Joint modulation format/bit-rate classification and signal-to-noise ratio estimation in multipath fading channels using deep machine learning

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We propose a novel algorithm for simultaneous modulation format/bit-rate classification and non-data-aided (NDA) signal-to-noise ratio (SNR) estimation in multipath fading channels by applying deep machine learning-based pattern recognition on signals' asynchronous delay-tap plots (ADTPs). The results for three widely-used modulation formats at two different bit-rates demonstrate classification accuracy of 99.8%. In addition, NDA SNR estimation over a wide range of 0–30 dB is shown with mean error of 1 dB. The proposed method requires low-speed, asynchronous sampling of signal and is thus ideal for low-cost multiparameter estimation under real-world channel conditions.

Introduction: Cognitive radio has received phenomenal attention over the past few years in both commercial and military domains. The transmitting nodes in cognitive radio networks are envisaged to be fully capable of dynamically adjusting different transmission parameters for e.g., modulation format, data rate, spectrum assignment, signal power etc., depending upon the time-varying traffic demands and channel conditions. Consequently, the receiving nodes in these networks are anticipated to have the capability of autonomous estimation of various crucial signal parameters. Over the past few years, a plethora of techniques for automatic modulation classification (AMC) and SNR estimation has been proposed [1,2]. A vast majority of these techniques assume the signals to be affected by only additive white Gaussian noise (AWGN). However, in reality, the signal transmissions through wireless channels are severely impaired by multipath fading. This leads to significant degradation in the performance of existing AMC and SNR estimation techniques. The problem of AMC and SNR estimation in frequency-selective fading channels remains largely unexplored and only a few works have so far been reported in the literature [1,3]. To the best of our knowledge, all the proposed solutions focus on either AMC or SNR evaluation rather than joint estimation of multiple signal parameters. Furthermore, these solutions often require high-speed, synchronous sampling of signal and involve complex pre-processing steps, which result in high implementation/computational complexity.

Deep machine learning is a new branch of machine learning which has achieved state-of-the-art results in numerous applications of artificial intelligence [4]. Deep learning architectures such as deep neural networks (DNNs) exploit the fact that higher-level data features can be extracted from lower-level ones, resulting in a hierarchical representation of data. This property is inspired from functional behaviour of a human brain which seems to process information through multiple levels of transformation and representation. A DNN consists of several nonlinear processing layers which automatically extract and learn data features at different levels of abstraction. This enables a DNN to learn complex relations between its inputs and outputs directly from the data. Recently, we demonstrated the use of ADTPs for modulation format/bit-rate classification and SNR estimation in AWGN channels [5]. In this letter, we extend our previous work and propose a novel technique which utilizes DNN architectures to hierarchically extract characteristic features of ADTPs obtained for multipath fading channels. These modulation format, bit-rate and SNR sensitive features are subsequently exploited by DNNs for estimation of multiple parameters. Numerical simulations conducted for six signal types namely 250/500 Mbps NRZ-2ASK, 250/500 Mbps RZ-QPSK and 1/2 Gbps NRZ-16QAM, having SNRs in the range of 0–30 dB, verify joint estimation of modulation formats, bit-rates and SNRs with good accuracies. Unlike existing methods which necessitate symbol-rate, synchronous sampling, the proposed algorithm requires only low-speed, asynchronous delay-tap sampling (which inherently avoids the need for timing information), thus enabling implementation simplicity.

Operating principle: Figure 1 shows ADTPs for six signal types considered in this work, where the signals are assumed to be impaired

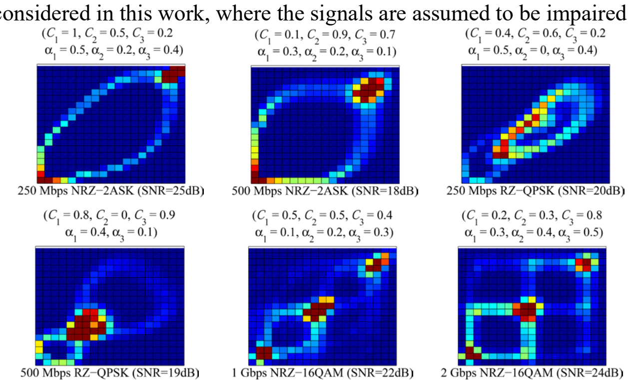

Fig. 1 *ADTPs for various modulation formats, bit-rates, SNRs, path delays and channel coefficients. A 0.75 ns tap-delay is used for all cases.*

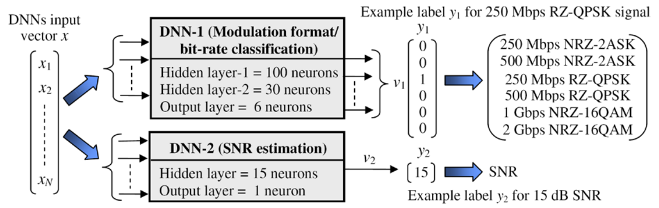

Fig. 2 *DNNs with bin-count vectors x as inputs and classified modulation formats/bit-rates and estimated SNRs as outputs.*

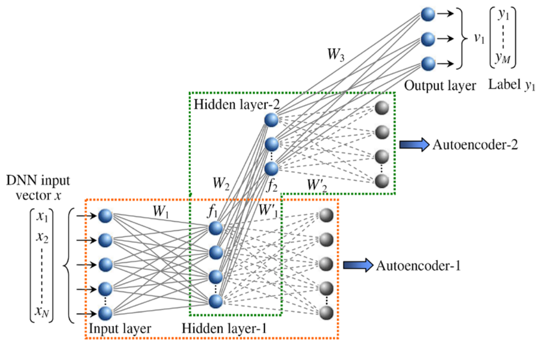

Fig. 3 *Schematic diagram of DNN-1. The decoder parts in both autoencoders are shown in grey colour with dotted weight lines.*

by both noise and three-path fading. It is evident from the figure that patterns reflected by ADTPs are sensitive to modulation formats, bit-rates, SNRs, path delays and channel coefficients. Therefore, they can be effectively exploited for joint estimation of these parameters by employing statistical pattern recognition techniques such as DNNs-based algorithms. In this work, we have used two DNNs i.e. first for modulation format/bit-rate classification (called DNN-1) and second for SNR estimation (called DNN-2) as shown in Fig. 2. Figure 3 depicts structure of DNN-1 consisting of two autoencoders and an output perceptron layer. The structure of DNN-2 is similar except that it contains only one autoencoder. The function of autoencoders is to hierarchically extract the features of input data. The output layers of DNN-1 and DNN-2 are selected to be *softmax* and *linear* layers, respectively. For the training of two DNNs, a large data set comprising of numerous ADTPs corresponding to various modulation formats, bit-rates, SNRs, path delays and channel coefficients, is generated. Each ADTP in this training data set is expressed as a one-dimensional vector x of bin-counts by concatenating all of its columns. Similarly, for each ADTP, a 6 × 1 binary vector y_1 (with single non-zero element whose location indicates the modulation format/bit-rate type pertaining to that ADTP) and a scalar y_2 which signifies the SNR value corresponding to that ADTP, are obtained. Vector y_1 and scalar y_2 are referred to as labels. For training DNN-1, vectors x and y_1 are employed as shown in Fig. 3. Firstly, autoencoder-1 is trained in isolation using vectors x in an unsupervised fashion. The first part of autoencoder-1 i.e. encoder maps an input vector x to a hidden representation whilst the second part i.e. decoder reverses this mapping in order to synthesize the initial input x.

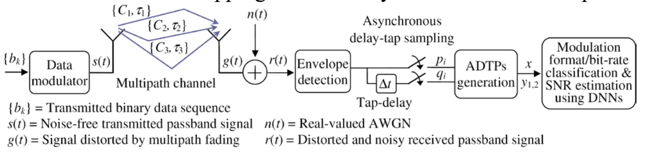

Fig. 4 *System model employed for numerical simulations.*

If the size of hidden layer-1 is chosen to be less than the size of vectors x, the encoder in autoencoder-1 gives compressed representations, known as feature vectors f_1, of input vectors x. The feature vectors f_1 are then utilized for unsupervised training of autoencoder-2 so as to obtain even more compressed representations f_2 of original input vectors x. The reduced-size feature vectors f_2 are used for the supervised training of output layer by setting labels y_1 as target outputs. After isolated training of individual components, the encoder parts of two autoencoders and the output layer are concatenated to form complete network. Finally, the whole multilayer network is trained using back-propagation algorithm in a supervised manner by employing vectors x and y_1. The training process of DNN-2 is similar except that vectors x and labels y_2 are utilized for training in this case as shown in Fig. 2. To analyze the performances of trained DNNs, a separate data set namely testing data set is used. Vectors x pertaining to this data set are applied at the inputs of both DNNs and corresponding outputs v_1 and v_2 are obtained. For DNN-1, argmax$\{v_1\}$ then provides classified modulation format/bit-rate while the scalar output v_2 of DNN-2 gives SNR estimate. The estimated signal types and SNRs are compared with true ones provided by labels y_1 and y_2 of testing data set and estimation accuracies are calculated.

System model and results: The system model utilized for numerical simulations is shown in Fig. 4. The set of signals chosen for evaluation purposes include 250/500 Mbps NRZ-2ASK, 250/500 Mbps RZ-QPSK and 1/2 Gbps NRZ-16QAM signals. The signal pulses are shaped using Gaussian filters and transmitted over a three-path channel. The channel coefficients C_i are assumed to be uniformly distributed random variables in the range of 0–1. Similarly, path delays $\tau_i = T + \alpha_i T_{\text{symbol}}$ are altered randomly, where T is the delay for line-of-sight path, T_{symbol} is the symbol period, and α_i are uniformly distributed random variables in the range of 0–0.5. We assumed the multipath channel to be slowly time-varying so that the channel coefficients and path delays remain constant during the observation interval. AWGN is added into the signal and SNR is varied in the range of 0–30 dB in steps of 1 dB. The envelope of received signal is sampled using asynchronous delay-tap sampling and 100,000 delay-tap sample pairs (p_i,q_i) are collected, which are subsequently utilized to generate ADTPs with 20 × 20 bins. A set of 3720 ADTPs, corresponding to 6 signal types, 31 SNRs, and 20 random combinations of path delays and channel coefficients, is obtained. The ADTPs in this data set are randomly divided into training and testing subsets containing 70% (i.e. 2604) and 30% (i.e. 1116) of overall ADTPs, respectively. For each ADTP in the two data sets, bin-count vector x as well as labels y_1 and y_2 are determined, which are then employed for the training and testing of two DNNs as discussed earlier.

The modulation format/bit-rate classification results for 1116 test cases in the testing data set are summarized in Table 1. It is clear from the table that the proposed technique achieves 100% classification accuracy for five out of six signal types. In case of 500 Mbps RZ-QPSK signal, the accuracy of 98.95% is though comparatively low, it is still reasonably good. The mean classification accuracy for six signal types considered in this work is 99.8%. Similarly, the SNR estimates obtained for the testing data set are also quite accurate as shown in Fig. 5 and the mean estimation error for SNR in the range of 0–30 dB is 1 dB. These results confirm that the proposed DNNs-based algorithm successfully enables joint modulation format/bit-rate classification and SNR estimation in frequency-selective fading channels with good accuracies.

From the above results, following main advantages of proposed technique over existing AMC and SNR estimation methods are evident. (i) The proposed algorithm demonstrates good accuracies under real-world propagation conditions where the signals are impaired by both frequency-selective fading and AWGN. On the other hand, the

Table 1: *Classification accuracies for various signal types.*

		Classified modulation format/bit-rate					
		250 Mbps NRZ-2ASK	500 Mbps NRZ-2ASK	250 Mbps RZ-QPSK	500 Mbps RZ-QPSK	1 Gbps NRZ-16QAM	2 Gbps NRZ-16QAM
Actual modulation format/bit-rate	250 Mbps NRZ-2ASK	100%	-	-	-	-	-
	500 Mbps NRZ-2ASK	-	100%	-	-	-	-
	250 Mbps RZ-QPSK	-	-	100%	-	-	-
	500 Mbps RZ-QPSK	-	0.52%	0.52%	98.95%	-	-
	1 Gbps NRZ-16QAM	-	-	-	-	100%	-
	2 Gbps NRZ-16QAM	-	-	-	-	-	100%

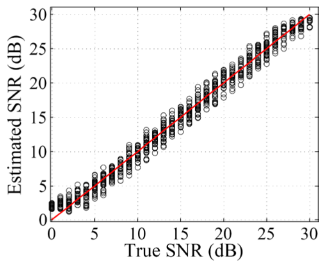

Fig. 5 *True vs. estimated SNRs employing the proposed algorithm.*

performances of most existing AMC and SNR estimation methods significantly deteriorate in multipath fading channels [1,3]. (ii) The proposed algorithm offers joint estimation of modulation format, bit-rate and SNR while the current methods focus on either AMC or SNR estimation and not joint determination of multiple parameters [1-3]. (iii) Unlike existing techniques which necessitate symbol-rate, synchronous sampling [1-3], the proposed algorithm uses low-speed, asynchronous sampling, thereby reducing implementation complexity substantially.

Conclusion: We demonstrated the use of DNNs in conjunction with ADTPs for joint modulation format/bit-rate classification and NDA SNR estimation in frequency-selective fading channels. The results show good classification accuracies for several commonly-used signal types under real-world channel conditions. Moreover, accurate SNR estimation over a wide range of 0–30 dB is validated. The proposed algorithm offers implementation simplicity and is thus attractive for cost-effective multiparameter estimation in cognitive radio networks.

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