncertainty. Nevertheless, this joint mode [5] results in a relatively high computational complexity. Against the impairments caused by multi-path fading, noise, etc., an alternative method for improving the TS correctness is to deploy neural networks (NNs). In this context, several

machine learning-based studies have been conducted in finding high-performance TS methods for OFDM systems [6]-[8]. In [6], a one-dimensional convolutional neural network (1-D CNN)-based TS method is investigated in OFDM systems, which improves the TS correctness relative to the conventional TS method. Yet, this method ignores the impacts of multi-path uncertainty. In [7], the fine synchronization problem is investigated by assuming that the coarse TS and channel equalization have been achieved. Accordingly, [7] omits the consideration for multi-path interference, i.e., the multi-path uncertainty is neglected. While the work in [8] attempts to find ways to improve the TS correctness by designing training labels, the prerequisite of predicting the maximum multi-path delay limits its generalization performance. To summarize, due to the lack of considering the high computational complexity in [5] and the multi-path uncertainty in [6]-[8], the machine learning-based TS for practical application is limited, inspiring us to investigate a lightweight machine learning-based TS method against the multi-path uncertainty.

In this paper, we propose a lightweight timing-metric learning-based TS method in OFDM systems. To our best knowledge, against the multi-path uncertainty, the improvement of TS correctness by learning the timing metric has not been investigated. The main contributions are listed as below.

- We propose the lightweight metric learning-based TS method. Different from [6], the receptive field of 1-D CNN layer is specially designed and flexible according to the length of cyclic prefix (CP). Also, compared with [7], [8], the computational complexity of the designed neural network is significantly reduced.
- From the perspective of de-noising task, we specially design the timing metric to be learned. Specifically, the impact of uncertain multi-path delay on timing metric is considered to design the timing metric, and the impact of uncertain multi-path gain is also considered into the training stage. Thus, the adaptability of NN-based TS against multi-path uncertainty is improved.

#### **II. SYSTEM MODEL AND PROBLEM FORMULATION**

### A. System Model

An OFDM system with N sub-carriers is considered. At the transmitter, the time-domain OFDM symbol  $\{s(n)\}_{n=0}^{N-1}$ is obtained by using the inverse DFT, i.e.,

$$s(n) = \sum_{k=0}^{N-1} S(k) e^{j2\pi \frac{kn}{N}},$$
(1)

where  $\{S(k)\}_{k=0}^{N-1}$  denotes the data/training symbol at the kth sub-carrier in the frequency domain.  $\mathbb{E}\{|s(n)|^2\} = P_t$  with  $P_t$ being the transmitted power.



Fig. 1. The proposed timing synchronizer.

After appending the  $N_g$ -length cyclic prefix (CP), the transmitted signal consecutively passes through a multi-path fading channel. With a  $N_w$ -length observed interval at the receiver, the received sample is expressed as

$$y(n) = e^{\frac{j2\pi\varepsilon n}{N}} \cdot \sum_{l=1}^{L} h_l s\left(n - \tau_l - \theta\right) + w(n), \quad (2)$$

where  $\varepsilon$  and  $\theta$  respectively denote the normalized carrier frequency offset (CFO) and the unknown timing offset to be estimated. In (2),  $h_l$  and  $\tau_l$  are the complex gain and normalized delay of the *l*th arriving path, respectively. Meanwhile,  $\tau_l = l-1$ and  $0 \le \tau_L < N_g$  are considered [9]. In (2), w(n) represents the complex additive white Gaussian noise with zero-mean and variance  $\sigma_n^2$ .

Then, the received  $N_w$ -samples  $\{y(n)\}_{n=0}^{N_w-1}$  are buffered to form an observed vector  $\mathbf{y} \in \mathbb{C}^{N_w \times 1}$ . To observe at least one complete training sequence,  $N_w \geq 2N + N_g$  is required, and thus a discrete searching interval of unknown timing offset is employed, with its length being  $N_s = N_w - N$ . In a classic synchronizer [10], the timing metric is utilized to estimate the unknown  $\theta$ . According to (2), the timing metric, denoted as  $\{M(d)\}_{d=0}^{N_s-1}$ , is calculated as [10]

$$M(d) = \frac{\left|\sum_{k=0}^{N-1} x^*(k) y(d+k)\right|^2}{\sum_{k=0}^{N-1} \left|y(d+k)\right|^2},$$
(3)

where  $\{x(k)\}_{k=0}^{N-1}$  represents a local training sequence. Due to the impacts of multi-path fading, noise, etc., the metric in (3) is easily impaired and then makes TS errors. Therefore, we develop a learning method to improve the TS correctness with lightweight network.

## B. Problem Formulation

Against the multi-path uncertainty, we focus on the improvements of the computational complexity and the adaptability of the deployed learning-based TS in OFDM systems. Therein, M(d) in (3) can be regarded as the extracted initial feature, and then the impairments (e.g., noisy, multi-path interference) represented in M(d) can be learned and remedied by NNs, as done in [8]. The de-noising problem can be mathematically formulated as

$$\min_{\mathbf{\Theta}} \|\mathbf{\Gamma} - G_{\mathbf{\Theta}}(\mathbf{M}, \mathbf{\Theta})\|_2^2, \qquad (4)$$

where  $\Theta$  is a set of network parameters to be optimized, and  $G_{\Theta}(\cdot)$  is a mapping function parameterized by  $\Theta$ . In (4), the vector forms that  $\mathbf{\Gamma} = [\Gamma(0), \Gamma(1), \cdots, \Gamma(N_s - 1)]^T$  and  $\mathbf{M} = [M(0), M(1), \cdots, M(N_s - 1)]^T$  denote the timing metric  $\{\Gamma(d)\}_{d=1}^{N_s}$  to be learned and the initial feature  $\{M(d)\}_{d=1}^{N_s}$  to be de-noised, respectively. Nevertheless, the trained  $G_{\Theta}(\cdot)$  may suffer from a severe TS error due to the multi-path uncertainty. This is due to the fact that the multi-path interference

TABLE I Network Architecture

Layer Name	Output Size	Filter Size	Filter Number	Activation
Input Layer	$(N_s, 1, 1)$	-	-	-
1-D CNN Layer	$(N_s, 1, 4)$	$N_{g} + 1$	4	ReLU
Pooling & Flattening	$(N_s, 1)$	-	-	-
FC Layer	$(N_s, 1)$	-	-	Sigmoid
Output Layer	$(N_s, 1)$	-	-	-

represented in M is randomly unpredictable. Therefore, M are uncertain to be hardly recognized, degrading the correctness of learning-based TS in wireless propagation scenarios. To handle this issue, the timing metric to be learned is specially designed to improve the TS correctness against multi-path uncertainty, which will be presented in *Section III-B*.

#### III. THE PROPOSED METRIC LEARNING-BASED TS

#### A. Lightweight NN Architecture

The proposed timing synchronizer is presented in Fig. 1 and summarized in *TABLE I*, which consists of a classic correlator along with a NN process. In the NN block, the single-layer 1-D CNN and single-layer fully connected NN are considered. For 1-D CNN layer, the rectified linear unit (ReLU) is employed as the activation function. As for fully connected layer, the tanh and softmax functions are employed in the hidden and output layers, respectively.

In the 1-D CNN block, the 1-D CNN deploys one convolution layer with 4 filters, and its the receptive field is selected as  $(N_g + 1)$ . Specifically, the receptive field of each filter layer is specially designed according to the finite lengths of channel impulse response (CIR) and CP. This is due to the fact that the significant TS features are mainly appeared at arriving paths, and also the CIR length is less than the CP length. The TS feature extracted by using (3) can be simplified as

$$M(d) \approx \frac{P_t / \sigma_n^2}{1 + P_t / \sigma_n^2} \cdot \sum_{l=1}^L h_l \delta\left(d - \tau_l - \theta\right).$$
(5)

Since  $N_g$  is usually less than one quarter of the symbol length N (i.e.,  $N_g < 0.25N$ ), the increase of computational complexity caused by a large receptive field can be alleviated. Thus,  $(N_g + 1)$ -size receptive field is suitable to capture the significant TS features extracted by the classic correlator. Also, the number of filter is set by considering that one complex multiplication (CM) equals 4 floating point operations (FLOPs), i.e., filter number is set as 4. Thus, the total CMs of 1-D CNN processing approximately are equal to a CP-based correlation processing.

In the fully connected NN block, its hidden layer is selected according to the maximum searching length of candidate timing offset, i.e.,  $N_s$ . To further reduce the data dimension sent for

the fully connected layer, an average pooling layer with patch equaling to the filter number is considered, i.e., 4-size patch.

In summary, the designed 1-D CNN and fully connected NN are constructed according to the parameters of  $N_g$  and  $N_s$ , which are flexible in different scenarios. Meanwhile, by using CM as the evaluation of computational complexity, the computational complexity of the designed NN is  $0.5N_s^2 + N_sN_g$ , while the correlation process in (3) requires  $N_sN$ . Since  $N_s$  and  $N_g$  are constrained by  $N_s = N_w - N = N + N_g$  and  $0 < N_g < 0.25N$ , we will have  $0.5N_s^2 + N_sN_g - NN_s < 0$ . Therefore, the designed NN is relatively lightweight compared with the classic correlator [10].

#### B. Timing Metric for TS Learning

In the ISI-free region of per OFDM symbol, each sampling point can be regarded as the correct TS point [2]. Consequently, the timing metric to be learned can be expressed as

$$\Gamma\left(d\right) = \sum_{\hat{\theta}=\theta+\hat{\tau}_{L}+1}^{\theta+N_{g}} \delta\left(d-\hat{\theta}\right),\tag{6}$$

where  $\hat{\theta}$  is the timing offset to be learned, and the  $\hat{\tau}_L$  denotes the normalized maximum multi-path delay for offline training. Usually,  $\hat{\tau}_L$  is assumed to be fixed during the training stage.

However, due to the multi-path uncertainty, the real  $\tau_L$  is unpredictable. For example, the root means square multi-path delay will change with time and propagation environments [11], making  $\tau_L$  uncertain. Thus, it is highly possible that  $\tau_L \neq \hat{\tau}_L$ , resulting in an incorrect labeling. When  $\theta$  is fixed, the incorrect timing metric learned can be given by

$$\gamma(d) = \sum_{\hat{\theta}=\theta+\hat{\tau}_L+1}^{\theta+N_g} \delta\left(d-\hat{\theta}\right) \oplus \sum_{\hat{\theta}=\theta+\tau_L+1}^{\theta+N_g} \delta\left(d-\hat{\theta}\right) \\ = \sum_{\hat{\theta}=\theta+\tau_L+1}^{\theta+\hat{\tau}_L} \delta\left(d-\hat{\theta}\right).$$
(7)

When  $\hat{\tau}_L = \tau_L$ , the case of  $\gamma(d) = 0$  can be achieved, which means ideally labeling. Due to the multi-path uncertainty, this case is hardly to be achieved. Hence, we relax this demand by jointly considering these following motivations:

- Although the cases of  $\hat{\tau}_L \geq \tau_L$  make  $\gamma(d) \neq 0$ , the set  $\{\hat{\theta}\}_{\theta+\tau_L+1}^{\theta+\hat{\tau}_L}$  still belongs to the ISI-free region.
- Since  $\tau_L$  is difficult to be predicted,  $\hat{\tau}_L$  is no exception. Therefore, other priori information needs to be exploited for determining the value of  $\hat{\tau}_L$ .
- As NNs can compensate for deficiencies by learning from a certain number of data set,  $\hat{\tau}_L$  for (6) can be expanded according to a set of random variables.

Given  $N_t$ -samples data set, we make  $\{\hat{\tau}_{L,i}\}_{i=1}^{N_t}$  for (6) satisfy that  $\hat{\tau}_{L,i} \stackrel{\text{i.i.d}}{\sim} U[N_g/2, N_g - 1]$ . By this mean, the timing metrics to be learned are expanded to increase the adaptability of NN against multi-path uncertainty.

**Remark 1.** According to (7), the main deficiency in (6) is caused by the dynamically changed  $\tau_L$ , resulting in error labeling and aggravating TS error. Since learning models can compensate for deficiencies by learning from the prior inputs and objectives, the features to be learned can be expanded to increase the adaptability of NN against multi-path uncertainty. To this end, the priori  $\hat{\tau}_L \stackrel{i.i.d}{\sim} U[N_g/2, N_g - 1]$  is derived to expand the features of timing metrics. Thus, the adaptability of trained model is enhanced against the uncertain  $\tau_L$ .

In *Section III-C*, the offline training and online deployment are described.

TABLE II Abbreviations of Different TS Methods

Abbreviation	Computational Complexity (CM) Example		
"Prop"	The proposed method		
"Prop without $\Gamma$ "	The proposed method directly learns the received signal without the initial feature extraction		
"Prop with fixed $\hat{\tau}_L$ "	The proposed method does not specially design the timing metric for model training, i.e., fix $\tau_L = 22$ for training		
"Ref [5]"	The joint TS and channel estimation method in [5]		
"Ref [8]"	The label designed-based ELM method in [8]		
"Ref [13]"	The classic TS method proposed in [13]		
"DNN"	"DNN" A conventional back-propagation NN which owns two hid dense layers, with both neuron nodes being $N_s$		

 TABLE III

 COMPUTATIONAL COMPLEXITY AMONG DIFFERENT TS METHODS

Method	Computational Complexity (CM)	Example
Ref [5]	$LNN_{s} + \sum_{l=1}^{L} (3lN_{s} + l^{3} + l^{2}N_{s})$	1371536
Ref [8]	$16N_s^2 + 4N_s + 1.5N - 4$	410428
DNN	$0.75N_s^2 + NN_s + 2N_s + N - 2$	40126
Proposed	$1.5N_s^2 + 3N_s + N - 2$	39006

#### C. Offline Training and Online Deployment

1) Offline Training: In this phase,  $N_t = 50,000$  is considered, which is split to the validation set and training set by 0.25. The data set is denoted as  $\{\mathbf{M}_i, \mathbf{\Gamma}_i\}_{i=1}^{N_t}$ , in which  $\mathbf{M}_i$  is obtained via (1)–(3) and  $\mathbf{\Gamma}_i$  is obtained by using (6). Therein,  $\hat{\tau}_{L,i} \stackrel{\text{i.i.d}}{\sim} U[\lfloor N_g/2 \rfloor, N_g - 1]$  is utilized to alleviate the effect of uncertain multi-path delay. An exponentially decayed channel model [9] with decayed exponent  $\eta$  is considered. Meanwhile,  $\eta_i \stackrel{\text{i.i.d}}{\sim} U(0.01, 0.2)$  is employed to alleviate the effect of uncertain multi-path gains. Besides,  $\theta_i \stackrel{\text{i.i.d}}{\sim} U[0, N - 1]$ .

For the designed NN in *TABLE I*, optimizer employs the stochastic gradient descent (SGD) algorithm, and its initial learning rate is set as  $\alpha = 0.002$  [12]. By respectively denoting *B* and *J* as the batch size and the number of steps, the network optimization is defined as [12]

$$\boldsymbol{\Theta}_{q+1} \leftarrow \boldsymbol{\Theta}_{q} - \alpha \nabla \frac{1}{B} \sum_{i=(q-1)B+1}^{qB} \left\| G_{\boldsymbol{\Theta}_{q}} \left( \mathbf{M}_{i}, \boldsymbol{\Theta}_{i} \right) - \boldsymbol{\Gamma}_{i} \right\|_{2}^{2},$$
(8)

where the subscript q denotes the qth iterative step for optimizing, and  $1 \le q \le J$ .

2) Online Deployment: By using (1)–(3), M(d) is obtained, forming  $\mathbf{M} = [M(0), M(1), \dots, M(N_s - 1)]^T$ . Then, with the optimized  $G_{\Theta}(\cdot)$ , the model output, denoted as  $\mathbf{O} \in \mathbb{R}^{N_s \times 1}$ , is given by  $\mathbf{O} = G_{\Theta}(\mathbf{M})$ . Finally, by expressing  $\mathbf{O}$  as  $[O(0), O(1), \dots, O(N_s - 1)]^T$ , the estimated timing offset is

$$\widehat{\theta} = \underset{0 \le d \le N_s - 1}{\operatorname{arg\,max}} \left\{ O(d) \right\}.$$
(9)

In Section IV-B and Section IV-C, the effectiveness and generalization of the proposed TS method against the multipath uncertainty are presented.

#### **IV. SIMULATION RESULTS**

In the simulations, we consider basic parameters as that N = 128,  $N_g = \lfloor N/4 \rfloor = 32$  [7],  $N_w = 2N + N_g = 288$ , and  $N_s = N_w - N = 160$ . For simulated channel models, they have not been utilized for offline training. For the sake of clarity, we list the abbreviations of different timing synchronization methods in *TABLE II*.



#### A. Computational Complexity

The comparison of computational complexity among different TS method is illustrated in *TABLE III*. Therein, the total channel paths are selected as 23, i.e., L = 23, and other parameters are adopted from *Section IV-A*. According to *TABLE III*, "Prop" reaches the smallest CM among the given TS methods. Therefore, "Prop" has the superiority in realizing lightweight network.

#### B. Effectiveness Analysis

To analyze the effectiveness, Fig. 2 depicts the error probability of TS. Wherein, an un-trained exponential decayed factor that  $\eta = -\ln(10^{-\frac{10}{10}})/(L-1)$  [9] is utilized and the maximum multi-path delay changes from 22T to 27T, which are utilized to simulate the multi-path uncertainty. In Fig. 2, for each given value of  $\tau_L$ , the probability of TS error for "Prop" is smaller than those of "Ref [13]", "Ref [5]", and "Ref [8]". Meanwhile, for all given SNRs, "Prop" achieves a lower probability of TS error than "DNN". This is because CNN is easier to capture data features compared with DNN methods. It is noteworthy that, although  $\tau_L$  increases from 22 to 27 caused by the multi-path uncertainty, "Prop" exhibits slight generalization error than "Prop with fixed  $\hat{\tau}_L$ ", due to the use of the designed timing-metric objective. Besides, "Prop" reaches a smaller TS error than "Prop without  $\Gamma$ ", which demonstrates the benefits of learning timing-metric. In summary, the performance improvements of "Prop" is effective against the multi-path uncertainty.

#### C. Generalization Analysis

Fig. 3 plots the comparison of the error probability of TS to analyze the generalization performance of "Prop" against different 5G tapped-delay-line (TDL) channel models [14].

Notably, these channel models have not been used for offline training. For each given channel model, "Prop" achieves smaller probability of TS error among the given TS methods in the whole SNR region. Besides, for "Prop", the fluctuation in the probability of TS error caused by different un-trained channel models are not obvious. Therefore, the proposed TS method (i.e., "Prop") has a good generalization capability against different 5G TDL channel models.

#### V. CONCLUSION

In this paper, we investigate a lightweight timing-metric learning-based TS in OFDM systems, which alleviates the multi-path uncertainty by utilizing the designed timing-metric objective. Different from [5]–[8], against the multi-path uncertainty, we utilize the proposed lightweight network along with the designed learning solution to learn the timing metric, which improves the TS correctness and generalization performance with less computational complexity. By simulations, numerical results exhibit the superiority of the proposed method in reducing the error probability of TS against multi-path uncertainty, whilst revealing its good generalization performance against different un-trained 5G TDL channel models.

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