A Deep Neural Network Approach For Time-Of-Arrival Estimation In Multipath Channels

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***Abstract*—Attaining accurate estimation of a signal time-of-arrival (TOA) in dense multipath channels is very challenging. This problem was traditionally solved with signal processing techniques. In this paper, a novel deep convolutional neural networks (DCNN) TOA estimator is developed. The DCNN was trained with synthetically generates multipath channel realizations based on statistical modeling, and then tested on real-life measurements from indoor environments. It is shown that the DCNN attains the performance of state-of-the-art signal processing based estimators (maximum likelihood performance), and has the advantage that it does not require knowledge of the channel statistics nor the knowledge of the transmitted signal waveform. This work inspires further study on the applicability of neural networks to other related problems, which have been traditionally solved with signal processing methods.**

I. Introduction

Precise positioning is important in many commercial, military, and public safety applications. Time-of-flight based positioning techniques rely on measuring the signal propagation time between two wireless devices, which essentially requires estimating the received signal time-of-arrival (TOA). In a free space environment, there is a single path between the transmitter and the receiver, and thus estimating the TOA is relatively simple. However, in indoor environment, the transmitted signal is reflected by the walls, floor, ceiling, and other objects. Therefore, there are many dense received replicas of the transmitted signal, which make the TOA estimation of the first signal (that corresponds to the direct line-of-sight path) very challenging.

In the last decades numerous signal processing methods have been proposed for estimating the TOA in multipath channels. The exact Maximum Likelihood (ML) estimator requires knowing the exact distribution of the multipath. In practice, the multipath first order statistics parameters are unknown, and may vary from one environment to the other. In the Generalized ML (GML) approach, all the multipath coefficients and their arrival times are jointly estimated [1]. In a typical indoor environment, the multipath is dense, the number of paths is large and unknown, and the GML is required to estimate too many parameters. An iterative approximation to the GML was introduced by [2] and referred to in this paper as SCC. In SCC the multipath coefficients are estimated one by one and removed from the received signal sequentially until the strongest remaining coefficient is below a threshold, and the TOA is determined according to the earliest arrival path. However, the successive cancelation is imperfect and, therefore, the error cannot decrease below a certain limit, even as the SNR increases. Simple approaches for TOA estimation are based on filtering the received signal with a match filter, and then searching for the first time that the match filter energy exceeds a threshold [3]-[9]. These methods have low complexity and perform well when the amplitude of the first arrival component is significantly stronger than the other multipath components, but attain inaccurate TOA estimation when this is not the case, as is often in indoor environments. Another approach is super resolution methods, which includes multiple signal classification (MUSIC) [10], and estimation of signal parameters via rotational invariance techniques (ESPRIT) [11]. These subspace methods rely on estimation of the received signal autocorrelation, which requires a large number of statistically independent channel realizations that are not available in many cases. In the absence of statistically independent realizations, spatial smoothing techniques can be applied at the expense of reducing the resolution. A different approach [12]-[13] is approximating the received signal as Gaussian with an autocorrelation that is a function of the channel power delay profile and the transmitted signal waveform. In this case, the maximum likelihood estimator is derived based on the Gaussian approximation, and it has been shown that the Gaussian estimator (GE) attains the exact maximum likelihood performance in dense multipath, which is justified by the central limit theorem [14].

The statistics of a multipath channel have been investigated [15]-[18]. The IEEE 802.15.4a study group has proposed a very well statistical channel model for indoor multipath environments, which was obtained from extensively empirical measurements. This channel model is frequently used in literature for evaluating TOA estimation performance. In this model the received signal rays arrive in clusters. The rays have independent uniformly distributed phases in the interval $[0, 2\pi)$, and independent Nakagami distributed amplitudes with variances that decay exponentially with cluster and ray delay. The time of arrival of the clusters, and the rays within the cluster have a mixture of Poisson distribution.

Recently, deep convolutional neural networks (DCNN) have achieved state-of-the-art performance in numerous computer vision tasks [19]-[20]. The main building block of such networks is the convolution operation. In images, commonly represented by $2D$ color channels, it allows to decode different visual features and their location in the images. The main power of DCNNs comes from a series of additional convolutions and non-linearities applied to the initial feature representation, which can learn very complex functions that relate the high-dimensional input to a desired output, for example - object detection in an image.

The main contribution of this paper is the development of a DCNN for estimating the TOA in multipath channels, and the performance comparison between the DCNN approach and signal processing estimation methods. The DCNN is trained with channel realizations that are synthetically generated from the IEEE 802.15.4a channel model, and then tested on real-life measurements from indoor multipath environments. The advantage of the DCNN approach over the signal processing methods is that it does not require knowledge of the channel statistics, nor to know the transmitted signal waveform.

II. System model

A standard OFDM communication scheme is considered in this paper, as depicted in Fig. 1. The OFDM transmitter is presented in Fig. 1(a). The transmitted signal is obtained by an inverse Fourier transform (IFFT) of the known preamble symbol, $\boldsymbol{b}$, and then adding a cyclic prefix (CP) before $\boldsymbol{s}$, which contains a segment of last samples in $\boldsymbol{s}$. The signals $x(t)$, $h(t)$, $\eta(t)$ and $r(t)$, in Fig. 1(a), denote the transmitted analog signal, the multipath channel, the white Gaussian additive noise, and the received analog signal, respectively.

The OFDM receiver is shown in Fig. 1(b). The received signal, $r(t)$, is sampled at rate $1/T_s$. A coarse estimation of the preamble TOA in the received samples, r_n, is applied, and an observation window of N samples, denoted by $\boldsymbol{y}$, is extracted, which is initiated at a time that is within the CP interval. Then the preamble TOA offset in the observation window is estimated from $\boldsymbol{y}$.

Fig. 2 illustrates a timing diagram of the observation window $\boldsymbol{y}$ with respect to the CP and the preamble received signals. The notation T_D, in the figure, is the maximal channel delay spread, and the notation τ_0 is the preamble TOA offset in $\boldsymbol{y}$. It is assumed that the CP duration is larger than the sum of the channel delay spread and the coarse TOA estimation inaccuracy.

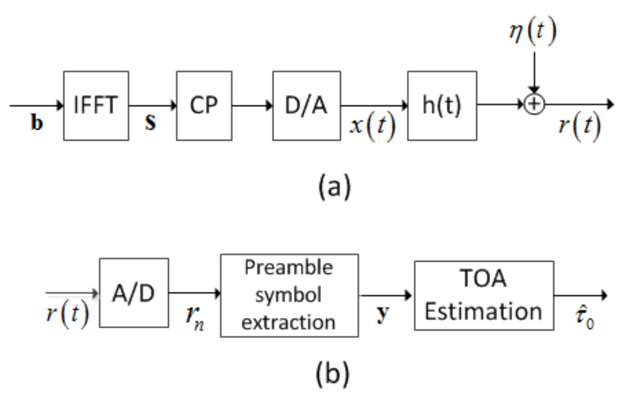

Fig. 1. Base band system model

The channel is assumed to be a time invariant multipath

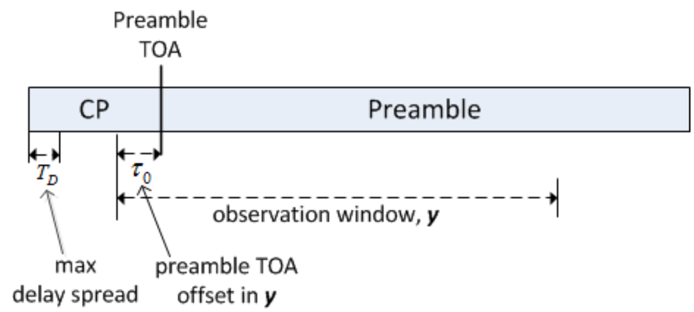

Fig. 2. Preamble observation window, $\boldsymbol{z}$

channel with impulse response given by

$$h(t) = \sum_{m=0}^{M-1} \alpha_m \delta(t - \tau_m), \tag{1}$$

where M is the number of unknown multipath components, $\delta(t)$ is the Dirac delta, α_m and τ_m are the random complex coefficient and the random delay of the m-th multipath component, respectively.

III. DCNN TOA Estimator

The DCNN was trained and tested to estimate the preamble TOA, τ_0, from the observation window $\boldsymbol{y}$. The tested OFDM communication system was a standard WIFI 802.11g, where the preamble signal, $\boldsymbol{b}$, is of length 64 with 52 nonzero bins that span a bandwidth of 16.25 MHz. It can be shown [22] that the observation vector $\boldsymbol{y}$ is obtained by a circular convolution between the transmitted preamble signal $\boldsymbol{s}$ and the channel $h(t)$. Therefore, the DCNN input, denoted as $\tilde{\boldsymbol{y}}$, was chosen as follows

$$\tilde{\boldsymbol{y}} = \left[\begin{array}{ccc} \boldsymbol{y}(33:64) & \boldsymbol{y}(1:64) & \boldsymbol{y}(1:32) \end{array} \right], \tag{2}$$

where $\boldsymbol{y}(i:j)$ is a row vector containing the elements from index i until index j in $\boldsymbol{y}$. The vector $\tilde{\boldsymbol{y}}$ was normalized to unit energy, and each of the 128 complex value was split to three inputs that were fed to the DCNN, which were the real, imaginary and magnitude of the complex sample.

The network architecture is depicted in Fig. 3. It was achieved through several trial and error iterations. The result is a relatively shallow architecture that includes three convolutional layers (1-3), three *residual blocks* (4-6) [19] and two fully connected layers. All convolutional layers use a 3×1 spatial kernel size. No pooling is used since in our case we want location sensitivity and not invariance. The residual blocks aim at learning the residual difference between the blocks input and its output which has been shown to be more simple to learn and hence more effective in visual recognition tasks [19]. Finally, in order to limit the output to a finite interval ($[0,1]$), we apply a sigmoid to the network's scalar output. The training labels are also normalized accordingly to ($[0,1]$). We used the L_2 loss function, $(\hat{\tau}_0 - \tau_0)^2$, as it corresponds directly to the target error measure. This option performed better in our experiments compared to the *Cross*

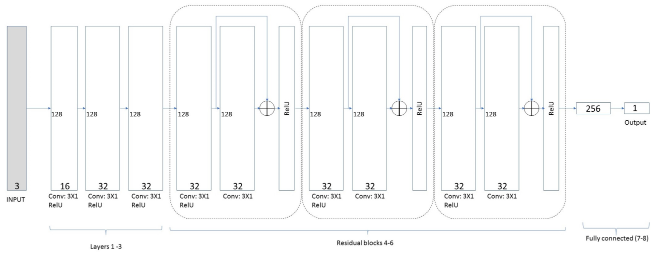

Fig. 3. Network architecture

Entropy loss. We also tested a network version in which the output was quantized to different TOA bins and trained it with the Piecewise-linear (PL) loss [21], which attained worse performance.

For training the DCNN we synthetically generated 10^7 observation vectors, $\boldsymbol{y}$, as in the OFDM scheme presented in Fig. 1. The transmitted signal was a simulated WIFI 802.11g symbol and the channel realization was randomly generated for each observation vector from the IEEE 802.15.4a indoor office statistical channel model [16]-[18]. The noise level was set such that the symbol signal to noise ratio was 40 dB, which is roughly the typical SNR value for WIFI in indoor environment. The validation set that was used to optimize the DCNN consisted of 10^4 channel realizations generated similar to the training set. As will be shown in Section IV, the test set that was used to evaluate the DCNN TOA estimation performance was measured observation vectors from real-life indoor multipath environments. Non of the measured observations were used to train the DCNN since the number of measurements was too small to train the network (only few hundreds).

Implementation details. The network learning was implemented in the *pyTorch* framework. We use the ADAM optimizer with a batch size of 1000, momentum 0.9, and no weight decay. The initial learning rate was 0.001.

IV. Results and Discussion

Next, we present the TOA estimation performance obtained with a test system, for two different indoor multipath environments. The test system had a universal software radio peripheral device [23] that recorded transmissions from off-the-shelf 802.11g WIFI routers [22]. The TOA of the received preamble was estimated in various locations and compared to the true TOA [1]. In each environment, the performance of the DCNN TOA estimator detailed in Sections III, was compared to three signal processing reference methods: Gaussian estimator (GE) [12]-[13], MUSIC [10], and successive component cancelation SCC [2]. The performance comparison criteria was the TOA estimation error's cumulative distribution function (CDF).

The two tested indoor environments were: office floor, and lobby floor, shown in Fig. 4, and Fig. 5, respectively. In these figures, the position of the transmitting WIFI router is marked by star sign, and the receiving unit was located at 100 different positions, approximately spread uniformly in all the gray shaded areas in the figures. Both test environments, had multipath reflections from the walls, floor, ceiling, and furniture.

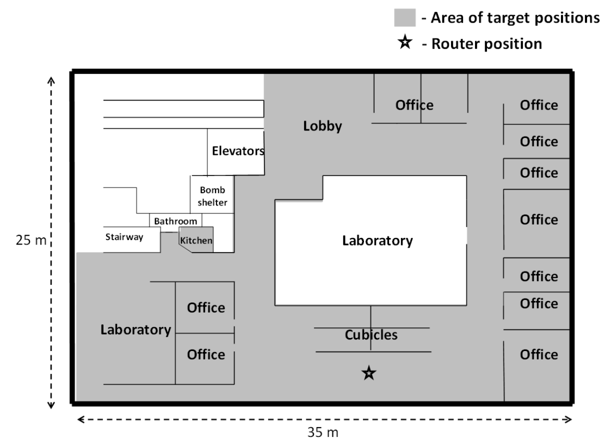

Fig. 4. Diagram of office floor test site

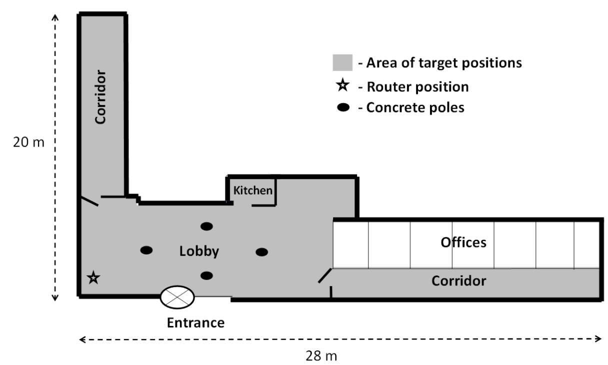

Fig. 5. Diagram of lobby floor

The CDF results are presented in Figures 6, and 7. The figures show that for both test environments the DCNN and the GE attain similar results and both outperform MUSIC and SCC. Fig. 8 shows a comparison between the TOA estimation errors of DCNN and GE in the office test environment. It is seen that the TOA estimation errors of both methods are highly correlated, and similar results were also observed for the lobby floor test environment. We have also compared the performance of the DCNN and GE for synthetically generated channel realizations from the IEEE 802.15.4a office channel model that was used for training the DCNN (but different realizations). These CDF results are presented in Fig. 9. In this case as well, the performance of DCNN and GE are very similar.

It has been shown [12] that in dense multipath environments (such as Fig. 4, Fig. 5, and IEEE 802.15.4a indoor office channel model) the GE attains the exact Maximum Likelihood performance. It is well known that the Maximum Likelihood

[1] the true TOA was measured by a parallel cable link

estimator asymptotically attains minimum variance (Cramer-Rao lower bound). Hence the results of Figs. 6-9 show that the DCNN TOA estimator attains the Maximum Likelihood performance, with no prior knowledge on the channel statistics nor the transmitted signal waveform. Furthermore, the fact that the DCNN network attained state-of-the-art performance in real-life indoor multipath channels, while it was trained with synthetically generated channels from the IEEE 802.15.4a channel models, shows that these channel models have close correspondence to the real-life multipath channels.

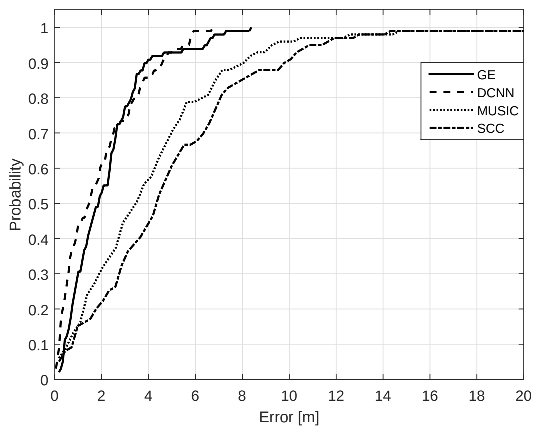

Fig. 6. TOA estimation error CDF for measurements of WIFI 802.11g in an office floor environment.

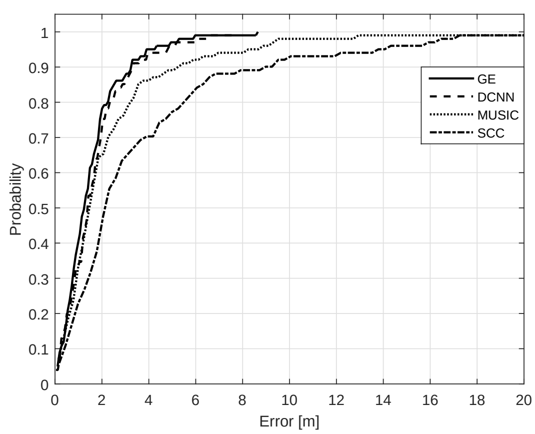

Fig. 7. TOA estimation error CDF for measurements of WIFI 802.11g in a lobby floor.

V. Conclusions

A classical signal processing problem of TOA estimation in multipath channels was solved using a nontraditional deep neural network approach. It has been shown that a deep neural network can attain the estimation accuracy of the state-of-the-art signal processing methods that achieve maximum likelihood performance in dense multipath. It was also shown that the IEEE 802.15.4a statistical channel models are sufficiently

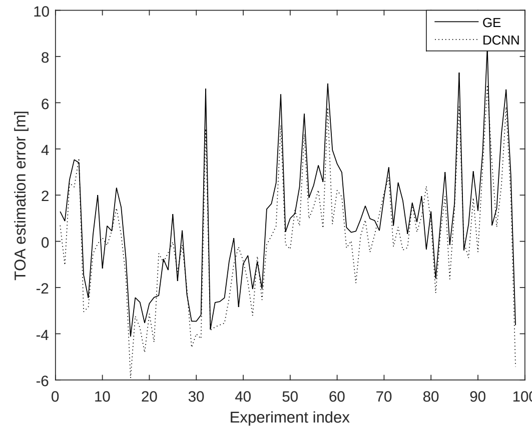

Fig. 8. TOA estimation errors in office floor

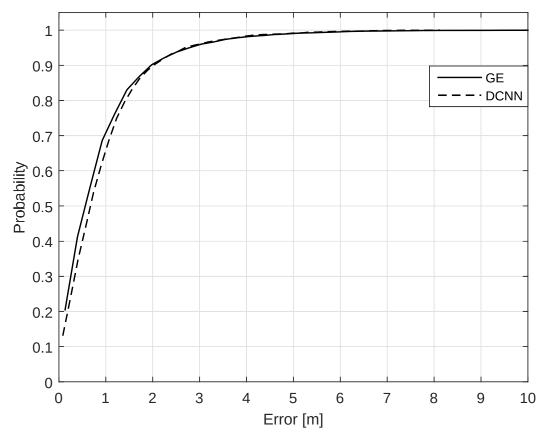

Fig. 9. TOA estimation error CDF for IEEE 802.15.4a office environment (Channel 3)

representative for training a network that is tested on real-life indoor multipath channels. This work inspires the use of deep neural networks to solve other related signal processing problems for which there exists a good statistical model for the measurements, yet deriving an analytical estimator that optimizes a certain performance criteria is not practicable/viable.

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